Optimising agriculture for a changing climate: which farming practices confer stability of food production and farm income?

Thesis submitted for the degree of Doctor of Philosophy

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Declaration of Original Authorship

I declare that this research is my own original work and all citations from other sources have been properly and fully acknowledged.

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Thesis Abstract

Food stability, described by the IPCC as the continuous availability and access to food without disruption, is one of the four pillars of food security. Extreme events and climatic variability can disrupt stability and are expected to increase due to climate change. Improving the stability of yields and farm income is identified as an important area of research. However, there remains few quantitative assessments examining the factors affecting stability of agricultural systems, particularly at the farm level.

The main objectives of this thesis are to examine changes in the probability of adverse weather events across the UK in the 21st Century, as well as, examine the relative effect of climate variability, subsidies and farming practices on the stability of food production and farm income. The main aims are to provide knowledge on the impact of adverse weather on the stability of agriculture, now and in the future, and provide recommendations to improve stability in the context of a changing climate and more variable conditions.

I used crop-climate modelling to examine changes in the frequency, magnitude and spatial patterns of adverse weather conditions throughout the UK during 21st century. I then analysed empirical data, using multilevel modelling, to examine the effects of farming practices, subsidies and climate variability on the stability of food production and income.

Results demonstrate that climatic changes, in particular rainfall patterns, threaten agricultural production and the stability of agriculture. However, farming practices have a large effect on stability in comparison to climate. The three key aspects of farm management and policy identified to improve stability were: increasing agricultural diversity, increasing the efficiency of agrochemical use and agri-environmental management. These novel findings have important implications for adaptation and suggest that farmers, supported by policymakers, may have opportunities to improve stability in the face of more variable conditions.

Contents

Chapter 1 - General introduction

1 Background: The multiple pressures on the stability of agriculture

Food stability, described by the IPCC as the continuous availability and access to food without disruption, is one of the four pillars of food security, and extreme events associated with climate change can disrupt stability (Mbow et al., 2019). Production shocks that can arise from adverse weather events also often increase food price volatility, which is particularly detrimental to food security of the poorest consumers (Haile et al., 2017; Tadesse et al., 2014). Such volatility intensifies the challenge of ending world hunger and achieving food security by 2030, one of the UN Sustainable Development Goals (Griggs et al., 2013). With the global population expected to rise to 9 billion in 2050 (FAO, 2009), increasing the stability of food production and farmer livelihoods, under variable conditions, will help address the challenge of producing enough food today and in the future.

The stability of agricultural production and farmers' incomes are being confronted by a series of multiple pressures, including production risks (e.g., adverse weather and climatic change), economic volatility (e.g., food price spikes), and changing policy incentives, which are expected to become more intense over the coming decades.

Production risks, for instance flooding, droughts or pests and disease, represent some of the key risks to agriculture, which can have a severe impact on yields (Deryng et al., 2014; Powell and Reinhard, 2015; Reyer et al., 2013; Trnka et al., 2014). Extreme weather events, such as the European wide heatwave in 2003, can have a dramatic impact on production even in temperate regions such as the UK, and these currently rare high temperature events could become normal by the middle of the 21st Century (Knox et al., 2012; Met Office, 2019). Farm incomes are also subject to production risks, as well as, economic volatility and uncertainty in price of outputs and inputs (Komarek et al., 2020; OECD, 2009). Recent food price spikes have often followed climate extremes in major producing countries, for example, droughts and heatwaves in key production areas are thought to have contributed to rapid food price inflation for wheat observed in 2007/8 (Gilbert and Morgan, 2010; Piesse and Thirtle, 2009; Porter et al., 2014).

Many of the events which threaten agricultural production and livelihoods will be further affected by climate change. Extreme weather events, such as widespread heatwaves, heavy precipitation and prolonged droughts, are expected to become more frequent and/or intense across many regions worldwide (Powell and Reinhard, 2015; Seneviratne et al., 2012). Climate change is also expected to alter the severity and distribution of pests and disease, with many pests thriving under warmer temperatures and higher CO_2 (Lamichhane et al., 2015). These risks and uncertainties challenge farmers ability to maintain consistency in production and income from year to year, which can have a knock-on effect on the sustainability of farm businesses and food supply.

In addition to the impact of climatic, economic and resource pressures, farmers also face risks from changing policies (e.g., changes in regulation or policy incentives). Farmers across Europe have previously reported that institutional risk associated with policy uncertainty as a major concern (Komarek et al., 2020). Following the UK's exit from the European Union the next few years are a pivotal moment for agricultural policy in the UK with the phased withdrawal of direct payments and the introduction of the Environmental Land Management schemes. This represents a significant change for farmers in the UK which is likely to drive change in farming practices and land use and may lead to abandonment in some of the more marginal, less productive land areas (e.g. the uplands; Arnott et al. (2021)). Understanding how policy and farm management effects the stability of food production and farm income, and how farmers could adapt to these multiple increasing pressures is therefore an important area of research.

The stability of agriculture is essential for future food security, however it is also important adaptation to improve stability is not at the detriment of the natural environment. Agriculture affects, and is affected by, the availability and quality of natural resources including water and soils and biodiversity. Preserving the quality of the environment and provision of ecosystem services is therefore also of vital importance to ensure the sustainability of agroecological systems, environmental resources and nature into the future (Pretty, 2008).

2 The focus of this thesis and structure of the introduction

The primary focus of this thesis is to identify farming practices and adaptation options for agriculture, to improve the stability of food production and farm income in the context of a changing climate and more variable conditions. Examining yield variability and identifying strategies to increase stability of yields is recognised as an important area of research (Porter et al., 2014). Maintaining stable farm income is also considered a key issue faced by farmers and addressed by policy makers (OECD, 2009; Severini et al., 2016), to ensure sustainable farm businesses that can continue to produce food.

This thesis focuses on UK agriculture. The temperate climate in the UK is well suited for agriculture, with the sector occupying around 70% of the UK's total land area (Knox et al., 2012). The agri-food sector is also an important sector for the UK economy, accounting for 6.3% (~£120 billion) of national Gross Value Added in 2018, and employing around 4 million people (Department for Environment Food and Rural Affairs. et al., 2019). However, rising temperatures, changing rainfall patterns and increased frequency of extreme events, as well as economic, environmental and technological risks threaten the stability of UK agriculture (Knox et al., 2010).

In this thesis I initially use crop-climate modelling to quantify changes in the frequency, magnitude and spatial patterns of a range of adverse weather events throughout the UK during 21st century. This is important to provide an understanding of the adverse weather conditions which may pose a risk to UK wheat production in a changing climate. In addition, this analysis also provides an understanding of the localised spatial patterns of weather across the UK to inform the future modelling in this thesis. This first study focuses on wheat, the most widely grown cereal crop in the world (FAOSTAT, 2018; Lobell et al., 2012) and an important crop for the UK, with approximately 40% of the UK arable cropping area dedicated to wheat production (Defra, 2018).

In subsequent chapters I then use statistical models that combine data from the Farm Business Survey and Met Office climate data (which are both further described in Chapter 2) from England and Wales, between 2005 and 2017, to examine how farming practices and subsidies affect the stability of farm income and food production in a variable climate. In combination these studies provide knowledge and understanding of how adverse weather affects the stability of agriculture, now and in the future, and important adaptation options to improve the stability of food production and farm income, in the context of a changing climate and more variable conditions.

Within this introductory chapter I will begin by providing an overview of each of the important components: extreme weather events, climate variability and change, and the effects of farm management and policy on the stability of agricultural systems. Finally, I provide a summary of the research gaps that this research project seeks to address.

3 Effects of extreme weather, climate variability and change on agriculture

Variations in agricultural production from year to year is, among other factors, affected by variations in weather, and our changing climate is associated with an increase in climatic variability and extremes (IPCC, 2012; Kovats et al., 2014; Rahmstorf and Coumou, 2011). The last three decades (1983-2012) have been successively warmer and the warmest period in the Northern hemisphere in the last 1400 years (during which such assessment is possible) (IPCC, 2014). Since the 1950s there has also been an increase in extreme weather events across many regions, including warm temperature extremes and the number of heavy precipitation events (IPCC, 2014). Across the Northern hemisphere, and specifically in Europe there has been an increase in the number of hot temperature extremes; the probability distribution of temperatures has shifted to the right and become broader due to an increase in the number of hot anomalies (Hansen et al., 2012) as illustrated by the schematic diagram in figure 1. Changes in both the mean climate and its variability will affect the frequency of climate extremes, although the specific mechanisms behind changes in these extremes remains largely unknown (van der Wiel and Bintanja, 2021). Across Europe, projections show an increase in summer temperature variability and heatwaves (Fischer et al., 2012; Fischer and Schär, 2009). There is also a projected increase in interannual variability in precipitation, in temperate regions, which has implications for the occurrence of droughts and flooding (He and Li, 2019). As a result, changes in climatic variability and extremes, and their effects on agricultural systems, has received increasing attention in the past few years.

Extreme weather can make food production unstable and arguably poses a more immediate threat to agricultural productivity than gradual changes in mean climate; which allow greater time for farmers to adapt (Blanc and Reilly, 2017). Heat waves, flooding and droughts can severely reduce crop yields (Reyer et al., 2013; Deryng et al., 2014; Trnka et al., 2014; Powell and Reinhard, 2015) and impact livestock systems, influencing both the direct health of the animal, as well as, grassland productivity and the availability of feed (Olesen and Bindi, 2002; Kipling et al., 2016). For example, a widespread heatwave across Europe in 2003 had a dramatic impact on the agricultural sector; in the worst affected areas of Italy and France, livestock became stressed and key crops saw record reductions in yield, farms suffered economically as a result of production losses (Battisti and Naylor, 2009; IPCC, 2007). Extreme weather can also affect farm management and operations, for example very wet conditions during sowing or harvesting can restrict access to fields and the timing of operations (Arnell and Freeman, 2021; Trnka et al., 2014). Climatic changes and the impact of adverse weather conditions may also affect soil fertility and the prevalence of pests and disease, which will alter what farmers choose to grow or can grow successfully.

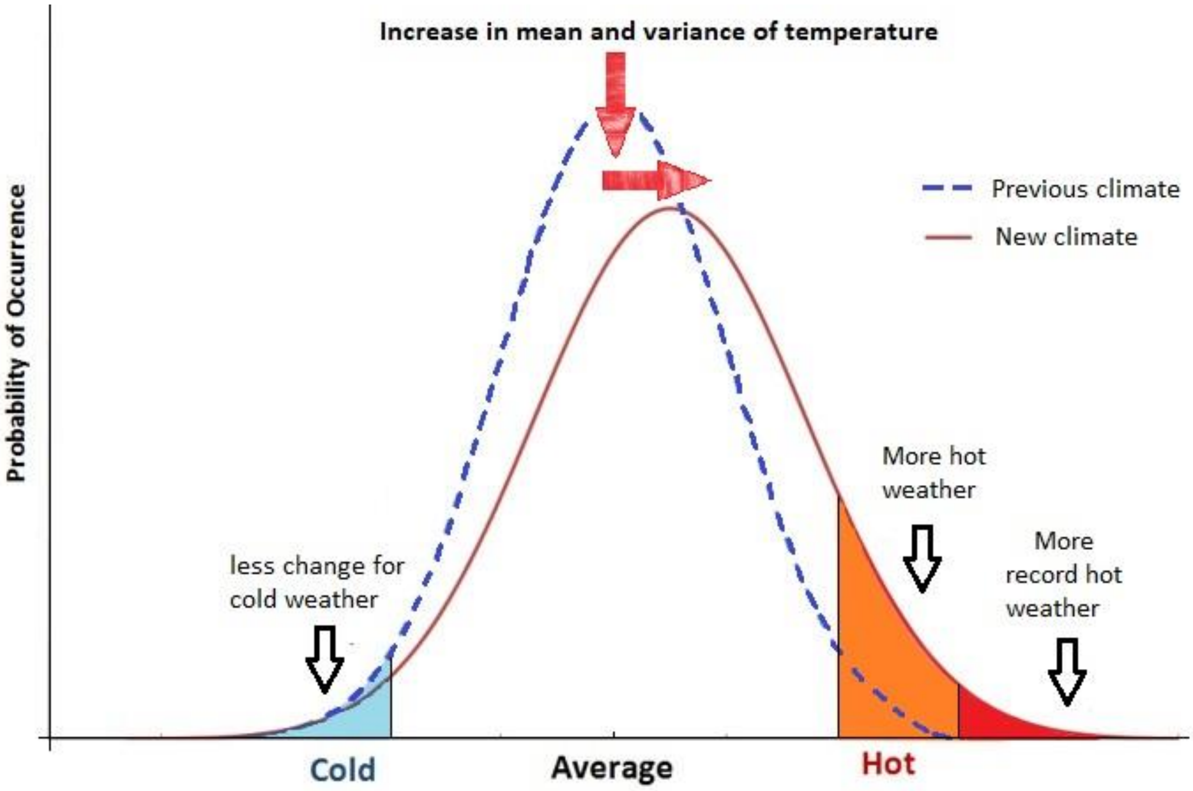

Figure 1 – Schematic showing the effect when both the mean and variance increase for a normal distribution of temperature. Source: adapted from Folland *et al.* (2001).

3.1 Extreme weather, climate variability and change in the UK

Climate change simulations predict an increase in both the frequency and intensity of extreme weather in Europe towards the end of the 21st Century. Climate projections show a marked increase in summer heatwaves and heavy precipitation events for Europe, however considerable variability is observed across regions and seasons (Kovats et al., 2015, Powell and Reinhard, 2015). In the UK, there is a trend towards wetter winters and drier summers, however, due to interannual climate variability, modelling indicates some individual seasons could go against this trend (Lowe et al., 2018).

The UK is well known for the variability of its weather, both spatially and changes in weather over time. The UK's climate has a high degree of spatial variation; precipitation in particular can exhibit large spatial variation, and temperatures can also vary considerably in different regions of the country (Kendon et al., 2020). Future climate projections, over the

21st century, show there are also seasonal and spatial variations across the country. In summer, for example, there is a north-south gradient, the south is expected to see larger reductions in precipitation, as well as greater warming (Lowe et al., 2018), which could reduce water availability for crops and increase heat stress in animals, subsequently reducing yields (e.g. Clarke et al., 2021; Fodor et al., 2018).

Research examining the effects of extreme weather and climate change on agricultural production is often performed at a global scale (e.g., Deryng et al., 2014; Iizumi and Ramankutty, 2016) or regional scale, which may use a small number of sites in the UK as part of larger scale assessment (e.g., Semenov et al. 2014; Trnka et al., 2014). Analysis at this broad scale can provide a tool to explore adaptation to climate variability and change for the global agriculture and food sectors. However, within UK at a local scale, weather conditions are likely to be wide ranging; for example Semenov, (2009) and Richter and Semenov, (2005) focused on the impacts of heat and drought stress in wheat across England and Wales, finding the probability of heat stress is higher in the south east, and drought stress will remain greater in the east of the UK throughout the 21st Century. Therefore, it is important to examine the effect of climate variability and change for the UK at a small spatial scale, in order to capture this spatial variability. There also remains a research gap to examine the effect of a wider range of extreme weather events at a small spatial scale on UK agriculture.

3.2 Definitions and indicators of extreme weather and climate variability

There are various ways in which extreme weather events and climatic variability have been defined in the literature considering agricultural systems and climatic change. These include by examining statistical extremes, interannual climatic variability, or specific "impact-related" weather conditions (or agroclimatic indicators) which have an adverse effect agricultural systems and food production.

An extreme weather event in meteorology is usually defined by the probability or frequency of occurrence; a climate variable exceeding a predefined percentile near the upper (or lower) ends of the observed probability function (e.g above 95th percentile; (Howarth and Brooks, 2017; IPCC, 2012). Such indicators can provide a broad understanding of how low-probability extreme events may change under future climate scenarios and their associated effects on agroecological systems, the environment, as well as society more generally.

Extreme weather events can also be described by specific "impact" events affecting agricultural systems or production; for example, cardinal temperatures above which crop development slows, or agricultural drought whereby reduced precipitation and/or increased evapotranspiration impinges on crop production (IPCC, 2012). These weather events are sometimes termed adverse weather conditions (Gobin, 2018; Trnka et al., 2015, 2014) or agroclimatic indicators (Rötter et al., 2018; Trnka et al., 2011, 2010), to distinguish from the meteorological definition.

An initial literature review covering experimental studies and crop-modelling research has identified a large range of agroclimatic indicators which define key thresholds affecting production for the main crops and livestock within the UK. A full list of the indicators is provided in the thesis appendix. The range of indicators identified in the literature recognises that adverse weather conditions can occur either over a few days during sensitive crop stages, particularly during flowering and early grain development, as well as longer-term stresses occurring throughout the growing season. Crops are sensitive to specific thresholds at key stages of their development, for example higher temperatures during the reproductive stage of development can impact pollen viability, fertilisation, and grain or fruit formation (e.g. U.S. Department of Agriculture (USDA), 2008). For example temperatures above 31°C can cause sterility and reduction in grain numbers for wheat (Alghabari et al., 2014; Porter and Gawith, 1999), whereas maize can tolerate higher temperatures up to 33°C during reproduction, which begin to reduce yields (Gabaldón-Leal et al., 2016; Rattalino Edreira and Otegui, 2012). Livestock can be particularly vulnerable to high temperatures and humidity during the warmer months. Heat stress can lead to increases respiration and decreased food intake, affecting reproduction and productivity in cattle (e.g. Key et al., 2014), sheep (e.g. Sejian et al., 2017), pigs (e.g. Cross et al., 2018) and poultry (e.g. Purswell et al., 2012). Temperature-Humidity Indices (THI) are a useful tool for classifying heatwaves and the severity of heat stress effecting livestock productivity, also considering the duration of exposure (e.g. Hahn et al. 2009; U.S. Department of Agriculture (USDA), 2008).

The thesis appendix provides a comprehensive summary of agroclimatic indicators, which can be used to quantify the impacts of adverse weather conditions on yields or other measures of farm performance. In addition, these indicators can be used to consider how the probability of experiencing adverse weather conditions may change under future climate scenarios, to identify the specific climatic risks facing crops and livestock.

I focused my review of agroclimatic indicators on the thresholds and subsequent yield impacts identified in experimental studies or modelling research which focus on individual crops or livestock, and therefore identify a clear physiological or biological mechanism causing the reduction in yields. Studies using these specific agroclimatic indicators may, as a result, detect stronger responses for individual crops or livestock. However, it is more difficult to generalise the effects of these agroclimatic indicators at the farm level, i.e., across crops or types of production. More recently, some broad agroclimatic indicators have been developed to assess the sensitivity of agricultural production, across a range of commodities (e.g. Trnka *et al.*, 2010; Arnell and Freeman, 2021) which help examine the effect of climate change on agricultural systems. These indicators can provide useful knowledge on how climatic conditions may change under future climate scenarios and help assess potential risks to agricultural systems and inform future adaptation strategies. These more generalised indicators provide proxies for agricultural impacts, rather than attempting to quantify the actual impacts on yields or output but as a result can be more flexible in their calculation. Broader agroclimatic indicators can, therefore, complement more specific crop or livestock modelling and provide an important contribution to assess the overall effect of climate change on agricultural production.

The effects of interannual climate variability on agriculture have also been examined using empirical data, by associating variability in climate to crop yield variability. Previous studies have examined the variation in temperature and precipitation over multiple periods, using measures of dispersion or spread such as standard deviation or relative measures including the coefficient of variation (e.g. Acheampong, Ozor and Owusu, 2014; Leng, 2017). Other studies have examined annual anomalies (deviations) in temperature or precipitation from the mean (over months or years), and their effect on mean yield or yield variability (e.g., Matiu et al. 2017, Ray et al. 2015, Reidsma et al. 2009). These studies highlight variations in climate (temperature, rainfall, and their interactions) are a dominant factor explaining crop yield variability.

4 Effects of farm management and policy on the stability of agriculture

To effectively guide adaptation to more variable conditions, it is important to understand the drivers of agricultural systems dynamics**,** i.e., changes over time in yields and profitability. A recent systematic review by Dardonville et al. (2020) identified that most quantitative assessments of agricultural systems dynamics focus on factors affecting crop yields, with fewer examining economic returns, and a very small number considering both. However, there remains few quantitative assessments examining these relationships, particularly at the farm level (Dardonville et al., 2020).

Agricultural diversity and level of intensification, of various types, are the factors most frequently examined for their effects on agricultural systems dynamics, highlighting their interest to scientists (Dardonville et al., 2020). More diverse agricultural systems, with a broader range of traits and functions, are associated with a range of benefits, such as improved soils and reducing the risk of crop failure, which could improve stability of farm performance in a changing climate (Degani et al., 2019; Lin, 2011). Greater use of agrochemicals, including fertiliser and pesticides, has been associated with higher yields, however the effect on the stability of yields is unclear (Dardonville et al., 2020). It is also important to consider that management strategies to enhance yield and its stability may not necessarily have complementary benefits for farm profitability, which requires expenditure to be considered. Therefore, a combined assessment examining how farm management and policy affect stability of both food production and farm income is important to ensure sustainability of farm businesses that can continue to produce food into the future.

A European study identified that farm characteristics (e.g. size, and farm type) can also have a large influence on yield and income variability, often larger than climatic conditions which can be more important at the regional level (Reidsma and Ewert, 2008). Larger farms may have a wider range of topography or soil conditions, and could also benefit financially from greater economies of scale, helping increase their capacity to cope with more variable weather and economic conditions (El Benni et al., 2012; Velandia et al., 2009). Farm or production type can also influence stability of farm performance, with livestock often considered a lower risk production output than crops (Chavas et al. 2019) and variability of income found to be higher on arable farms than dairy farms (Reidsma et al., 2009). Therefore, it is important to consider these farm characteristics when developing the modelling design to examine the factors affecting farm stability.

The Common Agricultural Policy (CAP) scheme supports farmers in the European Union (EU). Key aims of the CAP are to improve agricultural productivity, ensuring a stable supply of affordable food, as well as reducing income variation by reducing domestic price volatility (El Benni et al., 2012; European Commission, 2021; OECD, 2009). Agricultural subsidies are thought to stabilise farm incomes (Enjolras et al., 2014; OECD, 2009) as the variability in subsidies is potentially lower than other agricultural income (Severini et al., 2016). However, empirical research has found contrasting results, with direct payments found to increase the variability of agricultural income and crop yields across Europe (Enjolras et al., 2014; Reidsma et al., 2009), suggesting further quantitative studies are needed to evaluate these relationships.

The CAP provides payments to farmers across the EU via two main categories: Pillar 1 of the CAP provides direct (area-based) payments to farmers and market support. Prior research has primarily focused on the ability of direct payments to stabilise farm income.

Other government subsidy payments are directly tied to farm management and could therefore influence both yield and income. Pillar 2 pays farmers for implementing measures to benefit the environment or biodiversity, e.g., installing hedges, through voluntary agri-environment schemes (AES) or to support the wider rural economy (European Commission, 2005). Prior research has indicated options included in agri-environment schemes may help increase resilience of production to pests and disease (Menalled et al., 2003; Ottoy et al., 2018; Tschumi et al., 2016) and reduce the effects of extreme weather events (Bishop et al., 2016; Degani et al., 2019). However, the overall effectiveness of agri-environment schemes in delivering ecosystem service benefits remains poorly understood (Ottoy et al., 2018). The effect of participation in agri-environment schemes on the stability of agricultural production or income does not appear to have been examined previously.

The UK left the EU on 31 January 2020 and introduced a new Agriculture Bill providing the legislative framework for a new agricultural support scheme (Coe and Finlay, 2020). Under this new agricultural policy direct payments will be phased out and a series of new schemes will start, this includes the new Environmental Land Management scheme which focuses on the delivery of public goods and improving the health of our environment (DEFRA, 2018). These represent significant changes to agricultural policy in the UK. During the transitional period the government will review the effectiveness of past schemes and pilot new approaches (Downing and Coe, 2018). Evidence and analysis are needed to inform policymakers about the effect of prior schemes on the stability of food production and farm income and where additional support could be targeted.

5 Summary of knowledge gaps and thesis aims

This literature review has identified a number of research gaps and areas of focus for my research project, which are described in this section alongside the aims of the thesis. Here I summarise the subsequent chapters of this thesis and the main aims of each data chapter.

Firstly, in chapter 2, I introduce the farm and climate data used in the subsequent research chapters. I also critically evaluate the crop models which are used to identify adverse weather conditions which pose a risk to UK agriculture (chapter 3), as well as, the statistical methods used to examine factors affecting the stability of food production and farm income (Chapters 4 and 5).

Following this are the data chapters of the thesis. In Chapter 3 I focus on identifying adverse weather conditions which pose a risk to UK agriculture, by quantifying changes in the probability of adverse weather conditions throughout the 21st Century. Chapter 3 focuses on wheat production, an important crop for the UK, and seeks to provide a comprehensive analysis of projected changes in the frequency magnitude and spatial patterns of adverse weather conditions for UK wheat production. Previous research has often focused on single sites within the UK, however, adverse and extreme weather conditions are often localised, therefore I use 25 sites across the UK to examine differences in weather at a small spatial scale. Previous crop-modelling studies also often focus on specific weather conditions (e.g., heat and/or drought stress), not considering other adverse conditions which may threaten production, including waterlogging or lodging. I use both a process-based crop model (Sirius) and a range of agroclimatic indicators to provide a comprehensive analysis on a range of adverse weather conditions which may pose a risk to wheat production in a changing climate. In addition, this analysis also provides an understanding of the localised spatial patterns of weather across the UK to inform the model structure in Chapter 5, as well as enabling further discussion of the subsequent empirical analysis on farm stability (Chapters 4 and 5) in the context of future climate projections.

Having identified that weather conditions can have important impacts on wheat production, this research project then aims to identify farming practices and adaptation options to improve the stability of food production and farm income, in the context of a changing climate and more variable conditions. Following the literature review a number of specific research gaps have been identified, as well as important areas of focus for this analysis. Firstly, due to the often-localised nature of extreme weather and spatial variation of weather across the UK there is a need to link yields to weather data and assess the impact of these events for UK agriculture at a small spatial scale. Secondly, agricultural production and incomes can be affected by a range of factors, including climate variability, farm management and characteristics and policy, however, quantitative assessments of these factors on agricultural stability remain rare (Dardonville et al., 2020). Examining the importance of each of these factors will help to further understand these relationships and help guide adaptation at the farm level. Farm or production type has also been identified as an important factor influencing the stability of income and production, therefore I use separate multilevel models across a range of different farm types to provide targeted recommendations for farmers and policy makers. I focus on farm level adaptation to provide recommendations for farmers and policy makers which can improve the stability and therefore ultimately the sustainability of farm businesses and food production for consumers. The extensive information collected in the Farm Business Survey as well as the spatial extent and large numbers of farms included, combined with climatic data, provides an opportunity to examine the factors explaining these different aspects of farm performance.

Chapter 4 focuses on factors affecting the stability of farm income. I examine farms in England and Wales between 2007 and 2015, across a range of different farm types, using data from the Farm Business Survey. I use multilevel modelling to examine the effect of farming practices, farm characteristics and policy on the stability of farm income, whilst also considering how alternative measures of stability can affect these relationships. Chapter 4 does not explicitly consider the effects of climate on the stability of farm performance[1] as I wanted to focus initially on understanding the effects of farming practices, characteristics and policy on stability, whilst introducing and examining alternative measures of stability.

Chapter 5 then expands on chapter 4 to incorporate the effects of climate variability and additionally examine factors affecting the stability of total food production. I use multilevel modelling to examine the relative effects of farming practices, subsidies and climate variability on the stability of food production and farm income, at the farm level. I examine farms in England and Wales between 2005 and 2017, and link farms to climate data at a sub-regional scale. Examining the stability of farm income and food production is important for future food security, however empirical analysis on agricultural system dynamics remains rare, particularly at the farm level. Previous assessments of the factors affecting agricultural system dynamics have focused upon the stability of yields for individual crops. It is also important to look at stability of total food production at the farm level, across a range of commodities, as this allows us to examine the effects of farm level management decisions (e.g., diversifying production) on food production at the farm level. I consider the stability of food production from a consumer's perspective, by examining variability in calories produced at the farm level, which has not been explored previously. This therefore helps to understand the relative effects of climate and farm management on the stability of food available to the consumer. Loss of production following adverse weather conditions can also affect farm incomes, which could affect the ability of the farm business to sustain its operations from year to year. There are very few combined assessments of the factors affecting the stability of both food production and farm incomes, which will help effectively target adaption to improve the sustainability of farm businesses and food supply. This is, as far as I am aware, the first empirical study to examine the relative effects of farming

[1] While the effect of climate conditions are not quantified, the multilevel models incorporate random intercepts for each farm and county, which represent characteristics of variables not included in the model, including climatic conditions (refer to chapter 2 and chapter 4 methods).

practices, subsidies and climate variability on the stability of calories produced alongside farm incomes.

6 Thesis structure and chapter objectives

Chapter 1 – General introduction

- Summarise pressures on the stability of agriculture and related risks to food security
- Overview of the literature regarding the effects of extreme weather, climate variability and change on agriculture, including how to define and measure extreme weather and climate variability.
- Overview of existing literature examining the effects of farm management and policy on the stability of agriculture
- Describe key knowledge gaps surrounding adaptation to improve the stability of agriculture in the context of a changing climate and more variable conditions.
- Summarise research chapters and their objectives

Chapter 2 – Data and methodology

- Summarise and critique the climate and farm data used in the subsequent research chapters
- Critically evaluate the statistical methods used in the subsequent research chapters, including:
    - methods to examine the impacts of extreme weather, climate variability and climate change on agricultural outputs,
    - methods to measure agricultural systems dynamics (stability, vulnerability, resilience and robustness), and
    - methods for examining the factors affecting the stability of food production and farm income.

Chapter 3 – Adverse weather conditions for UK wheat production under climate change

- **Research question: Focusing on wheat production, how does the frequency, magnitude and spatial patterns of a range of adverse weather conditions change throughout the UK during 21st century?**

- This study aims to provide a comprehensive analysis of adverse weather conditions which may pose a risk to wheat production in a changing climate, throughout the UK in the 21st century.
- More broadly also to provide an understanding of the localised spatial patterns of weather across the UK and gain knowledge of projected climate trends for the UK.

Chapter 4 – Stability of farm income: The role of agricultural diversity and agri-environment scheme payments

- **Research question 1: What affect do farming practices and subsidies have on the stability of farm income across England and Wales?**
- **Research question 2: Do different measures affect the interpretation of stability and the relationships identified in the models?**
- This study aims to provide targeted recommendations for farmers and policy makers, by farm type, to improve the stability of farm income

Chapter 5 – Towards stability of food production and farm income in a variable climate

- **Research question 1: What is the relative effect of climate variability, subsidies and farming practices on the temporal stability of food production and farm income, in England and Wales?**
- This study aims to identify adaptation options, for farmers and policy makers, to improve the stability of food production and farm income, including where there may be trade-offs between improving these different aspects of farm performance.

Chapter 6 – General discussion

- Summarise research findings and their relevance within the existing literature.
- Discuss policy implications to improve the stability of agriculture.
- Discuss issues encountered during the research project
- Identify opportunities for future work.

References

Acheampong, E.N., Ozor, N., Owusu, E.S., 2014. Vulnerability assessment of Northern Ghana to climate variability. Clim. Change 126, 31–44. https://doi.org/10.1007/s10584-014-1195-z

Alghabari, F., Lukac, M., Jones, H.E., Gooding, M.J., 2014. Effect of Rht Alleles on the Tolerance of Wheat Grain Set to High Temperature and Drought Stress During Booting and Anthesis. J. Agron. Crop Sci. 200, 36–45. https://doi.org/10.1111/jac.12038

Arnell, N.W., Freeman, A., 2021. The effect of climate change on agro-climatic indicators in the UK. Clim. Change 165, 1–26. https://doi.org/10.1007/s10584-021-03054-8

Arnott, D., Chadwick, D.R., Wynne-Jones, S., Jones, D.L., 2021. Vulnerability of British farms to post-Brexit subsidy removal, and implications for intensification, extensification and land sparing. Land use policy 107, 104154. https://doi.org/10.1016/j.landusepol.2019.104154

Battisti, D.S., Naylor, R.L., 2009. Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. Science (80-.). 323, 240–244. https://doi.org/10.1126/science.1164363

Bishop, J., Jones, H.E., Lukac, M., Potts, S.G., 2016. Insect pollination reduces yield loss following heat stress in faba bean (Vicia faba L.). Agric. Ecosyst. Environ. 220, 89–96. https://doi.org/10.1016/j.agee.2015.12.007

Blanc, E., Reilly, J., 2017. Approaches to Assessing Climate Change Impacts on Agriculture: An Overview of the Debate. Rev. Environ. Econ. Policy 11, 247–257. https://doi.org/10.1093/reep/rex011

Clarke, D., Hess, T.M., Haro-Monteagudo, D., Semenov, M.A., Knox, J.W., 2021. Assessing future drought risks and wheat yield losses in England. Agric. For. Meteorol. 297. https://doi.org/10.1016/j.agrformet.2020.108248

Coe, S., Finlay, J., 2020. The Agriculture Bill 2019 - 2020.

Cross, A.J., Keel, B.N., Brown-Brandl, T.M., Cassady, J.P., Rohrer, G.A., 2018. Genome-wide association of changes in swine feeding behaviour due to heat stress. Genet. Sel. Evol. 50, 1–12. https://doi.org/10.1186/s12711-018-0382-1

Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184. https://doi.org/10.1016/j.agsy.2020.102913

Defra, 2018. Farming Statistics Provisional Crop Areas, Yields and Livestock Populations At June 2018 - United Kingdom.

Degani, E., Leigh, S.G., Barber, H.M., Jones, H.E., Lukac, M., Sutton, P., Potts, S.G., 2019. Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought. Agric. Ecosyst. Environ. 285, 106625. https://doi.org/10.1016/j.agee.2019.106625

Department for Environment Food and Rural Affairs., Department of Agriculture Environment and Rural Affairs (Northern Ireland)., Welsh Government Knowledge and Analytical Services., The Scottish Government Rural and Environment Science and Analytical Services., 2019. Agriculture in the United Kingdom 2019, National Statistics.

Deryng, D., Conway, D., Ramankutty, N., Price, J., Warren, R., 2014. Global crop yield response to extreme heat stress under multiple climate change futures. Environ. Res. Lett. 9. https://doi.org/10.1088/1748-9326/9/3/034011

El Benni, N., Finger, R., Mann, S., 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. Agric. Financ. Rev. 72, 301–324. https://doi.org/10.1108/00021461211277204

Enjolras, G., Capitanio, F., Aubert, M., Adinolfi, F., 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. New Medit 13, 31–40.

European Commission, 2021. Aims of the common agricultural policy [WWW Document]. URL https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/cap-glance_en (accessed 7.16.21).

European Commission, 2005. Agri-environment Measures Overview on General Principles, Types of Measures, and Application.

FAO, 2009. FAO's Director-general on how to feed the world in 2050. Popul. Dev. Rev. 35, 837–839. https://doi.org/10.1111/j.1728-4457.2009.00312.x

FAOSTAT, 2018. FAOSTAT Crops [WWW Document]. URL http://www.fao.org/faostat/en/#data/QC (accessed 11.22.18).

Fischer, E.M., Rajczak, J., Schär, C., 2012. Changes in European summer temperature variability revisited. Geophys. Res. Lett. 39, 1–8. https://doi.org/10.1029/2012GL052730

Fischer, E.M., Schär, C., 2009. Future changes in daily summer temperature variability: Driving processes and role for temperature extremes. Clim. Dyn. 33, 917–935. https://doi.org/10.1007/s00382-008-0473-8

Fodor, N., Foskolos, A., Topp, C.F.E., Moorby, J.M., Pásztor, L., Foyer, C.H., 2018. Spatially explicit estimation of heat stress-related impacts of climate change on the milk production of dairy cows in the United Kingdom. PLoS One 13, 1–18. https://doi.org/10.1371/journal.pone.0197076

Folland, C.K., Karl, T.R., Christy, J.R., Clarke, R.A., Gruza, G.V., Jouzel, J., Mann, M.E., Oerlemans, J., Salinger, M.J., Wang, S.-W., 2001. 2001: Observed climate variability and change, in: Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., Linden, P.J. van der, Dai, X., Maskell, K., Johnson, C.A. (Eds.), Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 99–181.

Gabaldón-Leal, C., Webber, H., Otegui, M.E., Slafer, G.A., Ordóñez, R.A., Gaiser, T., Lorite, I.J., Ruiz-Ramos, M., Ewert, F., 2016. Modelling the impact of heat stress on maize yield formation. F. Crop. Res. 198, 226–237. https://doi.org/10.1016/j.fcr.2016.08.013

Gilbert, C.L., Morgan, C.W., 2010. Food price volatility. Philos. Trans. R. Soc. B Biol. Sci. 365, 3023–3034. https://doi.org/10.1098/rstb.2010.0139

Gobin, A., 2018. Weather related risks in Belgian arable agriculture. Agric. Syst. 159, 225–236. https://doi.org/10.1016/j.agsy.2017.06.009

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M.C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., Noble, I., 2013. Sustainable development goals for people and planet. Nature 495, 305–307. https://doi.org/10.1038/495305a

Hahn, G.L., John, B.G., Terry, L.M., Roger, A.E., 2009. Chapter 5: Thermal Indices and Their Applications for Livestock Environments, in: Livestock Energetics and Thermal Environmental Management. ASABE, St. Joseph, Mich, pp. 113–130. https://doi.org/ASABE # 801M0309

Haile, M.G., Wossen, T., Tesfaye, K., von Braun, J., 2017. Impact of Climate Change, Weather Extremes, and Price Risk on Global Food Supply. Econ. Disasters Clim. Chang. 1, 55–75. https://doi.org/10.1007/s41885-017-0005-2

Hansen, J., Sato, M., Ruedy, R., 2012. Perception of climate change. Proc. Natl. Acad. Sci. 109, E2415–E2423. https://doi.org/10.1073/pnas.1205276109

He, C., Li, T., 2019. Does global warming amplify interannual climate variability? Clim. Dyn. 52, 2667–2684. https://doi.org/10.1007/s00382-018-4286-0

Howarth, C., Brooks, K., 2017. Decision-making and building resilience to nexus shocks locally: Exploring flooding and heatwaves in the UK. Sustainability 9. https://doi.org/10.3390/su9050838

Iizumi, T., Ramankutty, N., 2016. Changes in yield variability of major crops for 1981-2010 explained by climate change. Environ. Res. Lett. 11. https://doi.org/10.1088/1748-9326/11/3/034003

IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, Cambridge. https://doi.org/10.1017/CBO9781139177245

IPCC, 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK. https://doi.org/volume

Kendon, M., McCarthy, M., Jevrejeva, S., Matthews, A., Sparks, T., Garforth, J., 2020. State of the UK Climate 2019. Int. J. Climatol. 40, 1–69. https://doi.org/10.1002/joc.6726

Key, N., Sneeringer, S., Marquardt, D., 2014. Climate Change, Heat Stress, and U.S. Dairy Production. U.S. Department of Agriculture, Economic Research Service.

Kipling, R.P., Bannink, A., Bellocchi, G., Dalgaard, T., Fox, N.J., Hutchings, N.J., Kjeldsen, C., Lacetera, N., Sinabell, F., Topp, C.F.E., van Oijen, M., Virkajärvi, P., Scollan, N.D., 2016. Modeling European ruminant production systems: Facing the challenges of climate change. Agric. Syst. 147, 24–37. https://doi.org/10.1016/j.agsy.2016.05.007

Knox, J., Morris, J., Hess, T., 2010. Identifying Future Risks to UK Agricultural Crop Production. Outlook Agric. 39, 249–256. https://doi.org/10.5367/oa.2010.0016

Knox, J.W., Hurford, A., Hargreaves, L., Wall, E., 2012. Climate Change Risk Assessment for the Agriculture Sector.

Komarek, A.M., De Pinto, A., Smith, V.H., 2020. A review of types of risks in agriculture: What we know and what we need to know. Agric. Syst. 178, 102738. https://doi.org/10.1016/j.agsy.2019.102738

Kovats, R.S., Valentini, R., Bouwer, L.M., Georgopoulou, E., Jacob, D., Martin, E., Rounsevell, M., Soussana, J.-F., 2014. Europe, in: Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp. 1267–1326. https://doi.org/10.1017/CBO9781107415386.003

Lamichhane, J.R., Barzman, M., Booij, K., Boonekamp, P., Desneux, N., Huber, L., Kudsk, P., Langrell, S.R.H., Ratnadass, A., Ricci, P., Sarah, J.L., Messéan, A., 2015. Robust cropping systems to tackle pests under climate change. A review. Agron. Sustain. Dev. 35, 443–459. https://doi.org/10.1007/s13593-014-0275-9

Leng, G., 2017. Recent changes in county-level corn yield variability in the United States from observations and crop models. Sci. Total Environ. 607–608, 683–690. https://doi.org/10.1016/j.scitotenv.2017.07.017

Lin, B.B., 2011. Resilience in agriculture through crop diversification: Adaptive management for environmental change. Bioscience 61, 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Lobell, D.B., Sibley, A., Ivan Ortiz-Monasterio, J., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2, 186–189. https://doi.org/10.1038/nclimate1356

Lowe, J.A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard, T., Kaye, N., Kendon, E., Krijnen, J., Maisey, P., McDonald, R., McInnes, R., McSweeney, C., Mitchell, J.F., Murphy, J., Palmer, M., Roberts, C., Rostron, J., Sexton, D., Thornton, H., Tinker, J., Tucker, S., Yamazaki, K., Belcher, S., 2018. UKCP18 Science Overview report.

Matiu, M., Ankerst, D.P., Menzel, A., 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. PLoS One 12, 1–23. https://doi.org/10.1371/journal.pone.0178339

Mbow, C., Rosenzweig, C., Barioni, L.G., Benton, T.G., Herrero, M., Krishnapillai, M., Liwenga, E., Pradhan, P., Rivera-Ferre, M.G., Sapkota, T., Tubiello, F.N., Xu, Y., 2019. Food Security, in: Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. pp. 437–550.

Menalled, F.D., Costamagna, A.C., Marino, P.C., Landis, D.A., 2003. Temporal variation in the response of parasitoids to agricultural landscape structure. Agric. Ecosyst. Environ. 96, 29–35. https://doi.org/10.1016/S0167-8809(03)00018-5

Met Office, 2019. Severe or extreme weather in a changing climate, Briefing note.

OECD, 2009. Managing risk in agriculture: A holistic approach, Managing Risk in Agriculture: A Holistic Approach. https://doi.org/10.1787/9789264075313-en

Olesen, J.E., Bindi, M., 2002. Consequences of climate change for European agricultural productivity, land use and policy. Eur. J. Agron. 16, 239–262. https://doi.org/10.1016/S1161-0301(02)00004-7

Ottoy, S., Angileri, V., Gibert, C., Paracchini, M.L., Pointereau, P., Terres, J.M., Van Orshoven, J., Vranken, L., Dicks, L. V., 2018. Impacts of selected Ecological Focus Area options in European farmed landscapes on climate regulation and pollination services: A systematic map protocol. Environ. Evid. 7, 1–10. https://doi.org/10.1186/s13750-018-0122-6

Piesse, J., Thirtle, C., 2009. Three bubbles and a panic: An explanatory review of recent food commodity price events. Food Policy 34, 119–129. https://doi.org/10.1016/j.foodpol.2009.01.001

Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat a review. Eur. J. Agron. 10, 23–36.

Porter, J.R., Xie, L., Challinor, A.J., Cochrane, K., Howden, S.M., Iqbal, M.M., Lobell, D.B., Travasso, M.I., 2014. Food Security and Food Production Systems, in: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D. (Eds.), Climate Change 2014 Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 485–534. https://doi.org/10.1017/CBO9781107415379.012

Powell, J.P., Reinhard, S., 2015. Measuring the effects of extreme weather events on yields. Weather Clim. Extrem. 12, 69–79. https://doi.org/10.1016/j.wace.2016.02.003

Pretty, J., 2008. Agricultural sustainability: Concepts, principles and evidence. Philos. Trans. R. Soc. B Biol. Sci. 363, 447–465. https://doi.org/10.1098/rstb.2007.2163

Purswell, J.L., Dozier III, W.A., Olanrewaju, H.A., Davis, J.D., Xin, H., Gates, R.S., 2012. Effect of Temperature-Humidity Index on Live Performance in Broiler Chickens Grown From 49 To 63 Days of Age, in: 2012 IX International Livestock Environment Symposium (ILES IX). American Society of Agricultural and Biological Engineers, St. Joseph, MI, pp. 1–9. https://doi.org/10.13031/2013.41619

Rahmstorf, S., Coumou, D., 2011. Increase of extreme events in a warming world. Proc. Natl. Acad. Sci. 108, 17905–17909. https://doi.org/10.1073/pnas.1101766108

Rattalino Edreira, J.I., Otegui, M.E., 2012. Heat stress in temperate and tropical maize hybrids: Differences in crop growth, biomass partitioning and reserves use. F. Crop. Res. 130, 87–98. https://doi.org/10.1016/j.fcr.2012.02.009

Ray, D.K., Gerber, J.S., Macdonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6, 1–9. https://doi.org/10.1038/ncomms6989

Reidsma, P., Ewert, F., 2008. Regional Farm Diversity Can Reduce Vulnerability of Food Production to Climate Change. Ecol. Soc. 13, 38. https://doi.org/Artn 38

Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: A multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/s10113-008-0059-3

Reyer, C.P.O., Leuzinger, S., Rammig, A., Wolf, A., Bartholomeus, R.P., Bonfante, A., de Lorenzi, F., Dury, M., Gloning, P., Abou Jaoudé, R., Klein, T., Kuster, T.M., Martins, M., Niedrist, G., Riccardi, M., Wohlfahrt, G., de Angelis, P., de Dato, G., François, L., Menzel, A., Pereira, M., 2013. A plant's perspective of extremes: Terrestrial plant responses to changing climatic variability. Glob. Chang. Biol. 19, 75–89. https://doi.org/10.1111/gcb.12023

Richter, G.M., Semenov, M.A., 2005. Modelling impacts of climate change on wheat yields in England and Wales: assessing drought risks. Agric. Syst. 84, 77–97. https://doi.org/10.1016/j.agsy.2004.06.011

Rötter, R.P., Appiah, M., Fichtler, E., Kersebaum, K.C., Trnka, M., Hoffmann, M.P., 2018. Linking modelling and experimentation to better capture crop impacts of agroclimatic extremes—A review. F. Crop. Res. 221, 142–156. https://doi.org/10.1016/j.fcr.2018.02.023

Sejian, V., Bhatta, R., Gaughan, J., Malik, P.K., Naqvi, S.M.K.K., Lal, R., 2017. Adapting sheep production to climate change, Sheep Production Adapting to Climate Change. https://doi.org/10.1007/978-981-10-4714-5_1

Semenov, M.A., 2009. Impacts of climate change on wheat in England and Wales. J. R. Soc. Interface 6, 343–350. https://doi.org/10.1098/rsif.2008.0285

Semenov, M.A., Stratonovitch, P., Alghabari, F., Gooding, M.J., 2014. Adapting wheat in Europe for climate change. J. Cereal Sci. 59, 245–256. https://doi.org/10.1016/j.jcs.2014.01.006

Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., Rusticucci, M., Semenov, V., Alexander, L. V., Allen, S., Benito, G., Cavazos, T., Clague, J., Conway, D., Della-Marta, P.M., Gerber, M., Gong, S., Goswami, B.N., Hemer, M., Huggel, C., van den Hurk, B., Kharin, V. V., Kitoh, A., Tank, A.M.G.K., Li, G., Mason, S., McGuire, W., van Oldenborgh, G.J., Orlowsky, B., Smith, S., Thiaw, W., Velegrakis, A., Yiou, P., Zhang, T., Zhou, T., Zwiers, F.W., 2012. Changes in Climate Extremes and their Impacts on the Natural Physical Environment, in: Field, C.B., Barros, V., Stocker, T.F., Dahe, Q. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, pp. 109–230. https://doi.org/10.1017/CBO9781139177245.006

Severini, S., Tantari, A., Di Tommaso, G., 2016. Do CAP direct payments stabilise farm income? Empirical evidences from a constant sample of Italian farms. Agric. Food Econ. 4. https://doi.org/10.1186/s40100-016-0050-0

Tadesse, G., Algieri, B., Kalkuhl, M., von Braun, J., 2014. Drivers and triggers of international food price spikes and volatility. Food Policy 47, 117–128. https://doi.org/10.1016/j.foodpol.2013.08.014

Trnka, M., Eitzinger, J., Dubrovský, M., Semerádová, D., Štěpánek, P., Hlavinka, P., Balek, J., Skalák, P., Farda, A., Formayer, H., Žalud, Z., Change, C., Paper, A., 2010. Is rainfed crop production in central Europe at risk? Using a regional climate model to produce high resolution agroclimatic information for decision makers. J. Agric. Sci. 148, 639–

656. https://doi.org/10.1017/S0021859610000638

Trnka, M., Eitzinger, J., Semerádová, D., Hlavinka, P., Balek, J., Dubrovský, M., Kubu, G., Štěpánek, P., Thaler, S., Možný, M., Žalud, Z., 2011. Expected changes in agroclimatic conditions in Central Europe. Clim. Change 108, 261–289. https://doi.org/10.1007/s10584-011-0025-9

Trnka, M., Hlavinka, P., Semenov, M.A., 2015. Adaptation options for wheat in Europe will be limited by increased adverse weather events under climate change. J. R. Soc. Interface 12, 20150721. https://doi.org/10.1098/rsif.2015.0721

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4, 637–643. https://doi.org/10.1038/nclimate2242

Tschumi, M., Albrecht, M., Bärtschi, C., Collatz, J., Entling, M.H., Jacot, K., 2016. Perennial, species-rich wildflower strips enhance pest control and crop yield. Agric. Ecosyst. Environ. 220, 97–103. https://doi.org/10.1016/j.agee.2016.01.001

U.S. Department of Agriculture (USDA), 2008. The Effects of Climate Change on Agriculture , Land Resources , Water Resources , and Biodiversity in the United States, Synthesis and Assessment Product 4.3 Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research.

van der Wiel, K., Bintanja, R., 2021. Contribution of climatic changes in mean and variability to monthly temperature and precipitation extremes. Commun. Earth Environ. 2, 1–11. https://doi.org/10.1038/s43247-020-00077-4

Velandia, M., Rejesus, R.M., Knight, T.O., Sherrick, B.J., 2009. Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales. J. Agric. Appl. Econ. 41, 107–123. https://doi.org/10.1017/s1074070800002583

Chapter 2 - Data and Methodology

This data and methodology chapter provides an overview and justification of the data and methods used in this thesis and their limitations. In this thesis I combine several datasets and use a number of models to answer the research questions developed in the introduction (summarised in Table 1). Within this data and methodology chapter I firstly introduce the historical climate data (used in chapters 3 and 5) as well as the Farm Business Survey data (used in chapters 4 and 5). Secondly, in this chapter, I critically evaluate the methods used to examine the key aims of this thesis; discussing the crop models used in chapter 3, the alternative methods for measuring stability and agricultural systems dynamics (for chapters 4 and 5), and finally by discussing statistical methods for examining factors affecting the stability of food production and farm income. Specific details on the data and methods relevant to each study (including time periods examined, generation of the future climate projections, calculation of the key variables, and model specifications) are provided within each subsequent data chapter (3, 4 and 5).

Table 1 – Summary of the research questions, key data sources and models used in the thesis

Research Question(s)	Key datasets	Models used	Chapter
1) Focusing on wheat production, how does the frequency, magnitude and spatial patterns of a range of adverse weather conditions change throughout the UK during 21st century?	1) Met Office climate station data (used to generate climate projections, agri-climatic indicators and simulate wheat yields)	2 crop models (Sirius and AgriClim)	3
1) What affect do farming practices and subsidies have on the stability of farm income across England and Wales? 2) Do different measures affect the interpretation of stability and the relationships identified in the models?	1) Farm Business Survey data	Multilevel models	4
1) What is the relative effect of climate variability, subsidies and farming practices on the temporal stability of food production and farm income, in England and Wales?	1) Farm Business Survey data 2) HadUK-grid Met Office climate data	Multilevel models	5

1. Data

1.1 Climate data

I use two different sets of climate data in this thesis. In my first study (chapter 3) I use daily observed weather data from 25 Met Office meteorological stations to examine adverse weather conditions which may pose a risk to wheat production in a changing climate, throughout the UK in the 21st century. Site specific climate data is well suited for use in crop modelling studies, which can simulate yields or the probability of weather events occurring at specific locations, using historical data and under future climate projections (e.g., Semenov and Shewry (2011; Senapati et al. (2019a)). Site specific results can then be interpolated across larger growing areas. In chapter 3, I do so to examine spatial variation in adverse weather conditions for wheat across the UK. In my final data chapter (chapter 5), which links climatic data to the Farm Business Survey data, I use the HadUK-grid 5km gridded climate dataset from the Met Office (Hollis et al., 2019). HadUK-grid is a new set of gridded climate data variables derived from the UK meteorological station data, that has been interpolated to a regular grid with improved consistency of station data and after having been subject to a rigorous quality control analysis. I use HadUK-grid climate data in chapter 5 to provide an accurate and robust estimate of the weather experienced by each farm, using county locations and averages. The following sections (1.1.1 and 1.1.2) provide an overview of the climate data used, including how I considered the accuracy of the data and any limitations.

1.1.1 Met Office climate station data

To address the first aim of this thesis; provide a comprehensive analysis of adverse weather conditions which may pose a risk to wheat production in a changing climate, throughout the UK in the 21st century, I use historical climate data obtained from the Met Office station network (Met Office, 2019). Initially data was obtained for 85 climate stations across the UK stations within the Met Office network (Figure 1), spanning the period 1981-2012. The weather data includes daily records for maximum and minimum air temperature, precipitation and sunshine hours (or radiation) and the calculation of each of these variables is provided in Table 2. Monthly averages from weather station records are commonly used for long term climate analysis, however averages are not sufficient for analysing extreme weather events such as changes in intense rainfall and heat waves (Menne et al., 2012). In Chapter 3, I examine a range of adverse weather conditions, including heat and drought stress during the reproductive period, therefore daily weather data is necessary to calculate the phenological development of wheat and the effect of adverse weather conditions coinciding with sensitive stages.

To examine changes in adverse weather conditions at a small spatial scale across the UK, throughout the 21st Century, I chose 25 weather stations to examine in Chapter 3. These

25 sites (shown in Figure 1) provided a broad coverage of the UK, and in particular across the wheat growing area. These stations also reported <10% missing values in total and where missing values did exist, the consecutive daily missing values present were for 5 days or less.

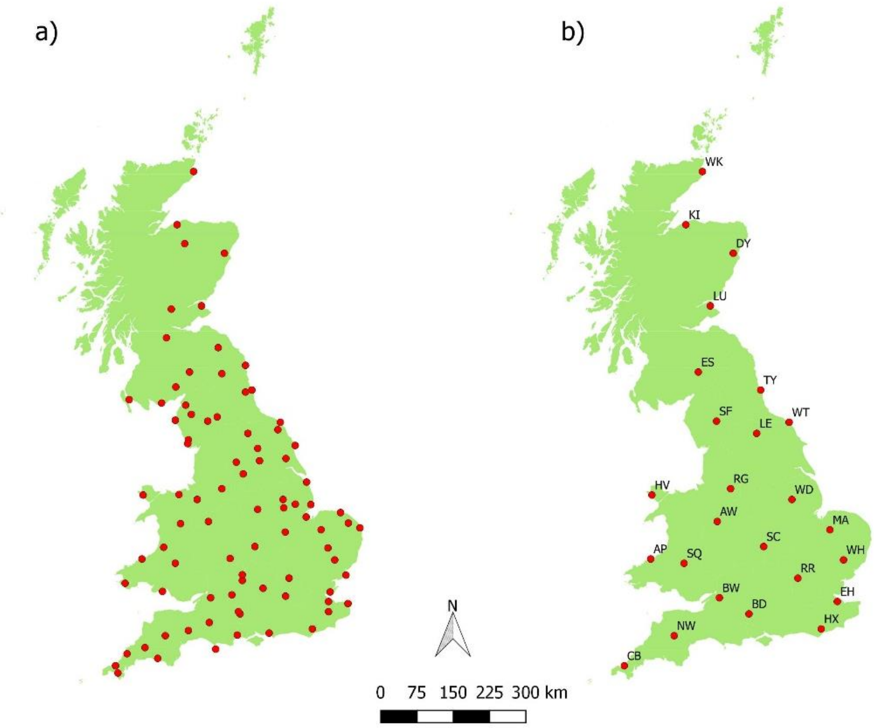

Figure 1 - Geographical location of a) all 85 Met Office weather stations and b) final 25 Met Office weather stations used in Chapter 3.

Table 2 - Description of climate variables included in the Met Office climate data

Climate variable	**Abbreviation**	**Description**	**Unit**
Maximum air temperature	Tmax	Maximum air temperature measured between 0900 GMT on day D and 0900 GMT on day D+1	Celsius (°C)
Minimum air temperature	Tmin	Minimum air temperature measured between 0900 GMT on day D-1 and 0900 GMT on day D	Celsius (°C)
Precipitation	Rain	Total precipitation amount measured between 0900 GMT on day D and 0900 on day D+1	Millimetres (mm)
Sunshine hours (or radiation)	SUN (or RAD)	Hours of sunshine (h) or Radiation (J/m2 or MJ/m2 or J/cm2) per day	

The Met Office climate data represents raw data obtained directly from the weather station recorders, therefore, to ensure the accuracy of this data I performed a range of quality control procedures (from Durre et al., 2010 and Feng et al., 2004) to identify and remove erroneous values. I use the climate station data to analyse and identify extreme or adverse weather events (Chapter 3); therefore, the primary aim of the quality control procedures were to identify the largest errors in daily values, principally those which could impact the analysis of extreme temperature and rainfall events. This process involves identifying as many errors as possible, whilst reducing the probability of considering valid weather observations as errors (i.e. false positives; Durre et al., 2010). Cleaning the climate station data involves a number of stages which have been outlined below. The first stage involves examining for any obvious inconsistencies in the dataset, comprising the following checks: firstly, by comparing the weather observations against UK climate records as published by the Met Office (2017), referred to as extreme value inconsistencies. The UK climate records as of 2018 are summarised in Appendix A. Secondly, examining the logical or physical relationships between the observations to identify internal inconsistencies, for instance the maximum temperature cannot be below the minimum temperature for any given day. Thirdly, investigating any repetition or duplication of zero values in the dataset, since zeros may be used incorrectly as a missing value code in climate data (Durre et al., 2010). Finally, checking for any records which represent a duplicate of the records at another weather station on the same day. The next stage involves examining for statistical outliers in the weather data, by identifying those observations which appear inconsistent with the set of weather data and therefore may represent an error (Barnett and Lewis, 1994). I standardised the temperature data (centred around zero, with a standard deviation of 1) using *Z*-scores to identify observations which lie more than 4 standard deviations from the mean (of each station and month across the duration of the dataset) and appear inconsistent with temperatures at neighbouring stations on that day. A summary of the conditions for identifying errors in the Met Office climate station data are provided in Appendix B. The observations which are considered obvious inconsistencies or statistical outliers were subsequently recoded as missing values within the data set. Values removed from the final dataset used in Chapter 3 represented less than 0.1% of the dataset. The number of erroneous values removed represent a very small proportion of the dataset, and therefore their inclusion may not have significantly affected the results. However, it is not possible to know in advance the number of erroneous values which will be identified through the quality control procedures, which aim to provide a more robust dataset for analysis.

Further details on the climate data, including periods examined, the calculation of adverse weather indices and future climate projections are provided in Chapter 3.

1.1.2 HadUK-grid Met Office climate data

In this thesis I also aim to identify farming practices and adaptation options to improve the stability of food production and farm income, in the context of a changing climate and more variable conditions. In Chapter 5 I link the Farm Business survey (FBS) data, from England and Wales, to the Had-UK grid climate data at a sub-regional scale, in order to examine the relative effect of climate variability alongside farming practices, farm characteristics and policy on the stability of food production and farm income.

The Had-UK grid dataset is based upon historical weather observations from Met Office climate stations, which is interpolated into a regular grid across the UK (Hollis et al., 2019). Daily climate variables, including maximum and minimum temperature and precipitation (measured using the same criteria described in Table 2) are available from 1960 for temperature and 1891 for precipitation. Quality control procedures (including range checks, internal consistency checks and near-neighbour checks), which correct or remove erroneous values, have been performed by the Met Office on the station data used to produce the grids (Hollis et al., 2019). In addition all the daily grids have been checked to ensure no erroneous station data was used, as described in Perry et al. (2009). These gridded climate observations provide consistent and reliable climate estimates, without missing values across the entire UK area. Had-UK grid gridded climate observations are beneficial in that regional values can be created for any arbitrary area (e.g., counties in our analysis) with accuracy and consistency, enabling data to be combined with other spatial datasets. I link the climate data to farm data to investigate the relationships between weather and farm stability.

To provide an estimate of the weather at each farm I calculate the daily weather variables for each county or unitary authority (the finest spatial resolution available for farm locations in the farm data, see section 1.2) using the average of each 5km grid square within each county boundary. Figure 2 shows the county and unitary authority boundaries, which represent the spatial characteristics (farm locations) used in the Farm Business Survey, overlaid with the 5km HadUK-grid 5km gridded cells used to calculate the daily weather observations for each county. The Farm Business Survey is discussed in the following section.

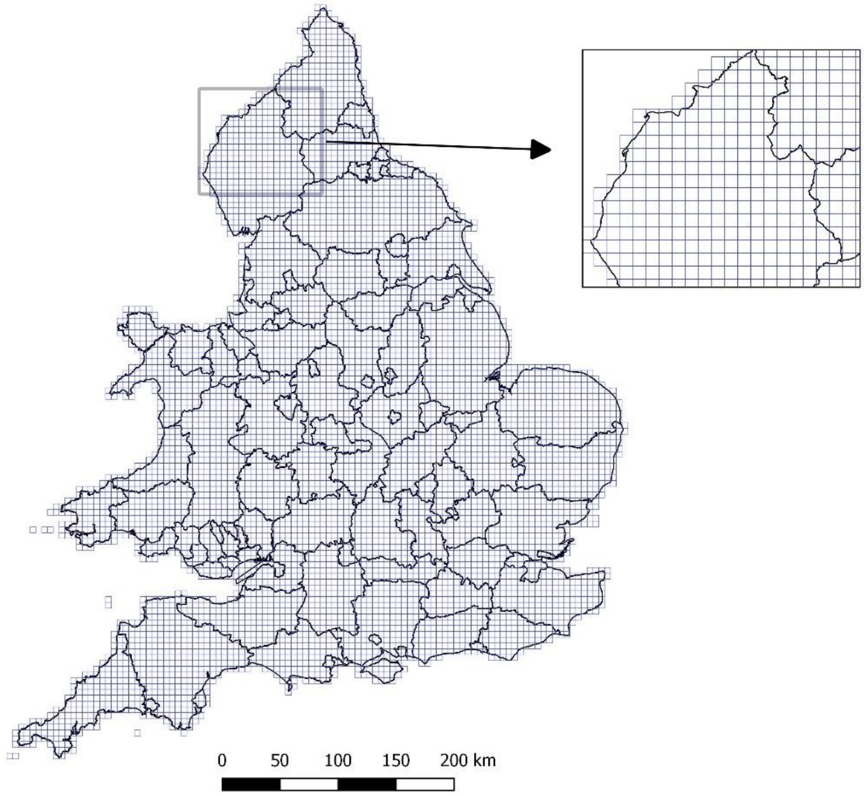

Figure 2 – Map of England and Wales showing county (or unitary authority boundaries) in the Farm Business survey data, overlaid on the 5km British National Grid; used in the HadUK-grid dataset and to calculate the weather for each county.

1.2 Farm Business Survey data

I use data from the Farm Business Survey (FBS) (Defra, 2020) to examine how a range of factors, including farming practices and subsidies, are associated with stability of farm income (Chapter 4) and food production (combined assessment in Chapter 5). The extensive information collected in the Farm Business Survey as well as the spatial extent and large numbers of farms included, combined with climatic data, provides an opportunity to examine the factors explaining these different aspects of farm performance.

The Farm Business Survey is an annual survey conducted in England and Wales, collecting business information for approximately 2,300 farms each year. The FBS provides information on the physical and economic performance of the farm business, including farm characteristics, crop yields, livestock production, income, costs and subsidies. The FBS data is available annually from 1982. In this project I examine data between 2005 and 2017 as the county boundaries used to spatially classify the farms remain consistent in the FBS data throughout this period. Furthermore, the FBS variables which are examined as part of this thesis, including farm business income, are defined and calculated using a consistent method since 2005.

The coverage of the FBS is restricted to farms which meet a minimum size criteria[1]. Small farms excluded from the survey only account for approximately 4% of agricultural production in England and Wales (Rural Business Research, 2020). The sample of farms is stratified across 14 farm types and 7 regions to provide a uniform sample across each stratum. Therefore, the Farm Business Survey provides a representative sample in terms of farm type, farm size and regional location across England and Wales. Around 93% of the panel of farms is retained annually, the remaining 7% leaving as a result of natural turnover, with replacements chosen at random retaining uniformity within each stratum (Department for Environment Food and Rural Affairs, 2016). The FBS therefore represents an unbalanced panel of farms over multiple years of farms across England and Wales.

To check the accuracy and quality of the FBS data several cleaning procedures were performed, to check for erroneous values which may have been imputed or calculated incorrectly in the survey. I performed statistical and consistency checks on the data, including inspecting significant outliers in each of the variables using *Z*-scores (>4) and visual inspection using scatterplots, as well as inspecting large changes in farm business income or utilised agricultural area from year to year. In addition, I recalculated the derived variables, including farm business income and yield from the underlying variables in the data to ensure their accuracy and that there were no internal inconsistencies in the data. Less than 1% of total observations, which were considered to be erroneous, were removed from the dataset as part of these checks.

For spatial analysis it was not possible to obtain a gridded or precise location of each farm, however the FBS data does include the Region (North/East/West England or Wales) and County, Metropolitan County or Unitary Authority in which each farm is located. The County, Metropolitan County or Unitary Authority areas generally correspond with the European Commission NUTS level 3 (European Commission, 2020) classification for England and Unitary Authority areas for Wales. Figure 2 shows the county and unitary authority boundaries which are used to spatially classify farms in the FBS data. In chapter 5, this geographical information is used to estimate the weather at each farm and link the

[1] The FBS population includes farms which meet a minimum size criteria, as follows: From 2010/11 >€25,000 of standard output (“SO”), 2004/05 to 2009/10 >0.5 standard labour requirements (“SLR” – half a full time equivalent) or negligible economic activity, and 2003/04 and earlier >8 Economic size units (ESUs) which measure the economic size of the farm based on the gross margin (refer to Defra, (2016) for more information).

climate data to FBS data, and subsequently farm stability. A more precise location of the farm would enable the weather and farm data to be linked at a smaller spatial scale, which may improve the estimation of weather at the farm, particularly in large counties or those with greater topographical variation. However, in previous research the effects of climate on the variability of income and yields have been linked at a regional scale across Europe (with 4 regions in England and Wales; Reidsma et al. (2009)), therefore using counties and unitary authorities in this thesis considers these relationships at a much smaller spatial scale than examined previously.

Further details on the farm types considered in each of the studies, as well as the calculation of dependent variables (stability of income and food production) and independent variables (farming practices, characteristics and subsidies) examined in the FBS data are provided in Chapters 4 and 5.

2 Methodology

In this section I discuss the methods used in each study in this thesis. Firstly, I discuss the crop models used in chapter 3, to examine changes in adverse weather conditions for UK wheat production, under baseline and future climate scenarios. Secondly, I discuss the alternative methods for measuring agricultural systems dynamics (i.e., changes over time), to examine the ability of farms to maintain performance in a non-stable environment, in order to identify adaptation options to improve farm stability. Finally, I evaluate the statistical methods, which allow the use of an unbalanced panel of farm data, to examine factors affecting the stability farm income and food production (chapters 4 and 5), including combining with climate data to examine the effect of climate variability (chapter 5).

2.1 Crop models and statistical models to assess climate change impacts crop production

There is a growing understanding that a range of methods are needed to fully assess the impacts of climate on agricultural yields and across global, regional and local scales (e.g., Lobell and Asseng, 2017). Crop modelling enable us to simulate relationships found in experiments, e.g. heat stress responses, interactions between crop management and weather, and explore the effects of future climate scenarios. The sensitivity of food production to extreme weather, climatic variability and climate change are usually assessed using physiological process-based crop models or statistical models. In this section I briefly overview these different approaches and explain my choice of methods for chapter 3.

Process-based crop models of varying complexity have been developed to simulate crop development, growth, yield, water and nutrient uptake at the site scale. For wheat, these include Sirius (Jamieson et al., 1998) and AFRCWHEAT2 (Porter, 1993). Process-based crop models use data and assumptions on soils (including available water holding capacity) and management (nitrogen applications, irrigation and sowing date) to model plant growth and phenological development and simulate yields using historical and projected weather. Therefore, these models provide a clear physiological mechanism for linking climate to yields, but they can be constrained due to the availability of data (Roberts et al., 2017). Process-based crop models have been used to model the effects of adverse weather under climate change by considering differences in the simulated yields using historical and projected weather data (Roberts et al., 2017), including the effect of heat, drought and water stress in wheat (Senapati et al., 2019a, 2019b; Stratonovitch and Semenov, 2015).

Agroclimatic indicators can also be used to examine changes in adverse weather conditions under baseline and future climates (e.g., Arnell and Freeman, 2021; Trnka et al., 2014, 2011). Agroclimatic indicators can also often consider adverse weather conditions not fully addressed by crop models e.g., waterlogging during sowing or harvest (Arnell and Freeman, 2021; Trnka et al., 2010). Methods used to calculate agroclimatic indicators do not model yields directly but can examine changes in the probability of occurrence or magnitude of a wide range of adverse weather conditions to complement crop models for an overall assessment of production conditions. Agroclimatic indicators are commonly based on crop specific thresholds and use simple thermal time models to calculate the timing of sensitive stages which may coincide with adverse weather conditions e.g., high temperature stress during anthesis for wheat (Trnka et al. (2014)).

In Chapter 3, I used a process-based crop model (Sirius) and the AgriClim model (which calculates the probability of a range of agroclimatic indicators), to provide a comprehensive analysis of adverse weather conditions which may pose a risk to wheat production in a changing climate, throughout the UK in the 21st century. Further details on the crop models used, including parameterisation, and the calculation of adverse weather indices are provided in Chapter 3.

Chapter 3 does not consider adaptation. To effectively target adaptation to climatic variability and change, it is necessary to understand the importance of climate alongside other factors which can affect the stability of agriculture, including farm management and policy, and assess their relative importance, as addressed in chapters 4 and 5. Section 2.2 discusses the alternative methods for measuring agricultural systems dynamics, i.e., changes over time, including farm stability. Section 2.3 then evaluates the statistical methods used to examine the effects of climate variability, in combination with farming practices, characteristics and government policy on the stability of agriculture.

2.2 Measuring agricultural system dynamics (stability, vulnerability, resilience and robustness)

Agriculture is exposed to unpredictable conditions, i.e., environmental or economic shocks or perturbations which often cannot be anticipated, therefore examining the ability of agriculture to maintain performance in a non-stable environment is an important area of research. In recent decades, different concepts of agricultural systems dynamics (i.e. changes over time) have been developed from different disciplines; *stability, robustness*, *vulnerability* and *resilience*. Literature may call for agricultural systems to be more *stable* (Mishra and Sandretto, 2002; Pacín and Oesterheld, 2014), more *robust* (ten Napel et al., 2011; Urruty et al., 2017), more *resilient* (Chavas and Di Falco, 2017) or less *vulnerable* (Reidsma and Ewert, 2008). While these concepts are related, all focus on the ability to maintain or recover functionalities under variable conditions (Dardonville et al., 2020; Urruty et al., 2016), there are differences in the definition and measurement of each concept. Table 3 defines each concept and describes how these have been measured in previous studies. A visual depiction of each concept is also shown in Figure 3. Stability is concerned with constancy of a given attribute over time or across space; the less it fluctuates the more stable it is (Holling, 1973; Urruty et al., 2016). Robustness can be considered to take this definition of stability further and consider the ability to maintain desired outputs following specific shocks or perturbations (Urruty et al., 2016). Vulnerability is concerned with the state of fragility and potential impacts of shocks, but is also a broader concept which encompasses the biological and social factors of agricultural systems (Urruty et al., 2016). Resilience has been defined by various literature (e.g. Holling, 1973, The Resilience Alliance, 2010, Folke, 2016, OECD, 2020) and this definition has also developed over time, however all recent definitions focus the ability of a system to absorb disturbances, adapt and transform. Resilience is notoriously difficult to examine empirically, at least in a way which examines all aspects and the full concept of resilience (Darnhofer, 2021). I chose to focus on the concept of stability for this thesis; seeking to quantify the ability of agricultural systems to cope with changeable conditions and maintain stability in output over time. Quantifiable measures of stability (or inversely variability) have been used in various agricultural studies and using different statistical methods (Urruty et al., 2016) which appear well suited and practical to calculate using the unbalanced panel of farms in the Farm Business Survey. The other concepts for measuring agricultural systems dynamics (robustness, vulnerability and resilience) focus on responses to specific perturbations and would involve tracking individual farms and their responses over time, this approach would be challenging with an unbalanced panel dataset and would not make full use of all datapoints available. Therefore, the concept of stability appears most appropriate and practical to use in this thesis.

This project seeks to identify farming practices and adaptation options for agriculture which confer greater stability of food production and farm income, in the context of a changing climate and more variable conditions. Stability of agricultural production or income is often measured by examining variability; high stability is associated with low variability in yield or income. There are a number of quantitative methods for measuring variability, including temporal measures of variability, standard deviation and coefficient of variation (e.g., Batisani, 2012, Döring and Reckling, 2018), or annual deviations from the mean (anomalies; e.g., Reidsma *et al.* 2009). These measures are commonly used, robust and meaningful measures of variability, which have been used across a range of disciplines, as well as to measure agricultural system dynamics. It is important, however, to recognise these alternative methods for measuring stability in agricultural systems may provide different results and therefore affect the interpretation of stability. In chapter 4, I examine factors affecting the stability of farm income and compare these relationships using 4 different measures of stability (measures and their calculations provided in chapter 4).

Concepts	**Definition in agricultural context**	**How to measure? (examples)**
(a) Stability	In natural sciences, stability is often defined as the constancy of a given attribute over time or across space; the less it fluctuates the more stable it is (Holling, 1973; Urruty et al., 2016).	Stability is often measured by examining the variability of data, e.g. using measures of dispersion over time such as standard deviation or coefficient of variation (Batisani, 2012; Döring and Reckling, 2018) or deviations from the mean (Reidsma et al., 2009).
(b) Robustness	Ability to maintain desired agricultural outputs despite perturbations (Urruty et al., 2016).	Impact (value) of perturbation on agricultural output, e.g., change in yield following abiotic stress (Urruty et al., 2017).
(c) Vulnerability	The sensitivity of a system to shock, or degree to which a system is harmed by disturbance (Dardonville et al., 2020; Urruty et al., 2016)	The degree to which a shock affects output or performance, e.g. the relative effect of climate variability on crop productivity across regions (Reidsma and Ewert, 2008).
(d) Resilience	Ecological resilience was originally defined by Holling, (1973) as the ability of a system to absorb change and withstand disturbance and persist in its configuration. More recently resilience is also defined as the ability of a system to withstand perturbation and anticipate future disturbance through its adaptive capacity (Dardonville et al., 2020; Urruty et al., 2016)	Todman *et al.* (2016) provides 4 quantifiable characteristics to describe resilience: 1. *Degree of return* to a reference level or original state. 2. *Return time* - Time taken to reach a new quasi-stable state. 3. *Rate of return* (gradient) at which the function reaches the new state. 4. *Efficiency* - Cumulative magnitude of the function (area under the curve) before reaching a new state.

Table 3 - Summary (definitions and measurement) of the concepts of stability, robustness, vulnerability and resilience.

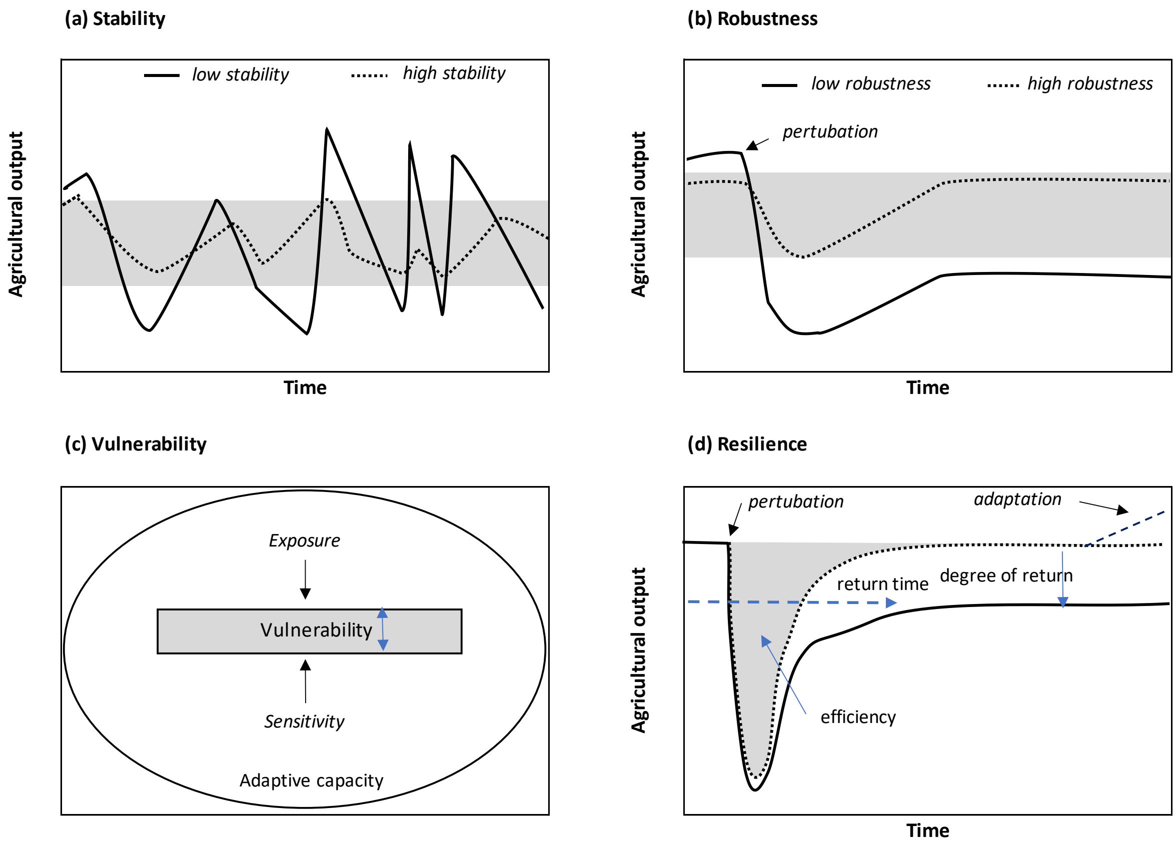

Figure 3 – Illustration of a) stability, b) robustness, c) vulnerability and d) resilience concepts. Resilience diagram shows how the resilience characteristics for degree of return, return time and efficiency are quantified from the modelled response curve (adapted from Todman *et al.*, (2016) and Urruty, Tailliez-Lefebvre and Huyghe, (2016)).

2.3 Statistical methods for examining factors affecting the stability of food production and farm income

A primary aim of this thesis is to identify farming practices and adaptation options for agriculture to improve the stability of food production and farm income, at the farm level, in the context of more variable conditions and climate change. To examine these relationships, I considered various multivariate statistical methods, including cluster analysis and multiple regression techniques, which are discussed in this section.

Cluster analysis is a multivariate statistical technique for classifying data and grouping observations into smaller and more homogenous groups, using distance matrices (Punj and Stewart, 1983). Cluster analysis can provide knowledge of the characteristics of groups within the data. In the context of this project, this technique could be used to identify the characteristics of groups of farms which have more stable yields or income. However, there are some limitations of cluster analysis which are relevant to this project and the data being examined. The Farm Business Survey data examined comprises panel data, with repeated observations over multiple years, which can be complex and challenging to interpret using cluster analysis, i.e., how are the results interpreted if farms are present in different clusters or groups over time? Cluster analysis is commonly used with cross-sectional data (e.g. Gaspar et al. (2007)) or for time series data when averaging observations over multiple years (e.g. Giannakis and Bruggeman, (2015)). In many circumstances cluster analysis is also not the sole analytical tool for investigating the multivariate data (Agarwal and Skupin, 2008). For example, Giannakis and Bruggeman (2015) used cluster analysis to identify significant differences in economic performance of farms across countries in the EU, followed by logistic regression to analyse the factors that affect economic performance of farms.

Cluster analysis was explored initially in developing the methods to use in Chapter 4; to identify the factors (farm characteristics, practices, and subsidies) affecting the stability of farm income. As mentioned above, when using farm data across multiple years I found farms often changed clusters over time, which was difficult to interpret. When examining individual years separately, clusters tended to represent obvious existing groupings in the data e.g., farm type, rather than more nuanced management factors, and when examining the data by year and farm type some of the samples were very small and the clusters appeared unstable. Cluster analysis was not deemed best suited to examine the complex and unbalanced panel data in the Farm Business Survey therefore alternative methods were investigated.

Multilevel modelling was investigated as an alternative method, to identify farming practices and adaptation options for agriculture to improve farm stability. Multilevel models (also termed hierarchical or linear mixed models) are extensions of regression analysis which are suited for data with complex patterns of variability and focus on nested levels of variability within the data (Snijders and Bosker, 1999). Multilevel models are particularly suited to panel data sets, with repeated measurements over time, by allowing observations from the same individual (or farm) to be correlated. Multilevel models can also incorporate a nesting structure, which allow multiple ‘levels’ of correlation, or groupings, within the dataset to be nested within each other. In the Farm Business Survey, we observe farms over multiple periods, in addition farms can be grouped spatially, e.g., by region or county, on the basis that farms in different regions of the country have certain characteristics, e.g., topography or soils, which could affect the stability of farm income or production. The advantage of using multilevel models is therefore in permitting the intercepts and/or slopes of variables (e.g., farming practices and climate variables) to vary between levels in the data, by using random effects which account for omitted variables, i.e., unobserved differences between farms and spatial differences (Lobell et al., 2011; Reidsma et al., 2009, 2007). Multilevel models can also easily accommodate unbalanced panels (Laird and Ware, 1982; Snijders and Bosker, 1999). A graphical representation of an example multilevel model is presented in Figure 4, which shows that random intercepts and slopes can be used to account for variation in the effect chemical use on the stability of crop yield across different regions.

Multilevel analysis has been used specifically to examine the effects of climate variability, including temperature, precipitation and drought, on crop yield variation (e.g., Matiu et al. 2017 and Rowhani et al. 2011). As with many statistical models, multilevel models can be used flexibly and have been used to examine the influence of a wide range of factors, including farming practices, subsidies and climate on the variability of crops yields and farm income across regions of Europe (Reidsma et al., 2009, 2007). Therefore, multilevel analysis is considered the most appropriate and robust method to identify adaptation options to improve the stability of food production and farm income, in the context of more variable conditions, whilst accounting for the unbalanced and nested panel farm business survey data used in this thesis.

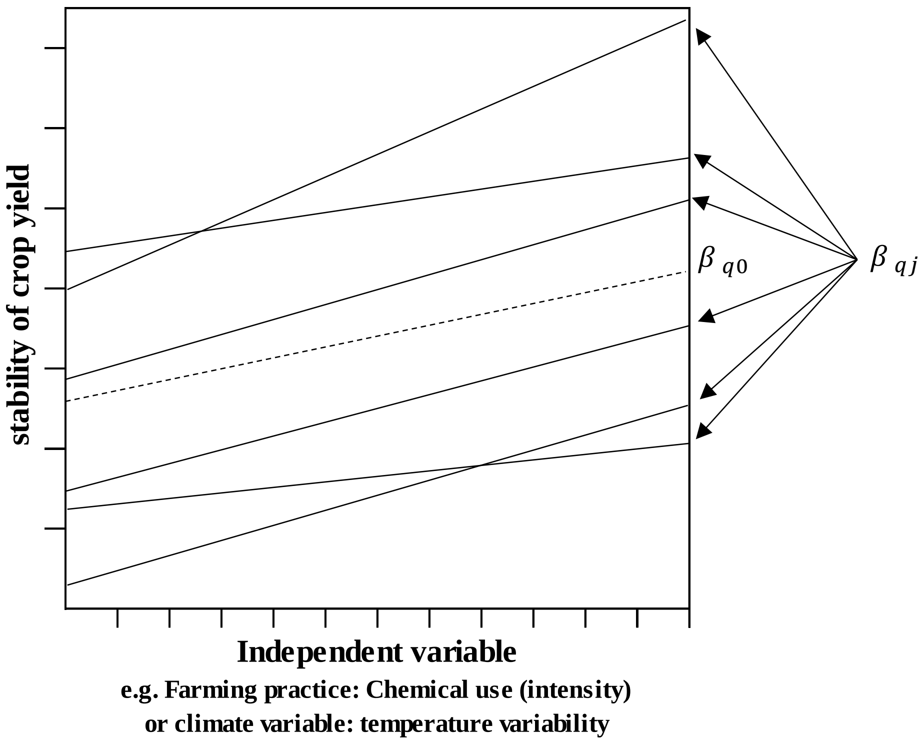

Figure 4 - Graphical example of multilevel model with a random intercept and slopes β_{qj} (accounting for variation between regions). Each solid line represents the effect of, for example, chemical use on the stability of crop yield in a specific region j. The dotted line is the mean relationship across all regions β_{q0} (adapted from: Reidsma et al., 2007).

2.3.1 Considerations and challenges in statistical analysis

Assessing the relationship between climate, management and farm performance over time and across regions is complex. As with all statistical analysis, it is important to recognise the challenges and considerations to be made when using multiple regression, as well as when using historical farm and climate data more generally.

Firstly, climatic variables can exhibit a strong correlation increasing the risk of confounding (coefficients can be unreliable which affects the interpretation of results), therefore it is important to consider multicollinearity between all variables in the statistical analysis (Bakker et al., 2005). I examined collinearity in the multilevel models using a variety of measures; using pairwise scatterplots, correlation coefficients and variance inflation factors (VIFs), which were all below the recommended thresholds for the final models reported in Chapters 4 and 5 (refer to the methodology sections in each of these chapters for further details).

Chapter 5 examines the relative effect of climate variability, subsidies and farming practices on the temporal stability of food production and farm income. In developing this model, I considered a range of variables to indicate climate variability. I calculated specific weather conditions which affect agricultural production, including drought (using the standardised precipitation evapotranspiration index (SPEI) and climatic water balance; Vicente-Serrano et al. (2010)), and warming and heat stress (using growing degree days (GDD) and killing degree days (KDD); e.g., Butler and Huybers, (2013)). I also considered the timing of these events across different seasons. The mean and variability of each climate variable was included to reduce the risk of confounding, however these were often correlated, as were the seasonal climate variables (Chapter 5 appendix C – table C.1). In addition, when using these seasonal adverse weather conditions, the model coefficients did not appear stable when adding or removing variables from the models, therefore raising concern over the reliability of the results. The final models presented in Chapter 5 examine variability in temperature and precipitation, across the main growing season, which appear better able to capture the effect of climate variability on food production at the farm level and provide more robust results. I also considered using interaction terms to consider how farming practices and subsidy payments moderate the relationship between climate variability and the stability of income. However, interpreting a clear relationship between two continuous variables was often difficult (Chapter 5 appendix C – table C.2 and C.3). It may have been preferable to interact farming practices of different groups e.g., those who do participate in agri-environment schemes and those who don’t, or which type of schemes they participate in (e.g., entry- or higher-level stewardship) or organic vs conventional farming. However, this could comprise a different piece of research in response to different research questions.

Another consideration when estimating regression models is endogeneity, which describes the issue of correlation between the explanatory variables and the error term in regression. This typically occurs in two main instances, firstly when an omitted variable is correlated with another variable or the error term, and secondly when there is simultaneity, meaning the dependent variable and independent variable jointly determine each other simultaneously. Endogeneity may arise in chapters 4 and 5, for example, farms which participate more in agri-environment schemes may be reflective of more progressive and forward-thinking farmers. Alternatively, farmers may seek to diversify agricultural activities to reduce exposure to variability in their incomes, which may be reflective of the risk averse attitude of some farmers (DiFalco and Perrings, 2003). Simultaneously, increased price volatility (and unstable incomes) could provide an incentive for farmers to diversify production (de Roest et al., 2018). One way to control for endogeneity is to use instrumental variables regression to split the explanatory variable and remove the part of the error term which is correlated in the main analysis. Finding instrumental variables, which affect the explanatory variable but have no other effect on the dependent variable, can be challenging, particularly when using secondary historical data. Therefore, whilst I was not able to empirically account for potential endogeneity in the models, the associations between the variables examined were often supported by previous empirical studies which found similar results, as well as experimental studies which indicated the underlying mechanisms to support the relationships identified. In Chapters 4 and 5 the model specifications are discussed in detail, including how each of the variables included in the models were calculated and any data transformations that were applied, as well as, further discussion on the relationships identified in each study in the context of previous research.

References

Agarwal, P., Skupin, A., 2008. Self-Organising Maps: Applications in Geographic Information Science, Self-Organising Maps: Applications in Geographic Information Science. https://doi.org/10.1002/9780470021699

Arnell, N.W., Freeman, A., 2021. The effect of climate change on agro-climatic indicators in the UK. Clim. Change 165, 1–26. https://doi.org/10.1007/s10584-021-03054-8

Bakker, M.M., Govers, G., Ewert, F., Rounsevell, M., Jones, R., 2005. Variability in regional wheat yields as a function of climate, soil and economic variables: Assessing the risk of confounding. Agric. Ecosyst. Environ. 110, 195–209. https://doi.org/10.1016/j.agee.2005.04.016

Barnett, V., Lewis, T., 1994. Outliers in statistical data, 3rd Editio. ed. Wiley, New York.

Batisani, N., 2012. Climate variability, yield instability and global recession: The multi-stressor to food security in Botswana. Clim. Dev. 4, 129–140. https://doi.org/10.1080/17565529.2012.728129

Butler, E.E., Huybers, P., 2013. Adaptation of US maize to temperature variations. Nat. Clim. Chang. 3, 68–72. https://doi.org/10.1038/nclimate1585

Chavas, J.P., Di Falco, S., 2017. Resilience, Weather and Dynamic Adjustments in Agroecosystems: The Case of Wheat Yield in England. Environ. Resour. Econ. https://doi.org/10.1007/s10640-015-9987-9

Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184. https://doi.org/10.1016/j.agsy.2020.102913

Darnhofer, I., 2021. Farming resilience: from maintaining states towards shaping transformative change processes. Sustain. 13. https://doi.org/10.3390/su13063387

de Roest, K., Ferrari, P., Knickel, K., 2018. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. J. Rural Stud. 59, 222–231. https://doi.org/10.1016/j.jrurstud.2017.04.013

Defra, 2020. Farm Business Survey [WWW Document]. URL beta.ukdataservice.ac.uk/datacatalogue/series/series?id=200018 (accessed 3.20.20).

Department for Environment Food and Rural Affairs, 2016. Farm Business Survey - Statistical information.

DiFalco, S., Perrings, C., 2003. Crop Genetic Diversity , Productivity and Stability of Agroecosystems. A Theoretical and Empirical Investigation. Scott. J. Polit. Econ. 50, 207–216.

Döring, T.F., Reckling, M., 2018. Detecting global trends of cereal yield stability by adjusting the coefficient of variation. Eur. J. Agron. 99, 30–36. https://doi.org/10.1016/j.eja.2018.06.007

Durre, I., Menne, M.J., Gleason, B.E., Houston, T.G., Vose, R.S., 2010. Comprehensive automated quality assurance of daily surface observations. J. Appl. Meteorol. Climatol. 49, 1615–1633. https://doi.org/10.1175/2010JAMC2375.1

European Commission, 2020. NUTS - Nomenclature of territorial units for statistics [WWW

Document]. URL https://ec.europa.eu/eurostat/web/nuts/background (accessed 6.15.21).

Feng, S., Hu, Q., Qian, W., 2004. Quality control of daily meteorological data in China, 1951-2000: A new dataset. Int. J. Climatol. 24, 853–870. https://doi.org/10.1002/joc.1047

Folke, C., 2016. Resilience (Republished). Ecol. Soc. 21, art44. https://doi.org/10.5751/ES-09088-210444

Gaspar, P., Mesías, F.J., Escribano, M., Rodriguez De Ledesma, A., Pulido, F., 2007. Economic and management characterization of dehesa farms: Implications for their sustainability. Agrofor. Syst. 71, 151–162. https://doi.org/10.1007/s10457-007-9081-6

Giannakis, E., Bruggeman, A., 2015. The highly variable economic performance of European agriculture. Land use policy 45, 26–35. https://doi.org/10.1016/j.landusepol.2014.12.009

Holling, C.S., 1973. Resilience and Stability of Ecological Systems. Annu. Rev. Ecol. Syst. 4, 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245

Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I., 2019. HadUK-Grid—A new UK dataset of gridded climate observations. Geosci. Data J. 6, 151–159. https://doi.org/10.1002/gdj3.78

Jamieson, P.D., Semenov, M.A., Brooking, I.R., Francis, G.S., 1998. Sirius: A mechanistic model of wheat response to environmental variation. Eur. J. Agron. 8, 161–179. https://doi.org/10.1016/S1161-0301(98)00020-3

Laird, N.M., Ware, J.H., 1982. Random-Effects Models for Longitudinal Data. Biometrics 38, 963. https://doi.org/10.2307/2529876

Lobell, D.B., Asseng, S., 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environ. Res. Lett. 12. https://doi.org/10.1088/1748-9326/aa518a

Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate Trends and Global Crop Production Since 1980. Science (80-.). 333, 616–620. https://doi.org/10.1126/science.1206034

Matiu, M., Ankerst, D.P., Menzel, A., 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. PLoS One 12, 1–23. https://doi.org/10.1371/journal.pone.0178339

Menne, M.J., Durre, I., Vose, R.S., Gleason, B.E., Houston, T.G., 2012. An overview of the global historical climatology network-daily database. J. Atmos. Ocean. Technol. 29, 897–910. https://doi.org/10.1175/JTECH-D-11-00103.1

Met Office, 2019. UK climate - Synoptic and climate stations [WWW Document]. URL https://www.metoffice.gov.uk/public/weather/climate-network

Met Office, 2017. UK climate - Extremes [WWW Document]. URL https://www.metoffice.gov.uk/public/weather/climate-extremes/#?tab=climateExtremes

Mishra, A.K., Sandretto, C.L., 2002. Stability of Farm Income and the Role of Nonfarm Income. Rev. Agric. Econ. 24, 208–221.

OECD, 2020. Strengthening Agricultural Resilience in the Face of Multiple Risks. OECD, Paris. https://doi.org/10.1787/2250453e-en

Pacín, F., Oesterheld, M., 2014. In-farm diversity stabilizes return on capital in Argentine agro-ecosystems. Agric. Syst. 124, 51–59. https://doi.org/10.1016/j.agsy.2013.10.008

Perry, M., Hollis, D., Elms, M., 2009. The Generation of Daily Gridded Datasets of Temperature and Rainfall for the UK. Met Off. Clim. Memo. 1–7.

Porter, J.R., 1993. AFRCWHEAT2: A model of the growth and development of wheat incorporating responses to water and nitrogen. Eur. J. Agron. 2, 69–82. https://doi.org/10.1016/s1161-0301(14)80136-6

Punj, G., Stewart, D.W., 1983. Cluster Analysis in Marketing Research: Review and Suggestions for Application. J. Mark. Res. 20, 134–148. https://doi.org/10.1177/002224378302000204

Reidsma, P., Ewert, F., 2008. Regional Farm Diversity Can Reduce Vulnerability of Food Production to Climate Change. Ecol. Soc. 13, 38. https://doi.org/Artn 38

Reidsma, P., Ewert, F., Oude Lansink, A., 2007. Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity. Clim. Change 84, 403–422. https://doi.org/10.1007/s10584-007-9242-7

Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: A multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/s10113-008-0059-3

Roberts, M.J., Braun, N.O., Sinclair, T.R., Lobell, D.B., Schlenker, W., 2017. Comparing and combining process-based crop models and statistical models with some implications for climate change. Environ. Res. Lett. 12, 095010. https://doi.org/10.1088/1748-9326/aa7f33

Rowhani, P., Lobell, D.B., Linderman, M., Ramankutty, N., 2011. Climate variability and crop production in Tanzania. Agric. For. Meteorol. 151, 449–460. https://doi.org/10.1016/j.agrformet.2010.12.002

Rural Business Research, 2020. FBS data builder - coverage [WWW Document]. URL http://www.farmbusinesssurvey.co.uk/DataBuilder/UserDocumentation/CoverageOfSurvey.htm (accessed 3.20.20).

Semenov, M.A., Shewry, P.R., 2011. Modelling predicts that heat stress, not drought, will increase vulnerability of wheat in Europe. Sci. Rep. 1, 66. https://doi.org/10.1038/srep00066

Senapati, N., Brown, H.E., Semenov, M.A., 2019a. Raising genetic yield potential in high productive countries: Designing wheat ideotypes under climate change. Agric. For. Meteorol. 271, 33–45. https://doi.org/10.1016/j.agrformet.2019.02.025

Senapati, N., Stratonovitch, P., Paul, M.J., Semenov, M.A., 2019b. Drought tolerance during reproductive development is important for increasing wheat yield potential under climate change in Europe. J. Exp. Bot. 70, 2549–2560. https://doi.org/10.1093/jxb/ery226

Snijders, T.A.B., Bosker, R.J., 1999. Multilevel Analysis An Introduction to Basic and Advanced Multilevel Modeling. SAGE Publications Ltd, London, UK.

Stratonovitch, P., Semenov, M.A., 2015. Heat tolerance around flowering in wheat identified as a key trait for increased yield potential in Europe under climate change. J. Exp. Bot. 66, 3599–3609. https://doi.org/10.1093/jxb/erv070

ten Napel, J., van der Veen, A.A., Oosting, S.J., Koerkamp, P.W.G.G., 2011. A conceptual approach to design livestock production systems for robustness to enhance sustainability. Livest. Sci. 139, 150–160. https://doi.org/10.1016/j.livsci.2011.03.007

The Resilience Alliance, 2010. Assessing resilience in social-ecological systems: Workbook for practitioners. Resil. Alliance 54. https://doi.org/10.1007/s11284-006-0074-0

Todman, L.C., Fraser, F.C., Corstanje, R., Deeks, L.K., Harris, J.A., Pawlett, M., Ritz, K., Whitmore, A.P., 2016. Defining and quantifying the resilience of responses to disturbance: a conceptual and modelling approach from soil science. Sci. Rep. 6, 28426. https://doi.org/10.1038/srep28426

Trnka, M., Eitzinger, J., Dubrovský, M., Semerádová, D., Štěpánek, P., Hlavinka, P., Balek, J., Skalák, P., Farda, A., Formayer, H., Žalud, Z., Change, C., Paper, A., 2010. Is rainfed crop production in central Europe at risk? Using a regional climate model to produce high resolution agroclimatic information for decision makers. J. Agric. Sci. 148, 639–656. https://doi.org/10.1017/S0021859610000638

Trnka, M., Olesen, J.E., Kersebaum, K.C., Skjelvåg, A.O., Eitzinger, J., Seguin, B., Peltonen-Sainio, P., Rötter, R., Iglesias, A., Orlandini, S., Dubrovský, M., Hlavinka, P., Balek, J., Eckersten, H., Cloppet, E., Calanca, P., Gobin, A., Vučetić, V., Nejedlik, P., Kumar, S., Lalic, B., Mestre, A., Rossi, F., Kozyra, J., Alexandrov, V., Semerádová, D., Žalud, Z., 2011. Agroclimatic conditions in Europe under climate change. Glob. Chang. Biol. 17, 2298–2318. https://doi.org/10.1111/j.1365-2486.2011.02396.x

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4, 637–643. https://doi.org/10.1038/nclimate2242

Urruty, N., Guyomard, H., Tailliez-Lefebvre, D., Huyghe, C., 2017. Factors of winter wheat yield robustness in France under unfavourable weather conditions. Eur. J. Agron. 90, 174–183. https://doi.org/10.1016/j.eja.2017.08.002

Urruty, N., Tailliez-Lefebvre, D., Huyghe, C., 2016. Stability, robustness, vulnerability and resilience of agricultural systems. A review. Agron. Sustain. Dev. 36, 1–15. https://doi.org/10.1007/s13593-015-0347-5

Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. J. Clim. 23, 1696–1718. https://doi.org/10.1175/2009JCLI2909.1

Appendices

Appendix A: UK climate records from the Met Office

The tables below report the national records for temperature and precipitation, as reported by the Met Office. Providing the highest and lowest maximum and minimum temperatures recorded for each month of the year, split by country. As well as the highest 24-hour rainfall totals for a rainfall day, by country.

Table A.1 UK temperature records from the Met Office - Highest and lowest daily maximum. Source: (Met Office, 2017)

Month	Highest Temperature (°C)	Lowest Temperature (°C)
England		
January	17.6	-11.3
February*	19.7	-10.0
March	25.6	-3.7
April*	29.4^	-1.1
May*	32.8	2.1
June*	35.6	5.7
July	36.7	9.1
August	38.5	8.9
September*	35.6^	6.2
October	29.9	1.1
November*	21.1	-4.0
December*	17.7	-8.2
Wales		
January*	18.3	-8.0
February	18.6	-5.8
March	23.9	-4.7
April	26.2	0.0
May*	29.2	3.1
June	33.7	6.9
July	34.6	9.8
August	35.2	10.0
September	31.1	6.5
October	28.2	2.2
November	22.4	-5.6
December*	18.0	-7.8
Scotland		
January	18.3	-13.0
February*	17.9	-10.0

March	23.6	-4.6
April	27.2	-1.0
May	30.9	1.6
June*	32.2	5.1
July	32.8	7.5
August	32.9	8.9
September	32.2	4.4
October	27.4	-0.2
November	20.6	-10.5
December*	18.3	-15.9

Notes: Temperature records exclude stations above 500 m AMSL and are based on the period 0900-0900 GMT. When compiling these tables, the Met Office has attempted to verify all records by comparing values with neighbouring stations. A ^ symbol denotes some reservations about the record value quoted.

Table A.2 UK temperature records from the Met Office - Highest and lowest daily minimum temperature records. Source: (Met Office, 2017)

Month	Highest Temperature (°C)	Lowest Temperature (°C)
England		
January	13.0	-26.1
February	13.0	-20.6
March	13.0	-21.1
April	15.2	-15.0
May	18.9	-9.4
June	22.7^	-5.6
July	23.3	-1.7
August	23.9	-2.0
September	21.7	-5.6
October	18.6	-10.6
November	15.9	-15.5
December	13.7	-25.2
Wales		
January	12.5	-23.3
February	13.0	-20.0
March	14.2	-21.7
April	14.5	-11.2
May	18.6	-6.1
June	19.9	-4.0
July	22.2	-1.5
August	22.0	-2.8
September	18.9	-5.5
October	19.4	-9.4

November	15.0	-18.0
December	15.0	-22.7
Scotland		
January	12.6	-27.2
February	13.7	-27.2
March	12.3	-22.8
April	15.2	-13.3
May	17.4	-7.7
June	19.3	-5.6
July	20.0	-2.5
August	20.5	-4.5
September	18.7	-6.7
October	16.1	-11.7
November	14.5	-23.3
December	12.5	-27.2

Notes: Temperature records exclude stations above 500 m AMSL and are based on the period 0900-0900 GMT. When compiling these tables, the Met Office has attempted to verify all records by comparing values with neighbouring stations. A ^ symbol denotes some reservations about the record value quoted.

Table A.1 UK precipitation records from the Met Office - Highest 24-hour rainfall totals for a rainfall day (0900-0900 GMT). Source: (Met Office, 2017)

Country	**Rainfall (mm)**	**Date**	**Location**
England	279	18/07/1955	Martinstown (Dorset)
Scotland	238	17/01/1974	Sloy Main Adit (Argyll & Bute)
Wales	211	11/11/1929	Lluest Wen Reservoir (Mid Glamorgan)

Notes: The highest 24-hour total for any 24-hour period is 341.4 mm on 5th December 2015 at Honister Pass (Cumbria).

Appendix B: Summary of conditions for identifying inconsistencies and outliers in the Met Office climate station data

Table A.3 Conditions for identifying inconsistencies and outliers within the weather data.

Variable	Condition for identifying errors
Extreme value inconsistencies	
Tmax	*Tmax > highest daily maximum temperature for month and country *Tmax < lowest daily maximum temperature for month and country
Tmin	*Tmin > highest daily minimum temperature for month and country *Tmin < lowest daily minimum temperature for month and country
Rain	*Rain > highest 24hour rainfall for each country
Internal inconsistencies	
Tmax	Tmax < Tmin
Tmin	Tmin> Tmax
Rain	Rain < 0
Erroneous zeros	
Tmax, Tmin, Rain	**all values = 0
Tmax, Tmin	Tmax and Tmin both = 0 °C or = -17.8°C (0°F)
Duplicate values	
Tmax, Tmin, Rain	**all values at one station = all values at another station and stations are >100km apart
Statistical outliers	
Tmin	Z ≥±4 and Tmin = 0°C or -0.4°C
Tmin	Z ≥±4 and large Tmin differences compared to neighbouring stations
Tmax	Z ≥±4 and large Tmax differences compared to neighbouring stations

Notes:
*Temperature records and rainfall totals are sourced from Met Office, (2017).
**Sun variables were also included in the Met Data dataset and included in checks above (to identify where all values = 0 and where values represent a duplicate of another station)

Chapter 3 - Adverse weather conditions for UK wheat production under climate change

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Author contribution: CH conducted the data analysis, produced all figures, led the interpretation of the results and wrote the paper. MS provided the Sirius crop model data, MT and J Balek provided the AgriClim crop model data. All co-authors provided comments on the paper.

Abstract

Winter wheat is an important crop in the UK, suited to the typical weather conditions in the current climate. In a changing climate the increased frequency and severity of adverse weather events, which are often localised, are considered a major threat to wheat production. In the present study we assessed a range of adverse weather conditions, which can significantly affect yield, under current and future climates based on adverse weather indices. We analysed changes in the frequency, magnitude and spatial patterns of 10 adverse weather indices, at 25 sites across the UK, using climate scenarios from the CMIP5 ensemble of global climate models (GCMs) and two greenhouse gas emissions (RCP4.5 and RCP8.5). The future UK climate is expected to remain favourable for wheat production, with most adverse weather indicators reducing in magnitude by the mid-21st century. Hotter and drier summers would improve sowing and harvesting conditions and reduce the risk of lodging. The probability of late frosts and heat stress during reproductive and grain filling periods would likely remain small in 2050. Wetter winter and spring could cause issues with waterlogging. The severity of drought stress during reproduction would generally be lower in 2050, however localised differences suggest it is important to examine drought at a small spatial scale. Prolonged water stress does not increase considerably in the UK, as may be expected in other parts of Europe. Climate projections based on the CMIP5 ensemble reveal considerable uncertainty in the magnitude of adverse weather conditions including

waterlogging, drought and water stress. The variation in adverse weather conditions due to GCMs was generally greater than between emissions scenarios. Accordingly, CMIP5 ensembles should be used in the assessment of adverse weather conditions for crop production to indicate the full range of possible impacts, which a limited number of GCMs may not provide.

1. Introduction

Climate change is associated with a warming trend, as well as, increasing climatic variability and extremes (Rahmstorf and Coumou, 2011; IPCC et al., 2012; Kovats et al., 2015). Agricultural production is highly dependent on weather conditions, and extreme and adverse weather events beyond the normal conditions experienced by crops can have a dramatic impact on their yield. When coinciding with sensitive stages of crop development, adverse weather events including high temperature, late frost, heavy precipitation and drought can severely reduce crop yield and affect its quality (Deryng et al., 2014; Powell and Reinhard, 2015; Trnka et al., 2014). Severe cases of heat stress or prolonged drought can also lead to a total crop failure (Gourdji et al., 2013; Lesk et al., 2016; Trnka et al., 2014). The impact and increased frequency of adverse weather events may pose more of an immediate risk to food production, in comparison to changes in mean climate, since farmers have less time to adapt. Losses in agricultural production due to adverse weather conditions, alongside potential for high volatility in food prices, intensifies the challenge of ending world hunger and achieving food security by 2030 (target of the UN Sustainable Development Goals; Griggs et al., 2013), for a world population anticipated to increase to 9 billion by 2050 (FAO, 2009). As a result, adverse weather has been the focus of increasing attention in crop-climate modelling studies.

Wheat is the most widely grown cereal crop in the world (FAOSTAT, 2018; Lobell et al., 2012). As a temperate species the typical weather conditions of western Europe, including the UK, are favourable for wheat production (Reynolds et al., 2010). Approximately 40 % (~1.8 million hectares) of the arable cropping area in the UK is dedicated to wheat production (Defra, 2018). Despite the relatively small acreage, the UK produces approximately 2% of the world's wheat benefitting from a high average yield of ~8 t ha^{-1}, compared to a world average of ~3.5 t ha^{-1} (FAOSTAT, 2018).

Wheat is sensitive to various adverse weather conditions and abiotic stresses which can significantly reduce yields. Heat stress during anthesis can reduce grain number by affecting floret fertility (Alghabari et al., 2014; Mitchell et al., 1993; Porter and Gawith, 1999) and heat stress during grain filling can reduce grain size and quality (Nasehzadeh and Ellis, 2017; Savill et al., 2018). Late frosts, particularly those during ear emergence and early anthesis, can cause damage to the ear and yield loss (Al-Issawi et al., 2013; Fuller et al., 2007). Approximately 30% of wheat in the UK is estimated to be grown on drought-prone soils (Weightman et al., 2005). Prolonged water stress reduces leaf expansion and accelerates leaf senescence, and can reduce radiation use efficiency (Jamieson et al., 1998). Short-term drought episodes are also a particular issue for wheat at stem elongation and grain filling, causing a reduction in growth and crop-die back, while drought stress during reproductive development reduces grain number (Dong et al., 2017; Ma et al., 2017). Heavy rainfall prior to and at maturity can also lead to lodging and yield losses, as well as, a reduction in quality (Berry et al., 2003; Russell and Wilson, 1994). In addition, wet conditions during sowing and harvest can restrict farming activities and the ability to sow or harvest at the most appropriate time (Trnka et al., 2014, 2011).

Notable adverse weather events that have impacted wheat production in the UK include severe flooding in the summer of 2007, which was estimated to reduce cereal yields by approximately 40 % in the flooded areas (Posthumus et al., 2009). Prolonged drought in 2011 affected growth of arable crops in England and Wales, followed by record high rainfall in the spring and summer of 2012, which in flooded areas reduced yields and delayed harvesting (Kendon et al., 2013; Parry et al., 2013). Prediction of the future occurrence of adverse weather events can, particularly at a large scale, be challenging due to the often localised nature of adverse weather events and uncertainty in future projections (Reyer et al., 2013; Seneviratne et al., 2012). Climate projections show a marked increase in summer heatwaves and heavy precipitation events for Europe (Kovats et al., 2014). There is considerable variability in projections across regions (Kovats et al., 2014; Powell and Reinhard, 2015), and seasons, with winters expected to become wetter and summers drier (Semenov, 2009). Previous studies predict the probability of adverse weather conditions for wheat may increase under a future climate, resulting in more frequent crop failure in Europe’s key wheat growing regions (Trnka et al., 2014). Identifying areas within the UK which may be sensitive to particular adverse weather conditions is therefore an important area of research in understanding these climatic risks. Prior assessment of the adverse weather conditions which pose a risk to wheat production across the UK could aid in early decision making regarding choice of cultivars and crop management strategies. Previous evidence has either focused on a limited number of adverse weather events, for example heat or drought stress, or examined a range of events at a single station within the UK, which cannot identify spatial variations within the wheat growing area. This study examines the magnitude and spatial patterns of a range of adverse weather events based on different adverse weather indices across the UK, providing comprehensive analysis for adverse weather conditions which may pose a risk to wheat production under changing climate. The main objectives of the present study were to provide a comprehensive analysis of projected changes in the frequency, magnitude and spatial patterns of a range of adverse weather conditions for wheat production throughout the UK in the mid-21st century.

2. Methods

2.1 Study area

This study used daily weather data from 25 sites across the UK (Figure 1). The 25 sites were selected from 85 climate stations within the Met Office network (Met Office, 2019) including sites which reported less than 10% missing values for temperature and precipitation, as well as, providing broad and even coverage of the key wheat growing areas in the UK.

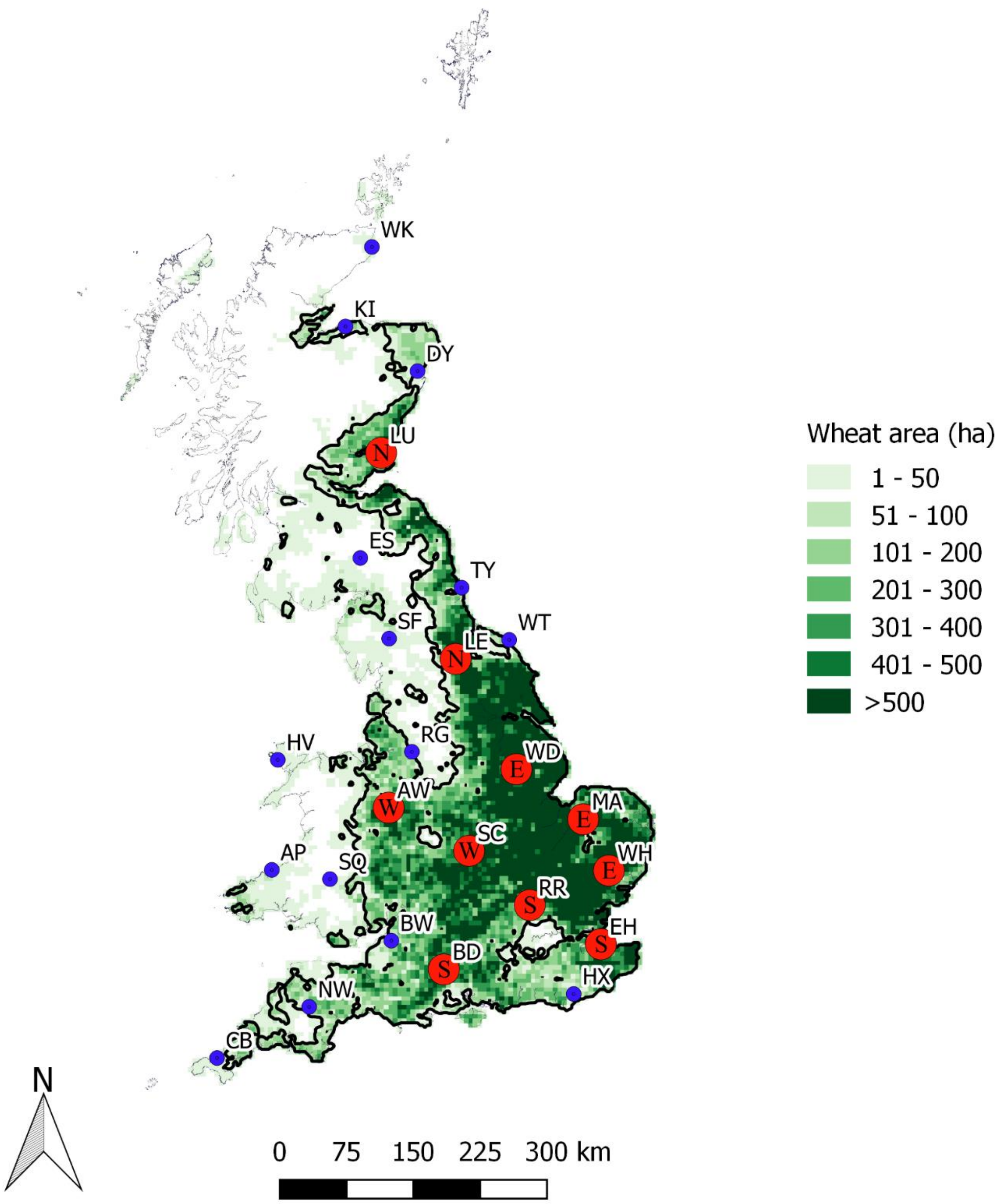

Figure 1 - UK wheat cropped area 2010 (ha per 25 km^2), data from EDINA (2018) including outline of key growing area. Location of the 25 UK sites included in the study (blue and red dots). Box plot results are presented for those sites with red dots (10 sites) and the letters within are used to split these 10 sites into 4 regions (referring to the cardinal direction of the site within the wheat growing area): north (N), east (E), south (S) and west (W).

2.2 Baseline and future climate scenarios

In the present study, the baseline climate was based on daily observed weather data during 1981-2010 including maximum and minimum air temperature, precipitation and sunshine hours (or solar radiation). We used quality control procedures (from Feng et al., 2004 and Durre et al., 2010) to identify and remove erroneous values which represented less than 0.1% of the dataset. To produce the local-scale future daily weather scenarios we used climate projections from 16 global climate models (GCMs; supplementary material) from the CMIP5 multi-model ensemble used in IPCC Assessment Report 5 (AR5) (IPCC, 2014). For the 2041-2060 and 2081-2100 climate scenarios (subsequently denoted as 2050 and 2090 respectively), two representative concentration pathways (RCPs) were used: a midrange mitigation scenario (RCP4.5) and a high emission scenario (RCP8.5). RCPs represent different targets of radiative forcing in 2100 i.e. 2.6, 4.5, 6.0, 8.5 W/m^2 (van Vuuren et al., 2011). Corresponding CO_2 concentrations (ppm) used in the simulations are presented in Table 1.

Table 1 - CO_2 concentrations (ppm) for the baseline, RCP4.5 and RCP8.5

	Baseline	RCP4.5	RCP8.5
1981 - 2010	364		
2041 - 2060		487	541
2081 - 2100		533	844

2.3 Construction of the local-scale climate scenarios using LARS-WG

Due to the coarse spatial and temporal predictions from GCMs, and large uncertainties in the model outputs, it is not appropriate to use daily output from GCMs when analysing extreme weather events (Semenov et al., 2010). For each of our 25 sites, we downscaled the climate projections to local-scale scenarios for use in the analysis. Both the baseline and all future climate scenarios were generated using LARS-WG (Semenov et al., 2010), a stochastic weather generator used in many recent European climate change impact and risk assessments (Trnka et al., 2015, 2014; Vanuytrecht et al., 2016), and found to perform well in a range of diverse European climates (Semenov et al., 2013, 2010). LARS-WG downscales the projections from the GCMs and incorporates changes in both the mean climate, climatic variability and extreme events derived from the GCMs (Semenov, 2007), by allowing modification to the statistical distribution of the weather variables. For the baseline climate, site-specific observed daily weather data from 1981-2010 was used to estimate site parameters and then LARS-WG was used to generate 300 years of daily weather data with the same statistical characteristics as the observed data. A large number of years (300) were generated to produce daily weather data with probability distributions close to those of the observed baseline climate and accurate reproduction of climatic variability and extreme weather events. For each site, future synthetic daily weather data (300 years) was generated by the LARS-WG weather generator based on changes in distributions of climate variables derived from each GCM and emissions scenario representing the climate in 2050 and 2090. Changes in monthly mean maximum and minimum temperatures and changes in monthly mean precipitation derived from each of the GCMs from the CMIP5 ensemble were incorporated into LARS-WG. Changes in the length of dry/wet spells were not considered due to coarse spatial resolutions of GCMs from CMIP5. For the UK, accounting for changes in the length in dry/wet spells should not affect the main conclusions (Vanuytrecht et al., 2014). In previous studies, LARS-WG demonstrated a good performance to reproduce extreme weather events in diverse climates including the UK (Gitau et al., 2018; Semenov, 2008).

2.4 Measuring adverse weather conditions for wheat production

Using the AgriClim software we computed the probability of 7 adverse weather conditions and used a crop simulation model, Sirius, to examine the severity of water, drought and heat stress. We used multiple GCMs, emission scenarios, and two future time periods to contrast a range of possible future climates and provide an indication of the uncertainty in predictions. Table 2 describes the indices used to evaluate changes in adverse weather conditions in the UK under climate change. These indices were developed in previous studies to represent adverse weather conditions during different phenological stages which could lead to crop failure or a significant yield reduction in winter wheat.

Table 2 - Overview of the adverse weather indices used in this study

	Indicator name	Effect on wheat	Event trigger / Indicator description
1	Frost with no snow	Leaf chlorosis; burning of leaf tips, severe crop damage (Trnka et al., 2010b)	Tmin [1] ≤ −20 °C for at least 1 day with no or very limited snow cover[2] (< 1 cm snow)
2	Late frost	After the loss of winter-hardiness leads to leaf chlorosis, floret sterility, damage to lower stem (Gusta and Fowler, 1976; Petr, 1991)	Tmin [1] is ≤ −2 °C, after mean air temperature is continuously 10 °C (for at least 5 days) and does not drop below 10 °C for more than 2 days in a row
3	Extremely wet early season	Occurrence of diseases, nitrogen leaching, waterlogging and root anoxia (Bartholomeus et al., 2008; Malik et al., 2002)	Soil moisture is at or above field capacity for >60 days from sowing to anthesis. Days with a mean temperature <3 °C are not counted
4	Lodging	Severe reduction of yield and grain quality, through increased harvest losses and exposure to diseases (Berry et al., 2003; Russell and Wilson, 1994)	At least 2 days (from anthesis to 5 days before maturity) with daily precipitation >40 mm, or >20 mm and soil moisture on the previous day at or above field capacity.
5	Grain filling extreme heat	Speeds up development and decreases yield until the growth stops (Nasehzadeh and Ellis, 2017; Savill et al., 2018)	Tmax[3] > 35 °C for at least 3 days during the period from 5 days after anthesis to maturity
6	Adverse sowing conditions	Restricts the ability to use the appropriate sowing window (Trnka et al., 2014, 2011)	Fewer than 3 days during the sowing window[4] with the soil moisture in the top layer <90% but >5% and rain on the day is <5 mm and ≤10 mm on the preceding day
7	Adverse harvest conditions	Restricts the ability to harvest at the most appropriate time (Trnka et al., 2014, 2011)	Fewer than 3 days during the harvest window[5] with soil moisture in the top layer <85 % and rain on the given day is <0.5 mm and ≤5 mm on the preceding day
8	Heat stress index (HSI)	Heat stress during the reproductive period causes partial or complete sterility of the florets (Alghabari et al., 2014; Porter and Gawith, 1999)	$HSI = (1 - Y_{wh}/Y_w)$ where Y_{wh} is water and heat limited yield of heat sensitive, drought tolerant, Mercia.
9	Drought stress index (DSI)	Drought stress during the reproductive period causes premature abortion of florets and sterility (Dong et al., 2017; Ma et al., 2017)	$DSI = (1 - Y_{wd}/Y_w)$ where Y_{wd} is water-limited yield of drought sensitive, heat tolerant, Mercia.
10	Water stress index (WSI)	Water stress during the entire growing season causes severe reduction of growth or crop die back (Jamieson et al., 1998)	$WSI = (1 - Y_w/Y)$ where Y is potential yield (not limited by water) of heat and drought tolerant Mercia, Y_w is water-limited yield (rain fed only) of heat and drought tolerant Mercia.

[1] The Tmin minimum daily temperature was measured 2 m above ground; thus, the actual crop temperature might be even lower. [2] The snow cover was estimated using a model validated by (Trnka et al., 2010b). [3] The Tmax maximum daily temperature was measured 2 m above ground. [4] The sowing window is sowing date ±15 days. [5] The harvest window is maturity date + 5 days, to maturity + 25 days.

We used the software AgriClim (Trnka et al. 2010) to compute the probability of a range of adverse weather conditions under the baseline and future climate scenarios, using indices 1-7 (Table 2). These thresholds were used in the European wheat study of Trnka et al. (2014) and determined using a combination of literature and expert judgement. The indicators include the effect of low temperatures. The lethal low temperature according to Porter and Gawith (1999) (−17.2 °C) was modified to incorporate the effect of snow cover. Based on experimental evidence −20 °C was considered a critical low temperature threshold, with no continuous snow cover, causing severe crop damage in winter wheat (Bergjord et al., 2008; Trnka et al., 2010b). Furthermore, following loss of winter-hardiness late frosts can lead to a substantial reduction in yield and based on previous findings a temperature threshold of −2 °C was used, following exposure of wheat to warm temperatures (>10 °C) (Gusta and Fowler, 1976; Petr, 1991). The adverse weather indices also consider the effect of high and heavy precipitation. Extremely wet conditions leading to waterlogging between sowing and anthesis was based upon the number of days with soil moisture at or above the field capacity (Trnka et al., 2014). A high risk of lodging occured with at least 2 days of heavy precipitation or high soil moisture and rainfall between anthesis and maturity (Trnka et al., 2014). The probability of high temperatures during grain filling was measured using the mean lethal maximum temperature (35 °C) identified in Porter and Gawith (1999). The final two indices calculated using AgriClim consider the effect of highly saturated topsoil and precipitation during the sowing or harvesting period and causing highly unsuitable conditions for field operations, making sowing or harvesting impossible (Trnka et al., 2014). The AgriClim software (Trnka et al. 2010), uses daily inputs of global radiation, maximum and minimum temperature and precipitation to calculate phenological development and the incidence of adverse weather conditions for winter wheat. Sunshine hours were converted to solar radiation using the approach described in Rietveld (1978). The daily reference (ET_r) evapotranspiration was estimated using the FAO Penman-Monteith method, with wind speed and relative humidity estimated (Allen et al., 1998). Actual evapotranspiration (ET_a) and soil moisture content were then estimated using the SoilClim water balance model, which accounted at least partly for preferential soil water flow and snow cover (Hlavinka et al., 2011). We used one soil profile across all sites with an available water capacity of 180 mm to focus on the signal from climate projections. The phenological phases were calculated in accordance with the methods described in Olesen et al. (2012), based upon thermal time above a base temperature for the following stages: sowing-emergence-anthesis-maturity. For each scenario, we used the first 50 years of our generated data for initiation of the calculations e.g. the soil moisture or phenological model. The data from this spinoff period were not used in the analyses. The presented results of adverse weather conditions within AgriClim were based on the remaining 250 years of data.

To provide evidence for a comprehensive range of adverse weather conditions, we used the Sirius crop model (Jamieson et al., 1998) to examine the impact of 3 adverse weather conditions on wheat yield, calculating the following indices: heat stress index (HSI) drought stress index (DSI) and water stress index (WSI) (Table 2; indicators 8-10). HSI measures the proportion of yield loss due to the effect of heat stress during the reproductive period, as described in Stratonovitch and Semenov (2015). For the heat sensitive wheat cultivars heat stress occurs at temperatures above 30 °C, during the following 2 periods: 10 days before anthesis to anthesis (meiosis and fertilisation) and 5-12 days after anthesis (beginning of grain filling). DSI measures the proportion of yield loss due to the effect of drought stress during the reproductive period, as described in Senapati et al. (2018). For the drought sensitive wheat cultivars daily photosynthesis and the rate of leaf senescence depend on the ratio of actual to potential transpiration and drought stress reduces the grain number when the ratio of actual transpiration to potential transpiration falls below 0.9 during the following reproductive period: 10 days before flowering to 5 days after flowering. WSI measures the proportion of yield loss due to water stress during the whole growing season. A water stress factor reduces leaf expansion and accelerates leaf senescence in the water-limited yield, as described in Semenov et al. (2009).

The Sirius crop model is described in detail in Jamieson et al. (1998). To summarise, Sirius is a process based wheat simulation model which uses daily weather data, soil description, and management information (nitrogen applications, irrigation and sowing date) to model phenological development and grain yield, including responses to adverse climatic effects including heat, drought and water stress (Senapati et al. 2018). Biomass production is calculated from intercepted photosynthetically active radiation and simple partitioning rules are used to calculate grain growth (Jamieson et al., 1998). Sirius has been used frequently in wheat studies and found to perform well under diverse climatic conditions, including the UK and across Europe (Ewert et al., 2002; Jamieson et al., 1998; Martre et al., 2006). We use Sirius version 2018, available from https://sites.google.com/view/sirius-wheat/. Wheat yields were simulated using Sirius for the *Mercia* wheat cultivar grown in the UK, which has been calibrated previously using agronomic experiments in the UK (Lawless et al., 2005; Richter and Semenov, 2005). No nitrogen limitation was considered in this study. A single soil-water profile, Hafren, with an available water capacity of 177 mm was used at all sites. A soil-water profile with a lower available water capacity of 127 mm was also used for comparison, with the results provided in the supplementary material. In the current version of Sirius (2018), there is no direct effect of increased CO_2 on water-use efficiency (no interaction between CO_2 and drought), therefore, we are not able to assess this effect on WSI and DSI. However, in previous studies, Sirius was able to simulate well the grain yield of wheat grown under elevated CO_2 and drought conditions in the FACE experiment at Maricopa (Ewert et al., 2002). We present the mean of each index: HSI, DSI and WSI. In addition, we present the extremes of each indicator using the 95th percentile (HSI95, DSI95 and WSI95); which shows the proportion of yield loss expected to occur on average once every 20 years due to each stress, termed ‘extreme heat stress’, ‘extreme drought stress’ and ‘extreme water stress’ respectively.

For all 25 sites the cultivars used in both models (AgriClim and Sirius) represent winter wheat which is typically sown in the UK between September and November; in this study we used a typical sowing date of 20th October for the baseline and future climate scenarios, consistent with Semenov and Stratonovitch (2015) and Senapati et al. (2019).

We examine the probability and severity of adverse weather conditions for the baseline and future climate scenarios using the median result from all 16 GCMs, as well as, analysing the range of results across the 16 GCMs to provide an indication of uncertainty. Box plot results are presented for 10 of the 25 sites, providing coverage of the UK wheat growing area (Figure 1). Maps are produced by interpolating the impact indices from all 25 stations using the inverse distance weighted (IDW) method. IDW is a fast and commonly applied interpolation technique (Lu and Wong, 2008) previously used for interpolation of climatic data and found to perform well at modelling temperature and precipitation (Hadi and Tombul, 2018; Li et al., 2011). Results for the 2090 climate are included in supplementary material.

3. Results

3.1 Future UK climate

CMIP5 future climate projections generally reflect a trend towards hotter and drier summers and warmer wetter winters for the UK, consistent with the UKCP18 probabilistic climate projections (Lowe et al., 2018). 2050 climate projections from the 16 GCMs analysed predicted an annual average temperature increase from the baseline between 0.4 and 2.5 °C for RCP4.5, and between 0.2 and 3.0 °C for RCP8.5 for all 25 sites in the UK, with greater warming in the summer months (Supplementary Figure 1). In 2050 sites EH and HX in the far south east of England showed the greatest rise in annual average temperatures (up to 3.0 °C under RCP8.5; Supplementary Table 3). Climate projections for rainfall showed variability throughout the year; the early part of the year (January to April) is predicted to be wetter, whereas summer and early autumn (June to October) is predicted to be drier (Supplementary Figure 2). The decrease in precipitation during the summer was greatest at sites RR and HX in the South East of England (~20 % decrease under RCP8.5), while sites in the North showed the smallest decrease, using the median of GCMs (Supplementary Figure 2; Supplementary Table 4). Climate projections in 2050 showed a wide range in monthly rainfall predictions across all 16 GCMs, with winter rainfall increasing up to ~40 % and decreasing as much as 10% and summer rainfall increasing or decreasing up to ~30 % (RCP8.5; Supplementary Table 4).

3.2 Advancing anthesis and maturity dates

Figure 2 shows the anthesis and maturity dates for winter wheat under baseline and future climate scenarios for 10 sites in the wheat growing area, as simulated using the AgriClim software. Mean anthesis dates, for the 10 sites, were between 10 and 11 days earlier under midrange emissions (RCP 4.5) and between 12 and 14 days earlier than the baseline using a high-emissions scenario (RCP 8.5). Mean maturity dates were approximately two weeks (13-15 days) earlier under midrange emissions and 16-19 days earlier under high emissions. This advancement is linked to faster crop development under higher temperatures due to a faster rate of thermal time accumulation (Figure 2). Winter wheat flowers and matures earlier in a warmer climate since the minimal thermal requirement is accumulated faster in both RCP4.5 and RCP8.5 in the mid-21st century, when using a fixed sowing date. This phenological advancement reduces the relative duration of the vegetative and reproduction stages (emergence-anthesis) by up to 2 weeks, whereas the grain filling period (anthesis-maturity) reduces by less than 1 week.

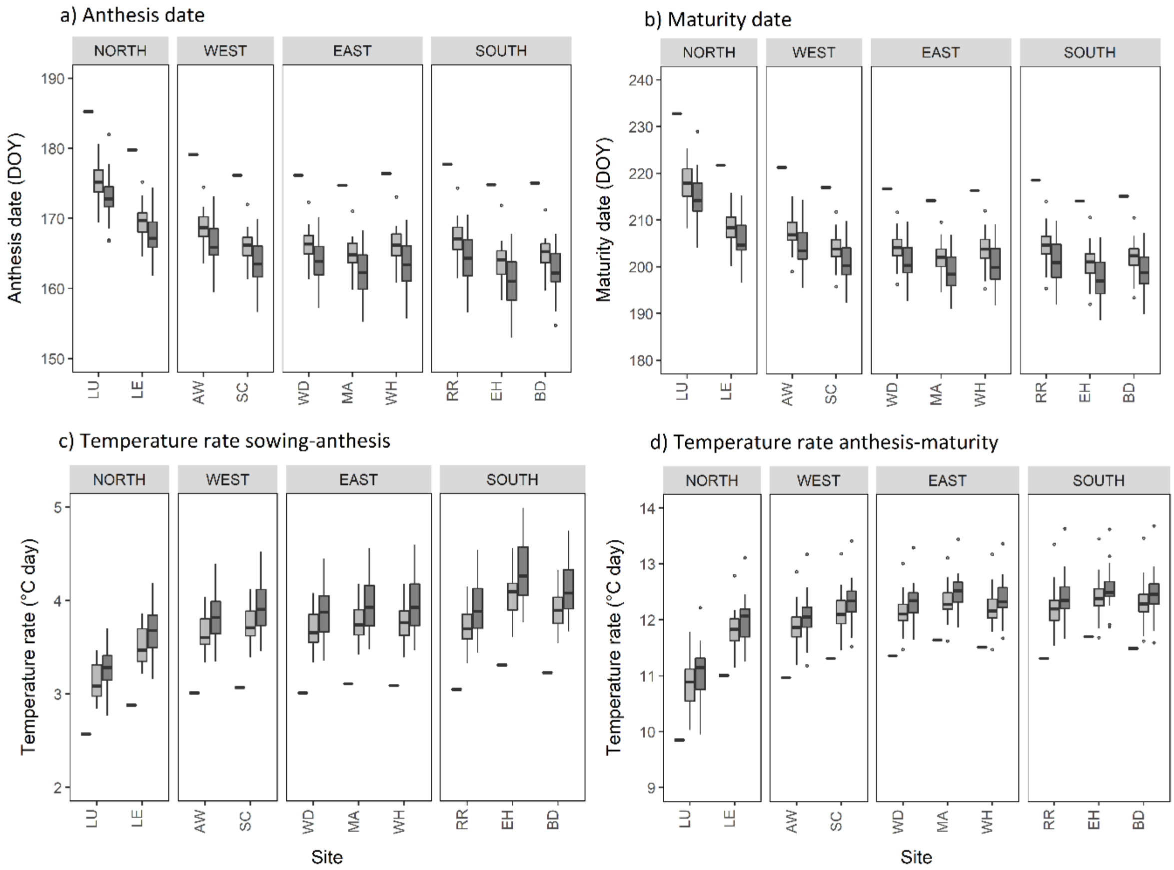

Figure 2 – Mean anthesis and maturity dates and values of temperature rate during sowing to anthesis and anthesis to maturity, calculated using AgriClim. Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey). The calculations consider a medium-ripening cultivar. DOY represents day of year.

3.3 Probability of adverse weather conditions under climate change

Figure 3 shows the probability of occurrence of a range of adverse weather conditions, under the baseline and 2050 climate, for RCP4.5 and RCP8.5 emissions scenarios. The box plots for the future climate present the range of results from 16 GCMs in the CMIP5 ensemble.

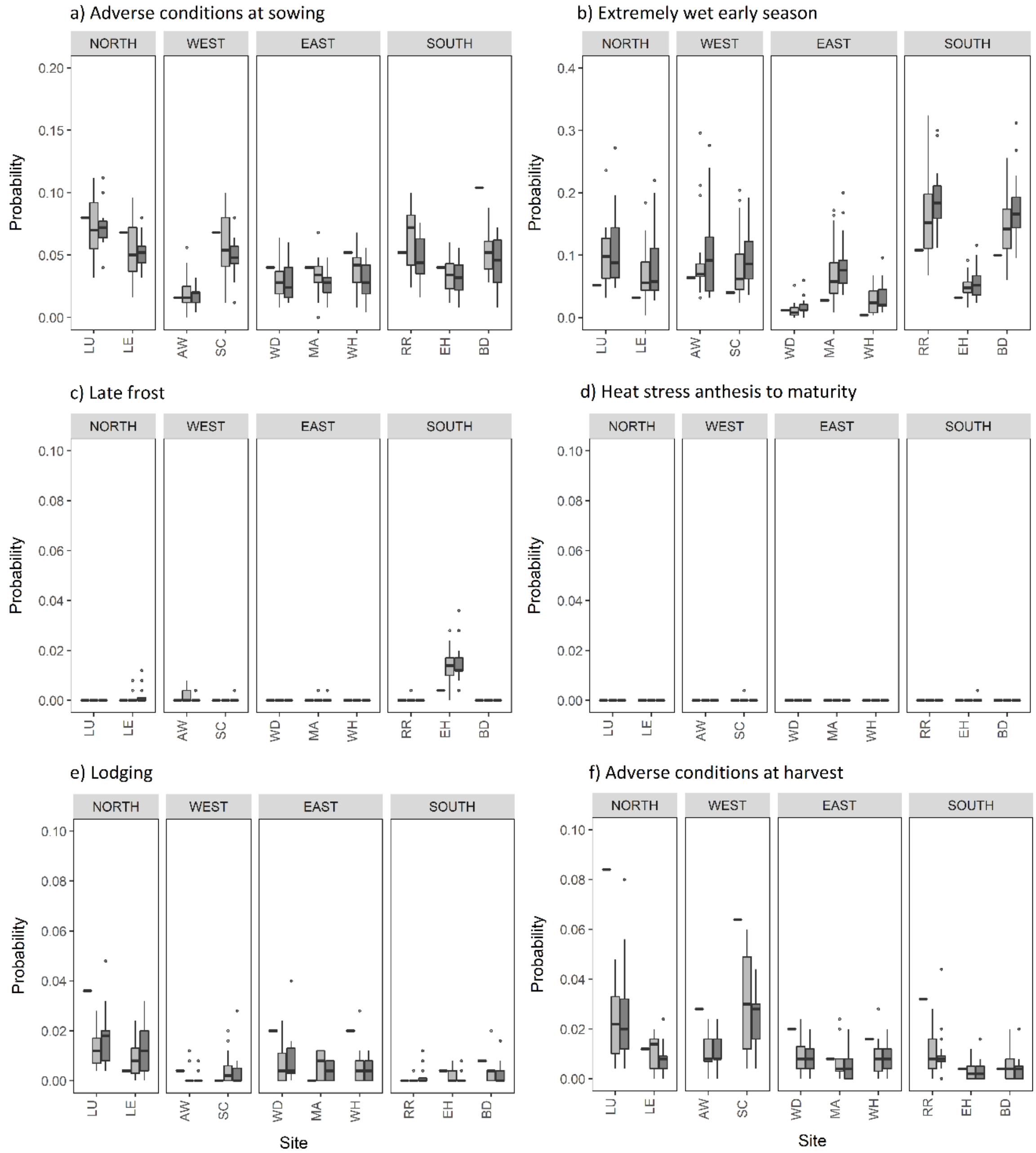

Figure 3 - Probability of the occurrence of adverse weather conditions under baseline and 2050 projected climate, calculated using AgriClim. Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey). The calculations consider a medium-ripening cultivar.

Sites in the north were consistently the wettest during the sowing period (sowing date ±15 days) under the baseline climate, showing a probability of adverse sowing conditions up to 8%. In contrast, sites in the east are driest, showing a probability less than 5% during the baseline period. The risk of adverse sowing conditions decreased at 8 out of 10 sites under 2050 climate scenarios (and in 2090) as a result of lower soil moisture during the sowing period following a drier summer, as predicted by the CMIP5 ensemble. Sites AW and RR indicated little change or an increase in probability.

An extremely wet early season, with possibility of waterlogging between sowing and anthesis, was projected to increase at 9 out of 10 sites under future climates due to increased rainfall and heavy precipitation events in the winter and spring. At sites RR and BD the probability of an extremely wet early season is 10% under the baseline climate, which almost doubles under high emissions in 2050 (and more than doubles in 2090, refer to supplementary material). The maps in Figure 4 illustrate the probability of an extremely wet early season under baseline and 2050 climate scenarios, with results from all 25 sites interpolated across the UK. The baseline climate in the far west of the country, generally beyond the key wheat growing area, was extremely wet during the early season. For the 2050 climate projections 'dry' and 'wet' maps use values from the driest and wettest GCMs to illustrate the range of results from the 16 GCMs used in our study. There is a large variation in the probability of an extremely wet early season between GCMs, which is greater than variation in probability of occurrence between emissions scenarios (Figure 3 & 4). The majority of GCMs showed an increase in the probability of an extremely wet early season, however a smaller number showed a decreased risk under 2050 climate scenarios. The probability of an extremely wet early season using the driest GCM (MPI-ESM-MR) shows there is generally little change in probability compared to the baseline. In contrast, the wettest GCM (GDFL-CM5) shows the probability of waterlogging increases across large areas of the English wheat growing area, as most areas of the country are becoming wetter during the early season.

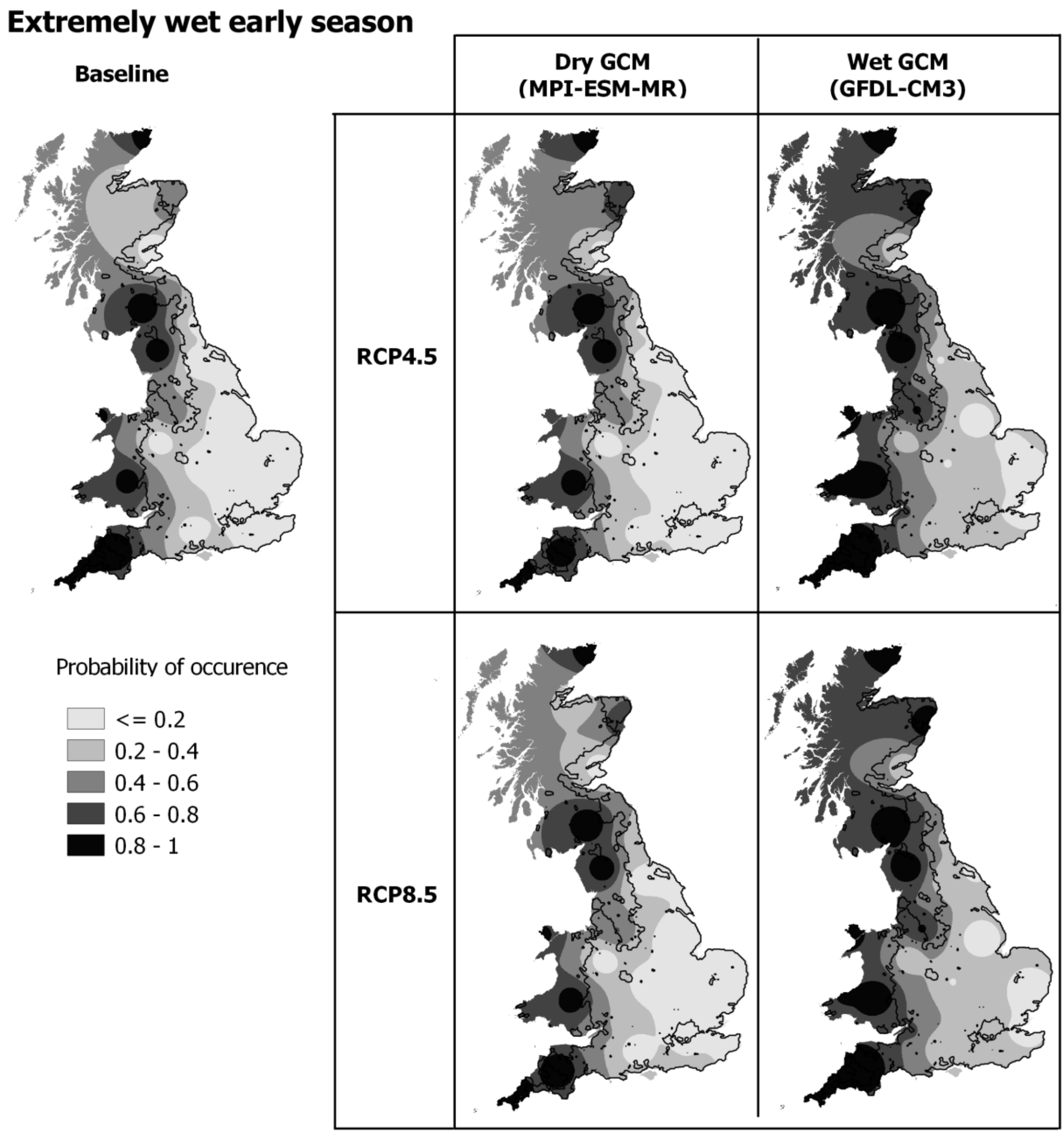

Figure 4 - The probability of an extremely wet early season (sowing – anthesis) for the 1981-2010 baseline and 2050 climate using RCP4.5 and RCP8.5 emissions scenarios and dry (MPI-ESM-MR) and wet (GFDL-CM3) GCMs. MPI-ESM-MR is one of the driest models in winter (predicting the largest decrease in rainfall at several sites; supplementary material) and shows a decrease in the probability of an extremely wet early season at a number of UK sites. GFDL-CM3 which is the wettest GCM in winter (shows the largest increase in rainfall; supplementary material) and commonly shows the largest increase in probability of an extremely wet early season.

The risk of a late frost was nil or negligible at 9 sites under the baseline climate and the probability increased slightly (to 1%) at only one site (EH) under 2050 climate scenarios (and in 2090). In the case of a severe frost with no snow cover (figure not presented) the probability was nil during the baseline and future climate scenarios. The probability of heat stress during grain filling (temperatures above 35 °C) was nil or negligible during the baseline and 2050 climate scenarios (and in 2090). The probability of heavy precipitation events between anthesis and maturity, which are a precursor to lodging, was small in the south with a baseline probability less than 1%, which reduced further under 2050 climate scenarios. Results demonstrated variability in the risk of lodging in other regions, the majority of sites showed a decrease under future climate scenarios (in 2050 and 2090), however the probability of lodging increased slightly at sites LE, SC and MA (up to 1%). The probability of adverse conditions at harvest was predicted to decrease under 2050 climate scenarios (and in 2090) across all regions, driven by hotter and drier summers reducing soil moisture at harvest.

3.4 Severity of heat, drought and water stress under climate change

Figure 5 shows the mean proportion of yield loss as a result of drought stress during reproduction (DSI) and water stress during the season (WSI), under baseline and 2050 climate scenarios, simulated using Sirius. Mean heat stress around anthesis (HSI) was nil or negligible under baseline and future climate scenarios.

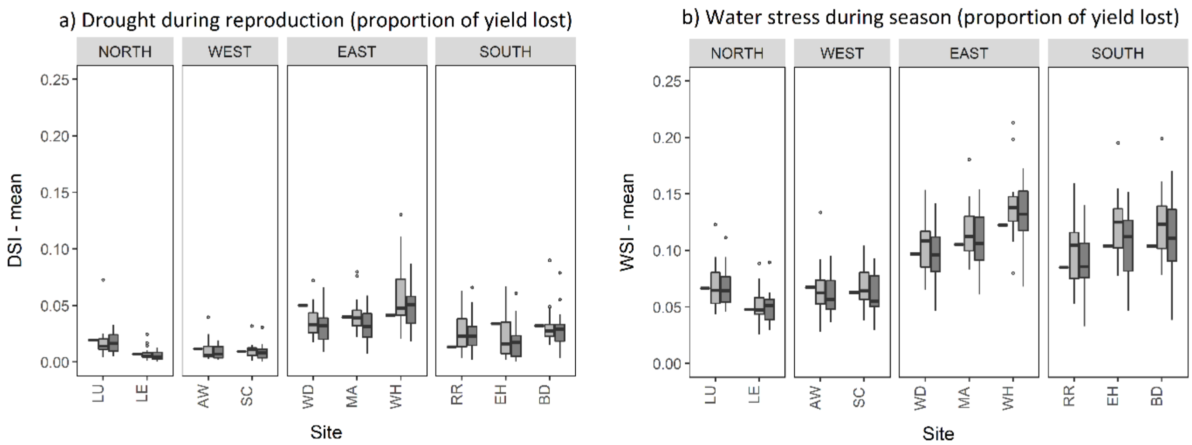

Figure 5 - Mean drought stress index (DSI) and water stress index (WSI). Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey).

Mean DSI was highest in the east of the UK with an average of 0.04-0.05 under the baseline climate, representing a 4-5% yield loss as a result of drought stress during reproductive development. In contrast, the north and west regions experienced the lowest drought stress, with DSI between 0.01 and 0.02 under the baseline climate. Most sites showed a decrease in mean drought stress during the reproductive period by 2050, with exception of sites WH and RR, which showed an increase.

Mean WSI ranged from 0.05-0.12 under the baseline climate, representing a 5-12 % yield loss as a result of water stress during the entire growing season, with the highest water stress in the south and east of the UK (9-12 % yield loss). Under midrange emissions in 2050 the mean proportion of yield loss due to water stress increased by up to 25 % in the south and east regions (to 10-14 %). Under high emissions in 2050, however, sites in these regions show a smaller increase in WSI (less than 10 %) in comparison to the baseline climate. The north and west regions experienced the least water stress with WSI less than 0.07 under the baseline climate and small change or a reduction in WSI under 2050 climate scenarios.

3.5 Extremes of heat, drought and water stress under the future climate

We used the 95th percentile of heat (HSI95) and drought stress (DSI95) during reproductive development and water stress (WSI95) over the entire wheat growing season to analyse extremes, termed as ‘extreme heat stress’, ‘extreme drought stress’ and ‘extreme water stress’ respectively. HSI95, DSI95 and WSI95 indicate the corresponding proportion of yield losses expected to occur on average once every 20 years. The proportion of yield loss due to extreme heat stress during the reproductive period (HSI95) was nil or negligible under baseline, 2050 and 2090 climate scenarios.

Figure 6 shows extreme drought stress (DSI95) under baseline and 2050 climate for RCP4.5 and RCP8.5 emissions scenarios. Figure 7 illustrates spatial patterns in DSI95, with results from the 25 sites interpolated across the UK, using the median of GCMs. DSI95 was consistently highest at sites in the east under the baseline climate, between 0.24-0.27, representing 24-27 % yield loss as a result of extreme drought during reproduction. DSI95 was also high in the south under the baseline climate, with high spatial variability. The highest extreme drought stress during reproductive development occurred in the far south east of England, as indicated by the darkest area in Figure 7. In contrast, other areas in Southern England experienced the lowest extreme drought stress, with the minimum at site RR (DSI95 <0.1). Overall, the north and west regions had the lowest extreme drought stress during reproduction, with less than 15 % yield loss under the baseline climate. Consistent with the mean DSI, most sites showed a decrease in extreme drought stress during reproduction (DSI95) by 2050 (and by 2090, refer to supplementary material). Our projections show a reduction in DSI95 across most regions of the UK under midrange emissions with a further reduction under high emissions (Figure 7). DSI95 was predicted to reduce by almost half by

2050 at site EH in South East England, reducing from 29 % yield loss under the baseline climate to 16 % under RCP4.5, and further to 11 % yield loss under RCP8.5. However, the box plot at site EH shows a large range, with results from all 16 GCMs showing greater uncertainty compared to other sites. In contrast, small areas in the UK projected an increased drought stress around anthesis by 2050. At site RR, DSI95 more than doubled from 8 % under the baseline period to 22 % and 21 % under midrange and high emissions respectively, with little difference between emission scenarios.

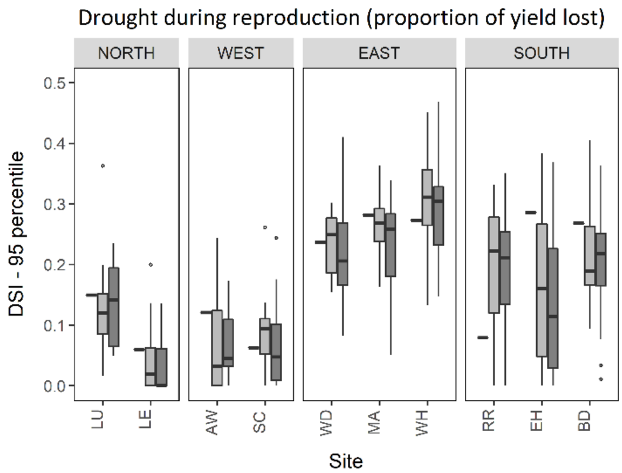

Figure 6 – 95-percentile drought stress index (DSI95). Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey).

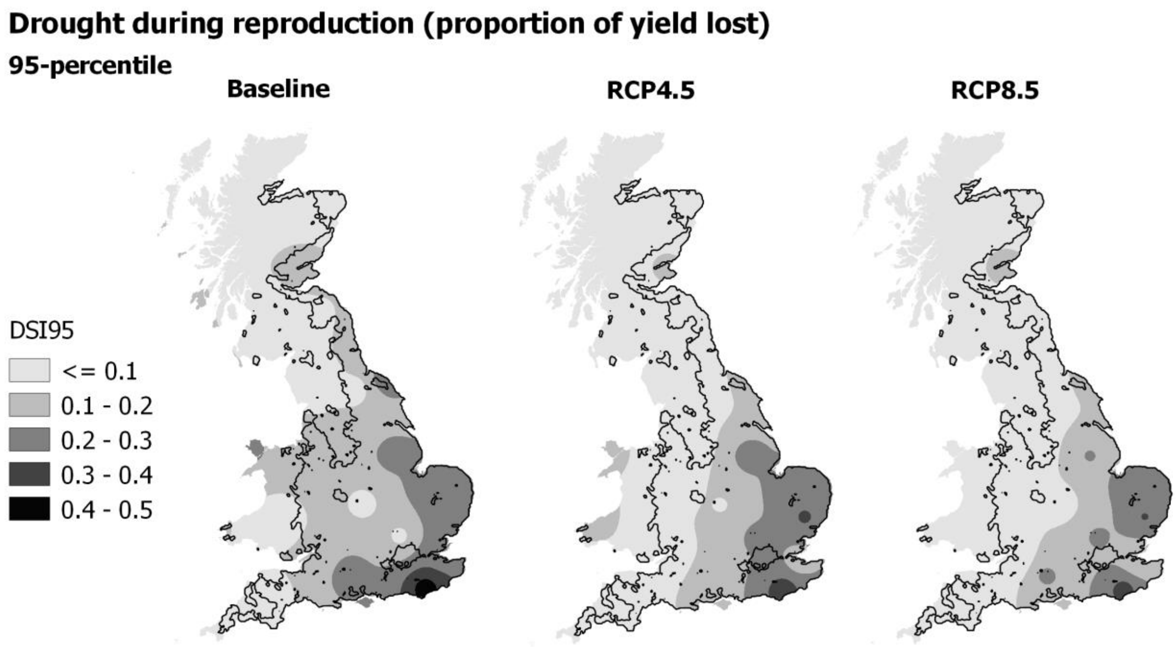

Figure 7 - 95-percentile of drought stress index (DSI95) for the 1981-2010 baseline and median 2050 climate using RCP4.5 and RCP8.5 emissions scenarios

Across most of the wheat growing area in England extreme water stress during the growing season (WSI95) ranged between 0.20 – 0.30, representing 20 and 30 % possible yield losses under the baseline climate (Figures 8 and 9). WSI95 was highest in the south and east of the country under the baseline climate. Extreme water stress was lowest (WSI95<0.20) across the north of the UK. However less spatial variation was found between sites for extreme water stress than extreme drought stress. At most sites WSI95 increased slightly (less than 0.05) between the baseline and future climate, therefore very little change in WSI95 was shown, with exception of the far west wheat growing area which showed a decrease in extreme water stress during the entire growing season (Figure 9). Extreme water stress was predicted to be greater under midrange emissions (RCP4.5) than high emissions (RCP8.5) at most sites in the south and east, with a greater increase in rainfall during the winter and spring under RCP8.5. In 2090, a reduction in extreme water stress was projected at most sites across the UK due to further increase in the winter and spring rainfall under RCP8.5.

Uncertainty in simulating the impacts of extreme drought (DSI95) and extreme water stress (WSI95) is highlighted by the range of projections of different GCMs (Figures 6 & 8) with some showing increases in risk and some showing decreases by 2050. This range is consistent with the variation in predicted monthly rainfall between the baseline and 2050 climate; with summer rainfall increasing or decreasing up to ~30 % across all 16 GCMs and winter rainfall increasing up to ~40 % and decreasing as much as 10% (RCP8.5). Greater variation is shown for extreme drought events during the reproductive period (DSI95) in comparison to water stress during the growing season (WSI95), highlighting particular uncertainty in GCM model predictions for simulating extreme drought during the reproductive period.

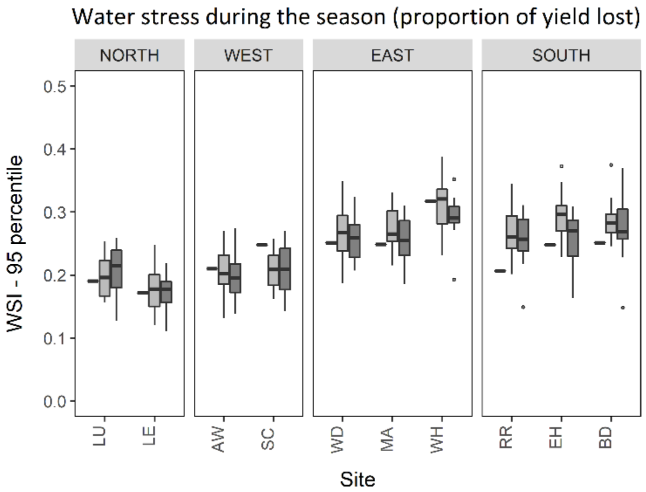

Figure 8 – 95-percentile water stress index (WSI95). Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey).

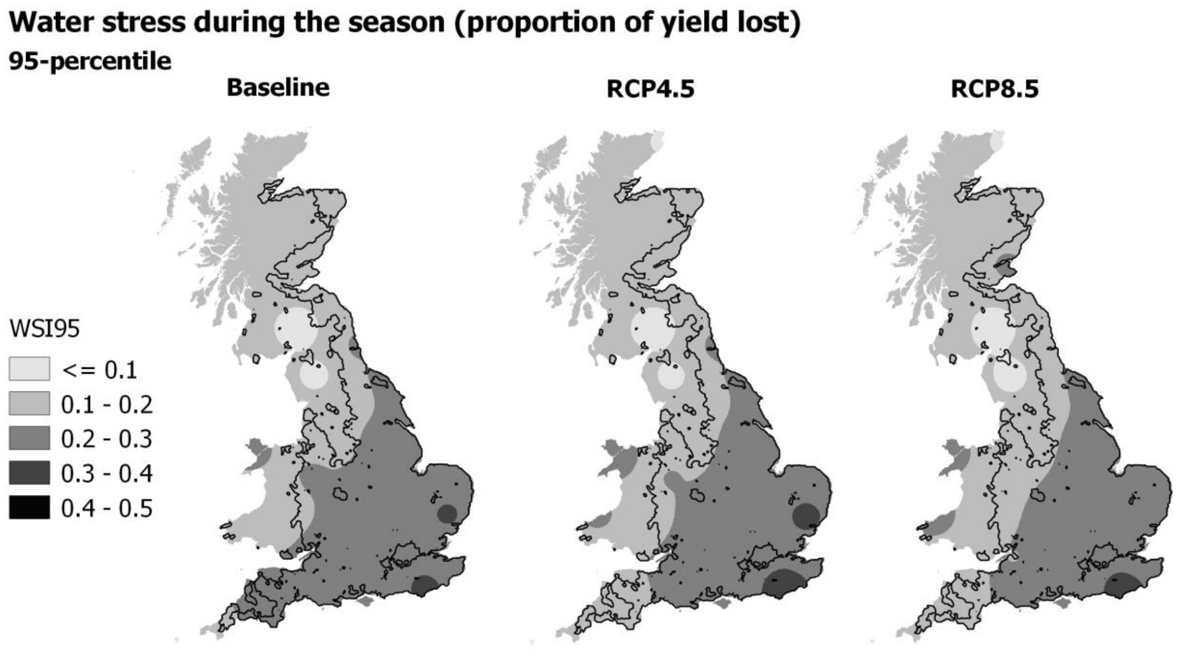

Figure 9 - 95-percentile of water stress index (WSI95) for the 1981-2010 baseline and median 2050 climate using RCP4.5 and RCP8.5 emissions scenarios

4. Discussion

Wheat is sensitive to various climatic stresses throughout the growing season. Overall, future climates in the UK are expected to remain favourable for wheat production under a midrange (RCP4.5) and a high emissions scenario (RCP8.5), with most adverse weather indicators reducing in frequency or magnitude during the 21st century. Drier summers are expected to reduce the probability of overly wet conditions during sowing and around the harvest period, which can restrict the ability to sow or harvest at the most appropriate time (Trnka et al., 2014). The risk of lodging which can lead to yield losses and a reduction in quality (Berry et al., 2003; Gobin, 2018; Russell and Wilson, 1994; Trnka et al., 2015), is also expected to decrease with fewer heavy rainfall events prior to and at maturity.

The risk of severe winter frosts, which can lead to severe crop damage including leaf chlorosis, following exposure to temperatures below −20 °C with no snow cover (Trnka et al., 2014), would most likely be zero under future climate, as temperatures will not fall this low. Late frosts, which occur after the loss of winter hardiness at temperatures below −2 °C, cause leaf chlorosis, floret sterility during anthesis and damage the lower stem, leading to medium to severe yield loss (Gusta and Fowler, 1976; Petr, 1991). The risk of a late frost seems negligible at all sites throughout the UK wheat growing area.

High temperatures and heat stress around anthesis could induce sterility and considerable yield loss in wheat, with a critical temperature during reproduction around 30 °C (Alghabari et al., 2014; Semenov et al., 2014; Porter and Gawith, 1999). Previous research found a small risk of heat stress around anthesis (>30 °C) at one site in South East England (RR) under mid-century climate scenarios (Semenov et al., 2014; Semenov and Shewry, 2011) and we found consistent results throughout the UK, with negligible yield losses due to heat stress during reproduction under both baseline and future climate scenarios. The probability of heat stress during grain filling (> 35 °C), which can reduce grain size and quality (Nasehzadeh and Ellis, 2017; Savill et al., 2018) was also negligible.

The probability of an extremely wet early season, driven by increased rainfall between sowing and anthesis, would increase under future climates across most of the UK wheat growing area. This can cause waterlogging, root anoxia, and fertilizer leaching (Trnka et al., 2014). Furthermore, wetter winters, coupled with the predicted warmer temperatures and fewer frosts may increase the prevalence of pests and disease such as *Zymoseptoria tritici* (Fones and Gurr, 2015; Pietravalle et al., 2007). The impact of pests and disease on wheat yield was not analysed in this study. Other landscape characteristics, including soil type and slope of the land, can influence the probability of waterlogging which were not analysed.

An increase in precipitation during the winter and early spring may reduce the impacts of hotter and drier summers under future climates in the UK. Prolonged water stress during the growing season reduces leaf expansion, accelerates leaf senescence and subsequently reduces yield (Jamieson et al., 1998). Despite a decrease in rainfall between May and October, water stress is predicted to decrease across England and Wales for two reasons also indicated by Semenov, (2009): Firstly, additional winter rainfall would be stored in the soil, depending on the available water capacity, and made available to the crop during the dry period. Secondly, winter wheat would mature earlier in a warmer climate, therefore reducing exposure to the hotter drier period towards the end of the crop growth. Senapati et al. (2019) also found a low probability of severe drought during reproduction in mid-century climate scenarios, at site RR in South East England. Our results show the proportion of yield loss due to drought stress during reproduction is generally higher in the south and east of the UK, which receives less rainfall than the north and west. Drought stress is however spatially and temporally diverse, showing variation between sites within the same region, and variation in future climate predictions. Yield loss due to drought stress is likely to decrease across most of the UK under future climates, with exceptions of two sites (RR and WH) which show an increase. We used one soil profile across all sites with an available water capacity of 177 mm (for drought and water stress calculations in Sirius) to focus on the signal from climate projections. However, soil depth and soil type, as well as, other landscape characteristics can influence the frequency and severity of adverse weather conditions, including short-term drought and prolonged water stress. Using a light soil, with an available water capacity of 127 mm, the relative yield losses due to drought and water stress were found to be substantially greater than when using a medium soil (refer to supplementary material). Relative yield losses due to water stress in the future climate are generally expected to be similar to the baseline or increase slightly across the south and east of the UK. However, water stress for sites in the west is expected to decrease. Climate signals indicate vulnerability to water stress will not increase considerably in the UK, as may be expected in other parts of the world. However, our results show that the impact of a changing climate on water and drought stress is spatially specific and likely to depend on local environmental conditions, including soil characteristics.

Different studies predicted the risk of adverse weather conditions, and subsequent crop failure under climate change across a large region of Europe (Trnka et al., 2015, 2011). The risk of heat stress and drought was projected to increase across Southern Europe, particularly around the Mediterranean (Olesen et al., 2011; Trnka et al., 2014). Furthermore, regions of Northern Europe (Scandinavia) are expected to suffer more from frost stress due to lower temperatures in the future climate (Trnka et al., 2014). However, the present study shows that the temperate climate of the UK is expected to be suitable for growing wheat in the future. The UK already dedicates a large proportion of agricultural land to wheat production and it may be difficult to expand outside of the current growing area with the west experiencing very wet conditions in the early part of the season. Efforts are therefore required to increase wheat production for future food security in the current growing region, through greater intensification or enabling wheat to cope better with region and season-specific climatic threats. The severity of adverse weather conditions will depend on cultivar characteristics. Our results highlight the importance of research focusing on early season waterlogging, which mostly occurs in the western growing regions but is expected to increase throughout the UK under future climates. Prolonged water stress will not increase considerably in the UK, but greater tolerance to water stress would help to increase overall yields by minimising ongoing yield losses for wheat grown in the south and east of the UK.

In the current study, we used future projections from 16 GCMs from CMIP5 to analyse adverse weather conditions for UK wheat production. The multi-model median provides an estimate of future conditions compared to the baseline climate, however the distribution of projections also provides important information about uncertainty. Predictions for the 2050 climate show a wide range in monthly rainfall predictions, which lead to uncertainty in the results of different adverse weather indices, for example: adverse conditions at sowing, wet early season and drought and water stress, as indicated by the wide range in results. At many sites the minimum values for these adverse weather conditions show a decrease in risk, whereas the maximum values show an increase. There is also generally a larger difference between the GCMs (minimum and maximum values) than between emission scenarios, highlighting the importance of using a range of models in the analysis of extreme and adverse weather conditions.

Our results highlight the importance of looking at a range of sites across the UK to provide results at a smaller spatial scale, in order to make inferences about the weather related risks for UK wheat production, and guide local adaptation or growing area expansion. Weather across the UK shows large spatial variation under the baseline and future climate, thus climate risk assessment relevant to wheat production needs to be analysed at a local scale, particularly when considering the risk of drought stress.

Underpredicting inter-annual variability is a well-known issue with weather generators including LARS-WG. However, this should not affect the calculation of adverse weather conditions analysed because the indices are based on extreme weather formulated using daily values, often during a short period of the crop development. It has been shown that LARS-WG reproduces extreme weather events well (Gitau et al., 2018; Semenov, 2008).

5. Conclusion

The UK climate is expected to remain favourable for wheat production, with most adverse weather indicators reducing in magnitude during the 21st century. Hotter and drier summers, and warmer wetter winters are expected to lead to improved sowing and harvest conditions, along with a reduced risk of lodging. The risk of late frosts and probability of heat stress during reproductive and grain filling periods would likely remain low in the future across the UK. The rainfall patterns appear more influential for wheat production in the UK. The probability of a wetter winter and spring, which generally cause issues with waterlogging, leaching and root anoxia in the western wheat growing regions, are expected to increase throughout the UK in the future. The severity of drought stress during the reproductive period is generally lower in the future climate, however there are localised differences across the wheat growing area and accordingly it is important to examine drought episodes at a small spatial scale so that adaptation can be targeted efficiently. Prolonged water stress does not seem to increase considerably in the UK, as may be expected in other parts of Europe and the world.

Climate predictions from the CMIP5 ensemble show a wide range in projections for monthly precipitation, and relative changes from the baseline climate. Based on adverse weather indices, our study shows GCMs revealed uncertainty in the adverse weather conditions, including waterlogging and yield losses due to drought and water stresses. This variation in adverse weather indicators due to GCMs is generally greater than the variation between RCP emissions scenarios. Accordingly, GCM ensembles should be used in the assessment of adverse weather conditions for crop production to indicate the full range of possible impacts, which a limited number of GCMs may not provide.

In the present study, we analysed the frequency and magnitude of a range of adverse weather conditions, which have been identified within the literature as resulting in a significant yield reduction. However, with existing process-based crop models, including Sirius, it is not possible to quantify the impact of all adverse weather conditions analysed in this study on wheat yields, for example waterlogging and lodging. In order to examine these impacts the adverse weather conditions and abiotic stresses simulated in crop models could be expanded. Similarly, the subsequent impact on farm income was not well known. In order to understand the full impact of adverse weather conditions on crop production, and in turn farm income, these aspects should be considered in future research to develop farm resilience and address future food insecurity, in a changing climate.

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References

Al-Issawi, M., Rihan, H.Z., El-Sarkassy, N., Fuller, M.P., 2013. Frost Hardiness Expression and Characterisation in Wheat at Ear Emergence. J. Agron. Crop Sci. 199, 66–74. https://doi.org/10.1111/j.1439-037X.2012.00524.x

Alghabari, F., Lukac, M., Jones, H.E., Gooding, M.J., 2014. Effect of Rht Alleles on the Tolerance of Wheat Grain Set to High Temperature and Drought Stress During Booting and Anthesis. J. Agron. Crop Sci. 200, 36–45. https://doi.org/10.1111/jac.12038

Allen, R.G., Luis, S.P., RAES, D., Smith, M., 1998. FAO Irrigation and Drainage Paper No. 56. Crop Evapotranspiration (guidelines for computing crop water requirements). Rome, Italy.

Bartholomeus, R.P., Witte, J.P.M., van Bodegom, P.M., van Dam, J.C., Aerts, R., 2008. Critical soil conditions for oxygen stress to plant roots: Substituting the Feddes-function by a process-based model. J. Hydrol. 360, 147–165. https://doi.org/10.1016/j.jhydrol.2008.07.029

Bergjord, A.K., Bonesmo, H., Skjelvåg, A.O., 2008. Modelling the course of frost tolerance in winter wheat. I. Model development. Eur. J. Agron. 28, 321–330. https://doi.org/10.1016/j.eja.2007.10.002

Berry, P.M., Sterling, M., Baker, C.J., Spink, J., Sparkes, D.L., 2003. A calibrated model of wheat lodging compared with field measurements. Agric. For. Meteorol. 119, 167–180. https://doi.org/10.1016/S0168-1923(03)00139-4

Defra, 2018. Farming Statistics Provisional Crop Areas, Yields and Livestock Populations At June 2018 - United Kingdom.

Deryng, D., Conway, D., Ramankutty, N., Price, J., Warren, R., 2014. Global crop yield response to extreme heat stress under multiple climate change futures. Environ. Res. Lett. 9. https://doi.org/10.1088/1748-9326/9/3/034011

Dong, B., Zheng, X., Liu, H., Able, J.A., Yang, H., Zhao, H., Zhang, M., Qiao, Y., Wang, Y., Liu, M., 2017. Effects of Drought Stress on Pollen Sterility, Grain Yield, Abscisic Acid and Protective Enzymes in Two Winter Wheat Cultivars. Front. Plant Sci. 8, 1–14. https://doi.org/10.3389/fpls.2017.01008

Durre, I., Menne, M.J., Gleason, B.E., Houston, T.G., Vose, R.S., 2010. Comprehensive automated quality assurance of daily surface observations. J. Appl. Meteorol. Climatol. 49, 1615–1633. https://doi.org/10.1175/2010JAMC2375.1

EDINA, 2018. EDINA agcensus [WWW Document]. Agric. census data. URL http://agcensus.edina.ac.uk/index.html (accessed 1.30.19).

Ewert, F., Rodriguez, D., Jamieson, P., Semenov, M.A., Mitchell, R.A.C., Goudriaan, J., Porter, J.R., Kimball, B.A., Pinter, P.J., Manderscheid, R., Weigel, H.J., Fangmeier, A., Fereres, E., Villalobos, F., 2002. Effects of elevated CO2 and drought on wheat: Testing crop simulation models for different experimental and climatic conditions. Agric. Ecosyst. Environ. 93, 249–266. https://doi.org/10.1016/S0167-8809(01)00352-8

FAO, 2009. FAO’s Director-General on How to Feed the World in 2050. Popul. Dev. Rev. 35, 837–839. https://doi.org/10.1111/j.1728-4457.2009.00312.x

FAOSTAT, 2018. FAOSTAT Crops [WWW Document]. URL http://www.fao.org/faostat/en/#data/QC (accessed 11.22.18).

Feng, S., Hu, Q., Qian, W., 2004. Quality control of daily meteorological data in China, 1951-2000: A new dataset. Int. J. Climatol. 24, 853–870. https://doi.org/10.1002/joc.1047

Fones, H., Gurr, S., 2015. The impact of Septoria tritici Blotch disease on wheat: An EU perspective. Fungal Genet. Biol. 79, 3–7. https://doi.org/10.1016/j.fgb.2015.04.004

Fuller, M.P., Fuller, A.M., Kaniouras, S., Christophers, J., Fredericks, T., 2007. The freezing characteristics of wheat at ear emergence. Eur. J. Agron. 26, 435–441. https://doi.org/10.1016/j.eja.2007.01.001

Gitau, M.W., Mehan, S., Guo, T., 2018. Weather Generator Effectiveness in Capturing Climate Extremes. Environ. Process. 5, 153–165. https://doi.org/10.1007/s40710-018-0291-x

Gobin, A., 2018. Weather related risks in Belgian arable agriculture. Agric. Syst. 159, 225–236. https://doi.org/10.1016/j.agsy.2017.06.009

Gourdji, S.M., Sibley, A.M., Lobell, D.B., 2013. Global crop exposure to critical high temperatures in the reproductive period: Historical trends and future projections. Environ. Res. Lett. 8, 1–10. https://doi.org/10.1088/1748-9326/8/2/024041

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M.C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., Noble, I., 2013. Sustainable development goals for people and planet. Nature 495, 305–307. https://doi.org/10.1038/495305a

Gusta, L. V., Fowler, D.B., 1976. Dehardening and rehardening of spring-collected winter wheats and a winter rye. Can. J. Plant Sci. 56, 775–779. https://doi.org/10.4141/cjps76-126

Hadi, S.J., Tombul, M., 2018. Comparison of Spatial Interpolation Methods of Precipitation and Temperature Using Multiple Integration Periods. J. Indian Soc. Remote Sens. 46, 1187–1199. https://doi.org/10.1007/s12524-018-0783-1

Hlavinka, P., Trnka, M., Balek, J., Semerádová, D., Hayes, M., Svoboda, M., Eitzinger, J., Možný, M., Fischer, M., Hunt, E., Žalud, Z., 2011. Development and evaluation of the SoilClim model for water balance and soil climate estimates. Agric. Water Manag. 98, 1249–1261. https://doi.org/10.1016/j.agwat.2011.03.011

IPCC, 2014. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://doi.org/10.1017/CBO9781107415324

IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, Cambridge. https://doi.org/10.1017/CBO9781139177245

Jamieson, P.D., Semenov, M.A., Brooking, I.R., Francis, G.S., 1998. Sirius: A mechanistic model of wheat response to environmental variation. Eur. J. Agron. 8, 161–179. https://doi.org/10.1016/S1161-0301(98)00020-3

Kendon, M., Marsh, T., Parry, S., 2013. The 2010-2012 drought in England and Wales. Weather 68, 88–95. https://doi.org/10.1002/wea.2101

Kovats, R.S., Valentini, R., Bouwer, L.M., Georgopoulou, E., Jacob, D., Martin, E., Rounsevell, M., Soussana, J.-F., 2014. Europe, in: Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp. 1267–1326. https://doi.org/10.1017/CBO9781107415386.003

Lawless, C., Semenov, M.A., Jamieson, P.D., 2005. A wheat canopy model linking leaf area and phenology. Eur. J. Agron. 22, 19–32. https://doi.org/10.1016/j.eja.2003.11.004

Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature 529, 84–87. https://doi.org/10.1038/nature16467

Li, Q., Chen, Y., Shen, Y., Li, X., Xu, J., 2011. Spatial and temporal trends of climate change in Xinjiang, China. J. Geogr. Sci. 21, 1007–1018. https://doi.org/10.1007/s11442-011-0896-8

Lobell, D.B., Sibley, A., Ivan Ortiz-Monasterio, J., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2, 186–189. https://doi.org/10.1038/nclimate1356

Lowe, J.A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard, T., Kaye, N., Kendon, E., Krijnen, J., Maisey, P., McDonald, R., McInnes, R., McSweeney, C., Mitchell, J.F., Murphy, J., Palmer, M., Roberts, C., Rostron, J., Sexton, D., Thornton, H., Tinker, J., Tucker, S., Yamazaki, K., Belcher, S., 2018. UKCP18 Science Overview report.

Lu, G.Y., Wong, D.W., 2008. An adaptive inverse-distance weighting spatial interpolation technique. Comput. Geosci. 34, 1044–1055. https://doi.org/10.1016/j.cageo.2007.07.010

Ma, J., Li, R., Wang, H., Li, D., Wang, X., Zhang, Y., Zhen, W., Duan, H., Yan, G., Li, Y., 2017. Transcriptomics Analyses Reveal Wheat Responses to Drought Stress during Reproductive Stages under Field Conditions. Front. Plant Sci. 8, 1–13. https://doi.org/10.3389/fpls.2017.00592

Malik, A.I., Colmer, T.D., Lambers, H., Setter, T.L., Schortemeyer, M., 2002. Short-term waterlogging has long-term effects on the growth and physiology of wheat. New Phytol. 153, 225–236. https://doi.org/10.1046/j.0028-646X.2001.00318.x

Martre, P., Jamieson, P.D., Semenov, M.A., Zyskowski, R.F., Porter, J.R., Triboi, E., 2006. Modelling protein content and composition in relation to crop nitrogen dynamics for wheat. Eur. J. Agron. 25, 138–154. https://doi.org/10.1016/j.eja.2006.04.007

Met Office, 2019. UK climate - Synoptic and climate stations [WWW Document]. URL https://www.metoffice.gov.uk/public/weather/climate-network

Mitchell, R.A.C., Mitchell, V.J., Driscoll, S.P., Franklin, J., Lawlor, D.W., 1993. Effects of increased CO2 concentration and temperature on growth and yield of winter wheat at two levels of nitrogen application. Plant, Cell Environ. 16, 521–529.

https://doi.org/10.1111/j.1365-3040.1993.tb00899.x

Nasehzadeh, M., Ellis, R.H., 2017. Wheat seed weight and quality differ temporally in sensitivity to warm or cool conditions during seed development and maturation. Ann. Bot. 120, 479–493. https://doi.org/10.1093/aob/mcx074

Olesen, J.E., Børgesen, C.D., Elsgaard, L., Palosuo, T., Rötter, R.P., Skjelvåg, A.O., Peltonen-Sainio, P., Börjesson, T., Trnka, M., Ewert, F., Siebert, S., Brisson, N., Eitzinger, J., van Asselt, E.D., Oberforster, M., van der Fels-Klerx, H.J., 2012. Changes in time of sowing, flowering and maturity of cereals in Europe under climate change. Food Addit. Contam. - Part A Chem. Anal. Control. Expo. Risk Assess. 29, 1527–1542. https://doi.org/10.1080/19440049.2012.712060

Olesen, J.E., Trnka, M., Kersebaum, K.C., Skjelvåg, A.O., Seguin, B., Peltonen-Sainio, P., Rossi, F., Kozyra, J., Micale, F., 2011. Impacts and adaptation of European crop production systems to climate change. Eur. J. Agron. 34, 96–112. https://doi.org/10.1016/j.eja.2010.11.003

Parry, S., Marsh, T., Kendon, M., 2013. 2012: From drought to floods in England and Wales. Weather 68, 268–274. https://doi.org/10.1002/wea.2152

Petr, J., 1991. Weather and yield. Elsevier, Amsterdam.

Pietravalle, S., Shaw, M.W., Parker, S.R., van den Bosch, F., 2007. Modeling of Relationships Between Weather and Septoria tritici Epidemics on Winter Wheat: A Critical Approach . Phytopathology 93, 1329–1339. https://doi.org/10.1094/phyto.2003.93.10.1329

Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat a review. Eur. J. Agron. 10, 23–36.

Posthumus, H., Morris, J., Hess, T.M., Neville, D., Phillips, E., Baylis, A., 2009. Impacts of the summer 2007 floods on agriculture in England. J. Flood Risk Manag. 2, 182–189. https://doi.org/10.1111/j.1753-318X.2009.01031.x

Powell, J.P., Reinhard, S., 2015. Measuring the effects of extreme weather events on yields. Weather Clim. Extrem. 12, 69–79. https://doi.org/10.1016/j.wace.2016.02.003

Rahmstorf, S., Coumou, D., 2011. Increase of extreme events in a warming world. Proc. Natl. Acad. Sci. 108, 17905–17909. https://doi.org/10.1073/pnas.1101766108

Reyer, C.P.O., Leuzinger, S., Rammig, A., Wolf, A., Bartholomeus, R.P., Bonfante, A., de Lorenzi, F., Dury, M., Gloning, P., Abou Jaoudé, R., Klein, T., Kuster, T.M., Martins, M., Niedrist, G., Riccardi, M., Wohlfahrt, G., de Angelis, P., de Dato, G., François, L., Menzel, A., Pereira, M., 2013. A plant’s perspective of extremes: Terrestrial plant responses to changing climatic variability. Glob. Chang. Biol. 19, 75–89. https://doi.org/10.1111/gcb.12023

Reynolds, M.P., Hays, D., Chapman, S., 2010. Breeding for adaptation to heat and drought stress., in: Climate Change and Crop Production. CABI, Wallingford, pp. 71–91. https://doi.org/10.1079/9781845936334.0071

Richter, G.M., Semenov, M.A., 2005. Modelling impacts of climate change on wheat yields in England and Wales: assessing drought risks. Agric. Syst. 84, 77–97. https://doi.org/10.1016/j.agsy.2004.06.011

Rietveld, M.R., 1978. A new method for estimating the regression coefficients in the formula relating solar radiation to sunshine. Agric. Meteorol. 19, 243–252. https://doi.org/10.1016/0002-1571(78)90014-6

Russell, G., Wilson, G.W., 1994. An Agro-Pedo-Climatological Knowledge-Base of Wheat in Europe, Joint Research Centre, European Commission, Luxembourg. Luxembourg.

Semenov, M., 2008. Simulation of extreme weather events by a stochastic weather generator. Clim. Res. 35, 203–212. https://doi.org/10.3354/cr00731

Semenov, M.A., 2009. Impacts of climate change on wheat in England and Wales. J. R. Soc. Interface 6, 343–350. https://doi.org/10.1098/rsif.2008.0285

Semenov, M.A., 2007. Development of high-resolution UKCIP02-based climate change scenarios in the UK. Agric. For. Meteorol. 144, 127–138. https://doi.org/10.1016/j.agrformet.2007.02.003

Semenov, M.A., Donatelli, M., Stratonovitch, P., Chatzidaki, E., Baruth, B., 2010. ELPIS: A dataset of local-scale daily climate scenarios for Europe. Clim. Res. 44, 3–15. https://doi.org/10.3354/cr00865

Semenov, M.A., Martre, P., Jamieson, P.D., 2009. Quantifying effects of simple wheat traits on yield in water-limited environments using a modelling approach. Agric. For. Meteorol. 149, 1095–1104. https://doi.org/10.1016/j.agrformet.2009.01.006

Semenov, M.A., Pilkington-bennett, S., Calanca, P., 2013. Validation of ELPIS 1980 − 2010 baseline scenarios using the observed European Climate Assessment data set. Clim. Res. 57, 1–9. https://doi.org/10.3354/cr01164

Semenov, M.A., Shewry, P.R., 2011. Modelling predicts that heat stress, not drought, will increase vulnerability of wheat in Europe. Sci. Rep. 1, 66. https://doi.org/10.1038/srep00066

Semenov, M.A., Stratonovitch, P., 2015. Adapting wheat ideotypes for climate change: Accounting for uncertainties in CMIP5 climate projections. Clim. Res. 65, 123–139. https://doi.org/10.3354/cr01297

Semenov, M.A., Stratonovitch, P., Alghabari, F., Gooding, M.J., 2014. Adapting wheat in Europe for climate change. J. Cereal Sci. 59, 245–256. https://doi.org/10.1016/j.jcs.2014.01.006

Senapati, N., Brown, H.E., Semenov, M.A., 2019a. Raising genetic yield potential in high productive countries: Designing wheat ideotypes under climate change. Agric. For. Meteorol. 271, 33–45. https://doi.org/10.1016/j.agrformet.2019.02.025

Senapati, N., Stratonovitch, P., Paul, M.J., Semenov, M.A., 2019b. Drought tolerance during reproductive development is important for increasing wheat yield potential under climate change in Europe. J. Exp. Bot. 70, 2549–2560. https://doi.org/10.1093/jxb/ery226

Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., Rusticucci, M., Semenov, V., Alexander, L. V., Allen, S., Benito, G., Cavazos, T., Clague, J., Conway, D., Della-Marta, P.M., Gerber, M., Gong, S., Goswami, B.N., Hemer, M., Huggel, C., van den Hurk, B., Kharin, V. V., Kitoh, A., Tank, A.M.G.K., Li, G., Mason, S., McGuire, W., van Oldenborgh, G.J., Orlowsky, B., Smith, S., Thiaw, W., Velegrakis, A., Yiou, P., Zhang, T., Zhou, T., Zwiers, F.W., 2012. Changes in Climate Extremes and their Impacts on the Natural Physical Environment, in: Field, C.B., Barros, V., Stocker, T.F., Dahe, Q. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, pp. 109–230. https://doi.org/10.1017/CBO9781139177245.006

Stratonovitch, P., Semenov, M.A., 2015. Heat tolerance around flowering in wheat identified as a key trait for increased yield potential in Europe under climate change. J. Exp. Bot. 66, 3599–3609. https://doi.org/10.1093/jxb/erv070

Trnka, M., Eitzinger, J., Dubrovský, M., Semerádová, D., Štěpánek, P., Hlavinka, P., Balek, J., Skalák, P., Farda, A., Formayer, H., Žalud, Z., Change, C., Paper, A., 2010a. Is rainfed crop production in central Europe at risk? Using a regional climate model to produce high resolution agroclimatic information for decision makers. J. Agric. Sci. 148, 639–656. https://doi.org/10.1017/S0021859610000638

Trnka, M., Hlavinka, P., Semenov, M.A., 2015. Adaptation options for wheat in Europe will be limited by increased adverse weather events under climate change. J. R. Soc. Interface 12, 20150721. https://doi.org/10.1098/rsif.2015.0721

Trnka, M., Kocmánková, E., Balek, J., Eitzinger, J., Ruget, F., Formayer, H., Hlavinka, P., Schaumberger, A., Horáková, V., Možný, M., 2010b. Simple snow cover model for agrometeorological applications. Agric. For. Meteorol. 150, 1115–1127. https://doi.org/10.1016/j.agrformet.2010.04.012

Trnka, M., Olesen, J.E., Kersebaum, K.C., Skjelvåg, A.O., Eitzinger, J., Seguin, B., Peltonen-Sainio, P., Rötter, R., Iglesias, A., Orlandini, S., Dubrovský, M., Hlavinka, P., Balek, J., Eckersten, H., Cloppet, E., Calanca, P., Gobin, A., Vučetić, V., Nejedlik, P., Kumar, S., Lalic, B., Mestre, A., Rossi, F., Kozyra, J., Alexandrov, V., Semerádová, D., Žalud, Z., 2011. Agroclimatic conditions in Europe under climate change. Glob. Chang. Biol. 17, 2298–2318. https://doi.org/10.1111/j.1365-2486.2011.02396.x

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4, 637–643. https://doi.org/10.1038/nclimate2242

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The representative concentration pathways: an overview. Clim. Change 109, 5–31. https://doi.org/10.1007/s10584-011-0148-z

Vanuytrecht, E., Raes, D., Willems, P., 2016. Regional and global climate projections increase mid-century yield variability and crop productivity in Belgium. Reg. Environ. Chang. 16, 659–672. https://doi.org/10.1007/s10113-015-0773-6

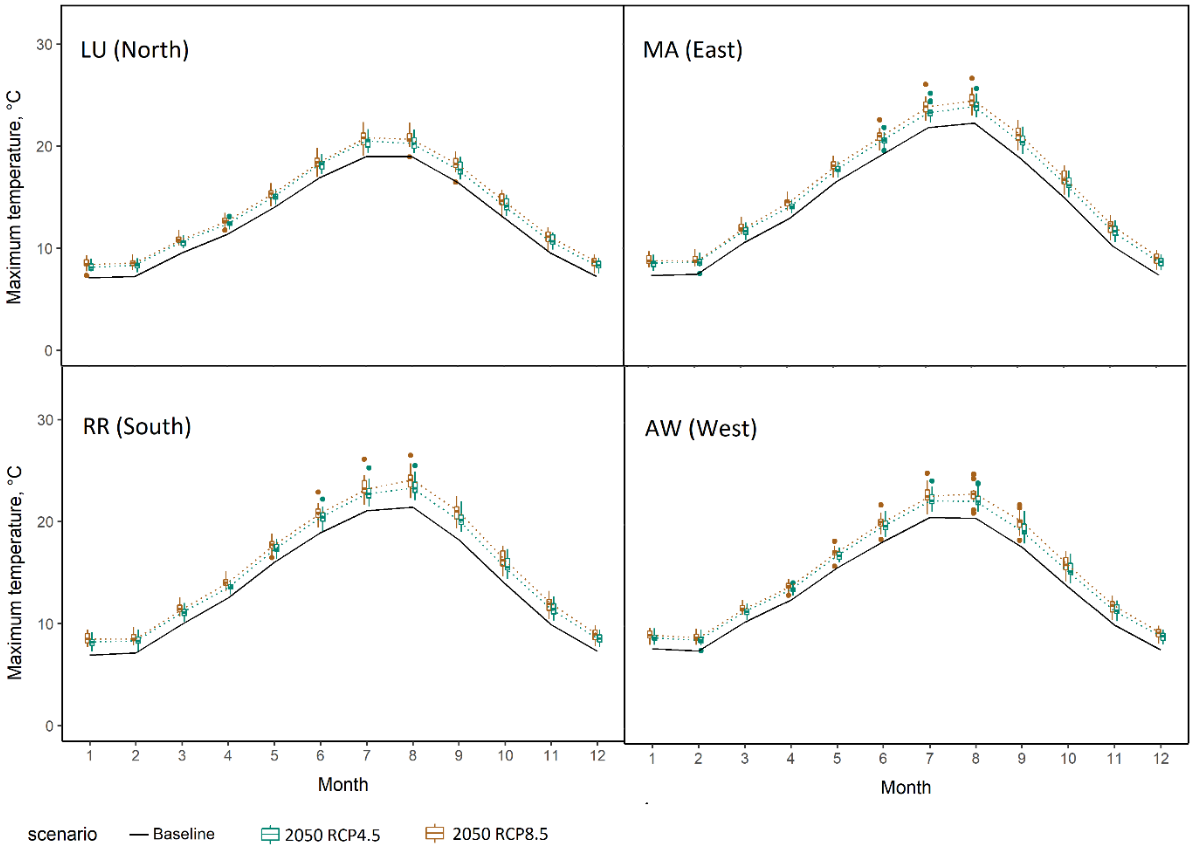
Vanuytrecht, E., Raes, D., Willems, P., Semenov, M.A., 2014. Comparing climate change impacts on cereals based on CMIP3 and EU-ENSEMBLES climate scenarios. Agric. For. Meteorol. 195–196, 12–23. https://doi.org/10.1016/j.agrformet.2014.04.017

Weightman, R., Foulkes, J., Snape, J., Fish, L., Alava, J., Greenwell, P., 2005. Physiological traits influencing hardness and vitreosity in wheat grain, in: Using Cereal Science and Technology for the Benefit of Consumers. pp. 220–224. https://doi.org/10.1533/9781845690632.6.220

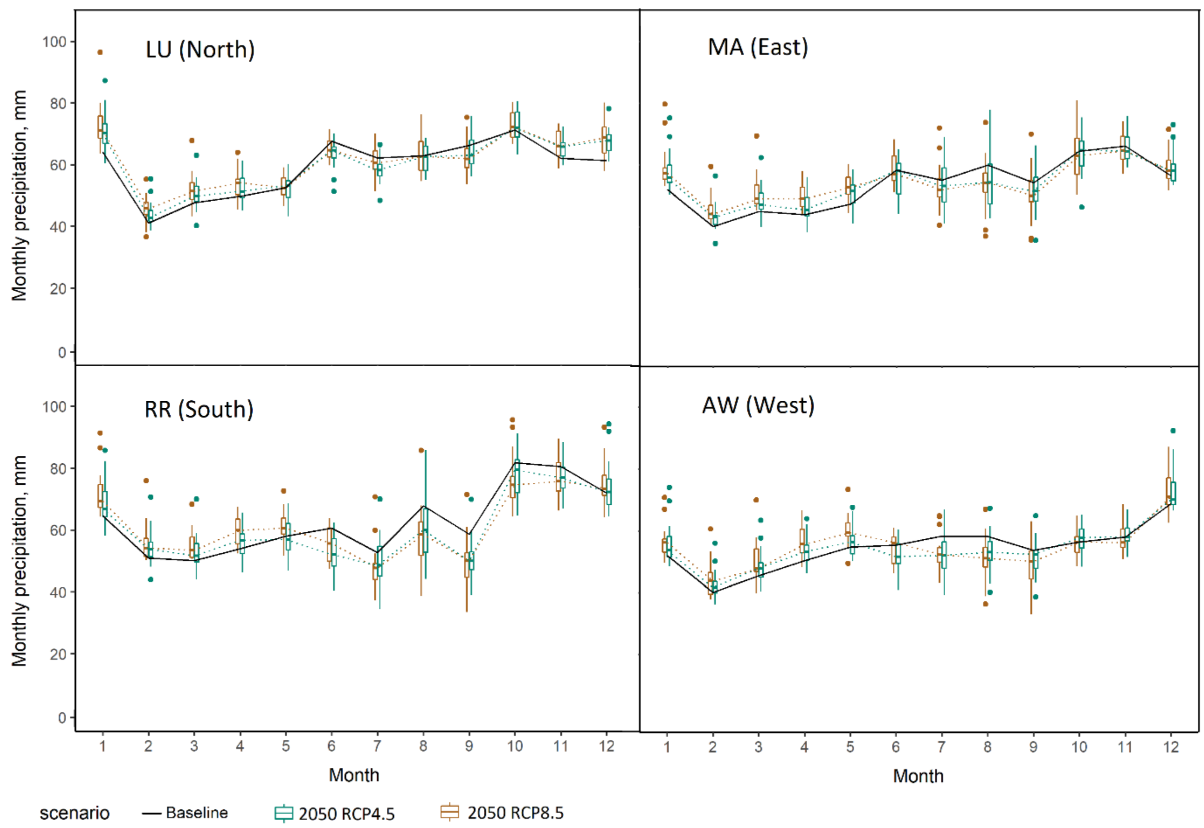
Supplementary Material

Adverse weather conditions for UK wheat production under climate change

1. Future UK climate



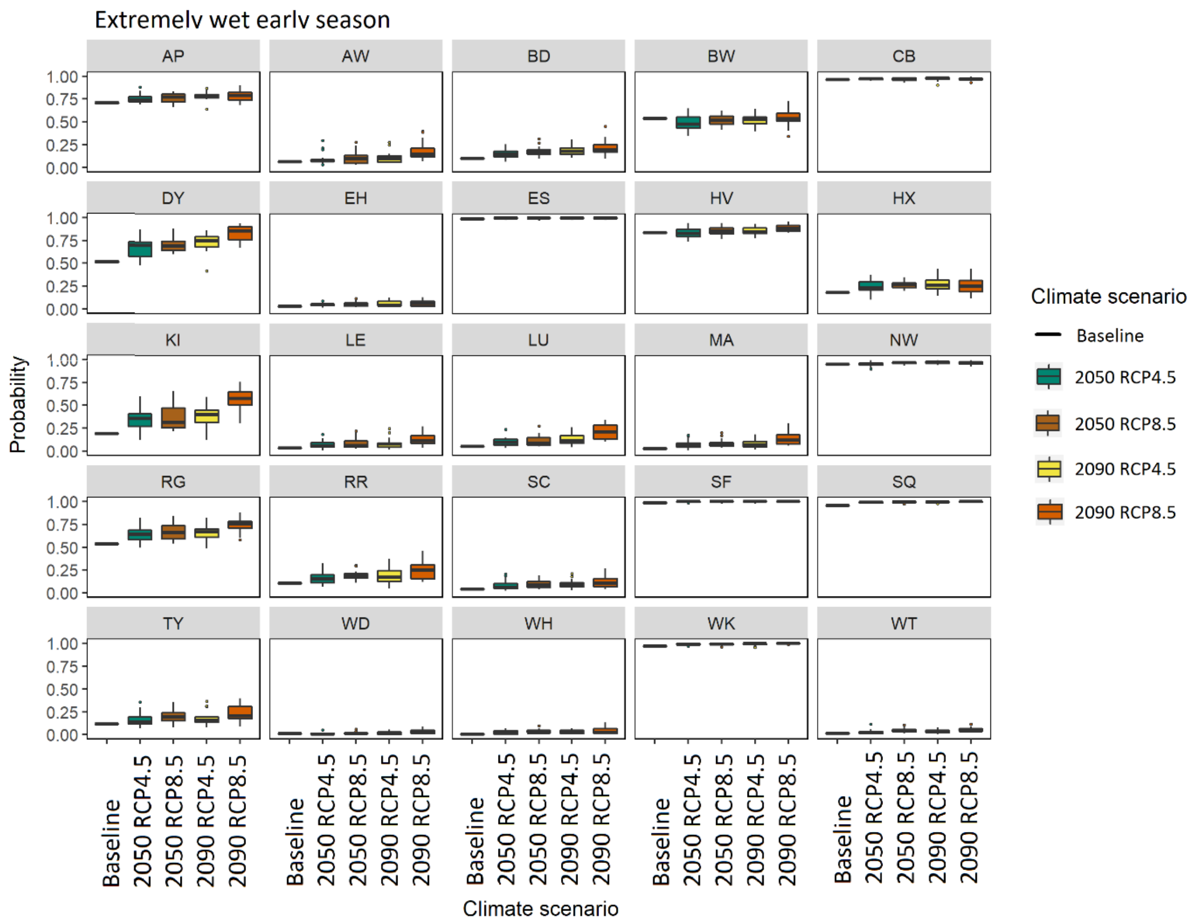
Supplementary Figure 1 – Mean maximum monthly temperature for the 1981-2010 baseline (solid line) and box plots for the 2050 climate scenarios (RCP4.5 and RCP8.5). At four sites across the UK wheat growing area.



Supplementary Figure 2 - Mean monthly precipitation for the 1981-2010 baseline (solid line) and box plots for the 2050 climate scenarios (RCP4.5 and RCP8.5). At four sites across the UK wheat growing area.

2. Frequency and severity of adverse weather conditions in 2090

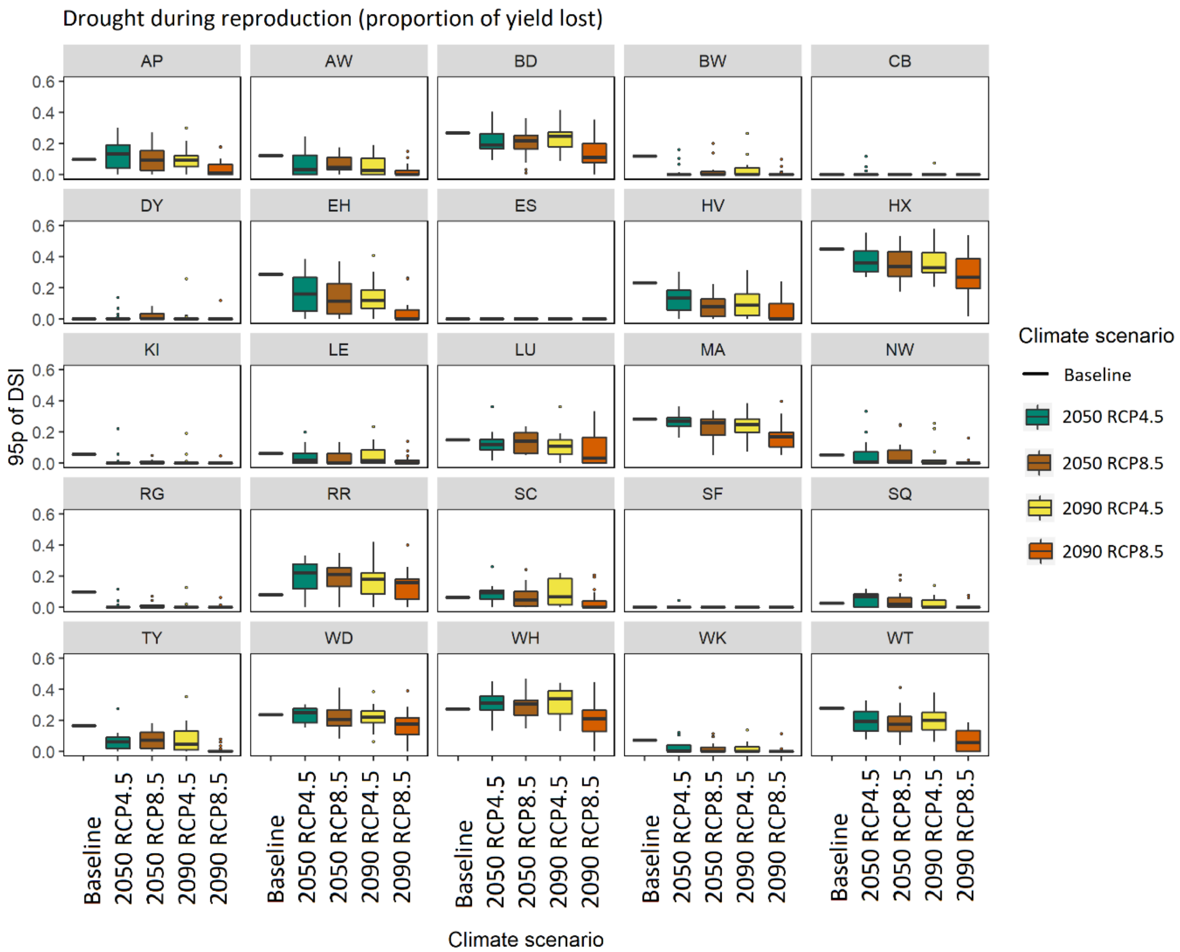
The probability of an extremely wet early season for wheat production is projected to increase by the 2050 (as discussed in the main text). Supplementary Figure 3 provides the probability of an extremely wet early season at all 25 sites and all climate scenarios, illustrating an increasing trend across time and emissions scenarios. In 2090 the probability of an extremely wet early season is expected to increase more than two-fold at 10 sites across the wheat growing area under high emissions (RCP8.5), including sites RR, MA and WH which are located within a key wheat growing region of the South East.



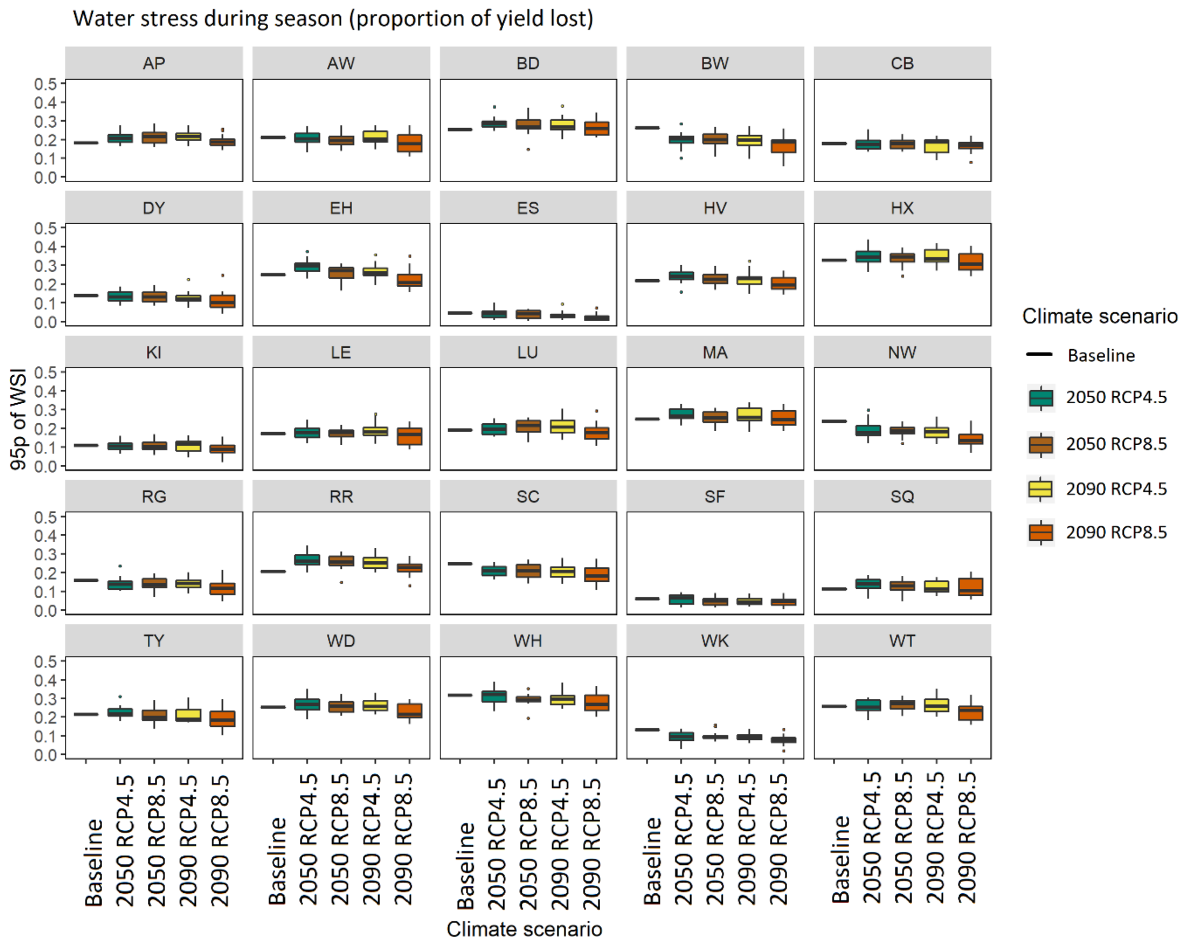
Supplementary Figure 3 - Probability of the occurrence of extremely wet early season under baseline and projected climate. Black rectangles indicate the 1981-2010 baseline. Box plots indicate the 2050 climate scenarios for RCP4.5 and RCP8.5 and 2090 climate scenarios for RCP4.5 and RCP8.5, from left to right. The calculations consider a medium-ripening cultivar.

Supplementary Figure 4 and Supplementary Figure 5 provide the 95-percentile of drought stress index (DSI95) and water stress index (WSI95), respectively, at all 25 sites and all climate scenarios.

In 2090 most sites project a lower DSI95 under both RCP4.5 and RCP8.5 in comparison to the baseline period. In contrast site RR is unique in projecting an increase in DSI95 by 2100 under both emission scenarios. In 2090, using the median of GCMs, most sites show little change or a lower WSI95 under RCP8.5 in comparison to the baseline climate. HSI95 (heat stress index) continues to be negligible or very low in 2090.



Supplementary Figure 4 - 95-percentile of drought stress index (DSI95) Black rectangles indicate the 1981-2010 baseline. Box plots indicate the 2050 climate scenarios for RCP4.5 and RCP8.5 and 2090 climate scenarios for RCP4.5 and RCP8.5, from left to right.

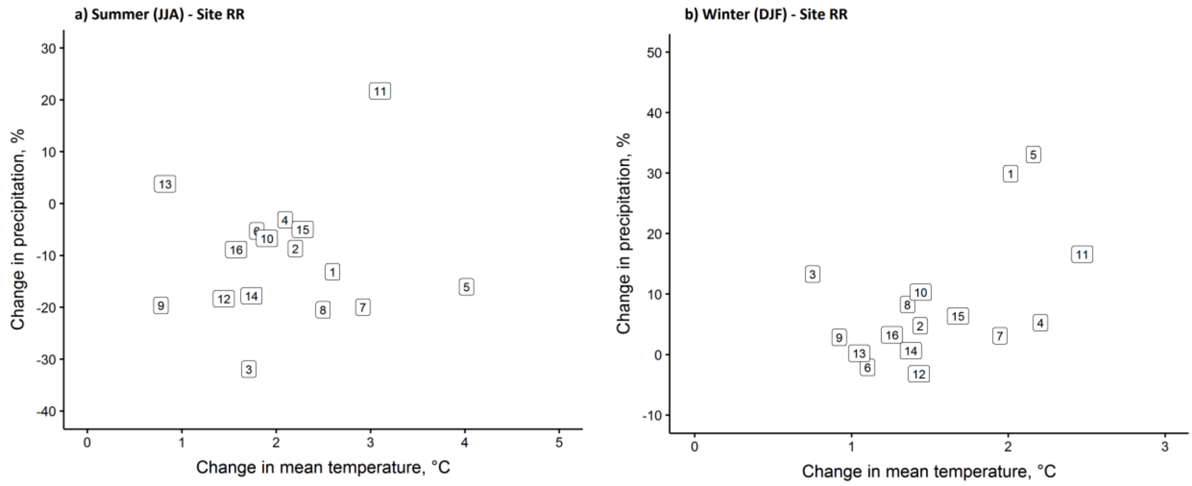


Supplementary Figure 5 - 95-percentile of water stress index (WSI95) Black rectangles indicate the 1981-2010 baseline. Box plots indicate the 2050 climate scenarios for RCP4.5 and RCP8.5 and 2090 climate scenarios for RCP4.5 and RCP8.5, from left to right.

3. Range of projections from the CMIP5 ensemble

For most sites CSIRO-MK36 (GCM model no. 3) is the driest model in summer, with the largest reduction in rainfall between the baseline and 2050 climate, as illustrated by Supplementary Figure 6, however this is cooler than other models. For most sites GFDL-CM3 (GCM model no. 5) is the hottest model in the CMIP5 ensemble in the summer, which is also consistently very dry across UK sites. INM-CM4 (GCM model no. 9) is frequently the coldest model in summer and MIROC-ESM (GCM model no. 11) commonly the wettest.

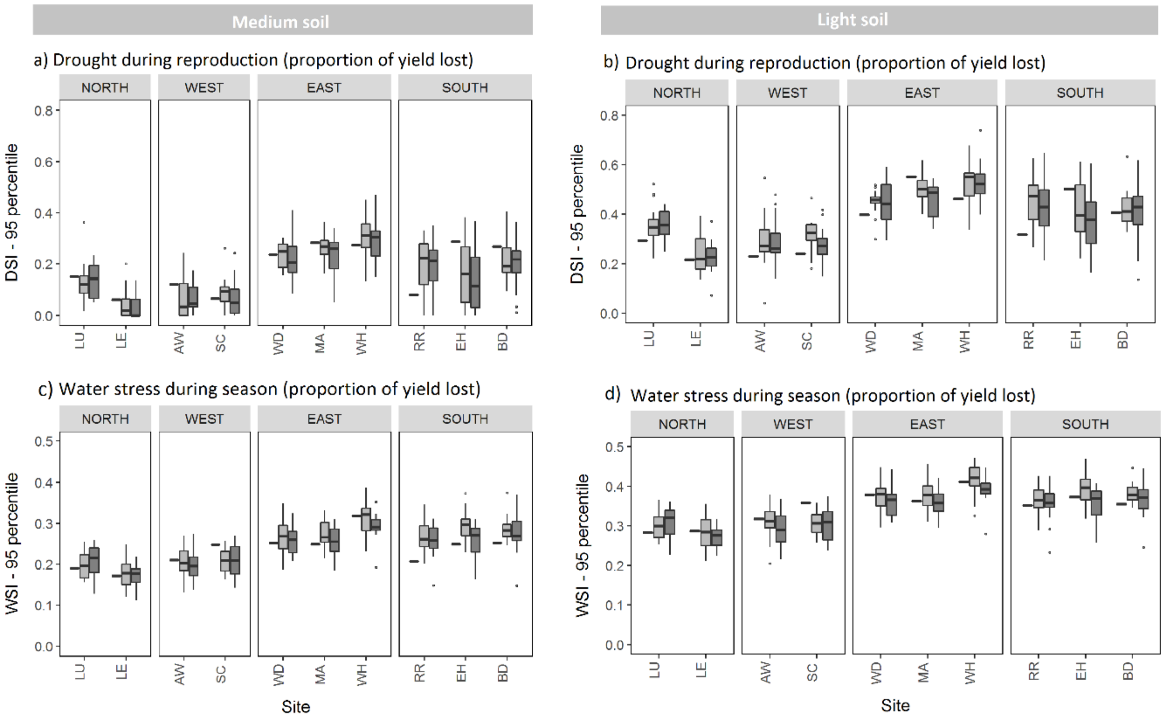
For most sites GFDL-CM3 is the wettest model in winter, with the largest increase in precipitation between the baseline and 2050s (RCP8.5) as illustrated by Supplementary Figure 6. For most sites MIROC-ESM the hottest model in the CMIP5 ensemble for winter. CSIRO-MK36 is the coldest model in winter. A number of GCMs predict no change or a small decrease in winter precipitation, however there is not one model which is consistently the driest in winter across all sites in the UK. MPI-ESM-MR (GCM no. 12) is the driest for site RR and a number of other sites.



Supplementary Figure 6 – Absolute changes in mean temperature and relative changes in mean precipitation at site RR (Rothamsted Research) during a) the summer months (JJA) and b) the winter months (DJF), between baseline (1981-2010) and 2050 climate, under RCP8.5 for 16 GCMs from the CMIP5 ensemble. Model numbers correspond with Supplementary Table 2.

4. Drought and water stress for light soils

We consider the effect of soil available water capacity (AWC) on extreme drought stress (DSI95) and extreme water stress (WSI95) (Supplementary Figure 7). The AWC used in these calculations represents a medium and light soil, with the majority of wheat in England and Wales grown on soils with an AWC 95-215 mm (Clarke, 2017; Hallett et al., 1996)



Supplementary Figure 7 – 95-percentile of drought stress index (DSI95) (a, b) and water stress index (WSI95) (c, d) The first column (a, c) shows results for the medium soil with AWC of 177 mm (as used in Figures 5-9 and Supplementary Figures 4-5), and the second column (b, d) shows results for light soil with AWC of 127 mm. Black rectangles indicate the 1981-2010 baseline and box plots indicate the 2050 climate scenarios for RCP4.5 (light grey) and RCP8.5 (dark grey).

Supplementary Table 1 - Characteristics of the 25 UK sites for the 1981-2010 baseline conditions
The mean dates of the phenological stages represent the AgriClim model estimates for early-, medium- and late-ripening cultivars. (The sowing, anthesis and maturity dates are expressed as the day of the year – DOY from January 1st).

Site	Acronym	Lat	Long	Alt	Mean precip. Annual, mm	Mean temp, °C		Sowing DOY
						Jan, min	Jul, max	
Wick	WK	58.45	-3.09	36	793	1.7	15.7	293
Kinloss	KI	57.65	-3.56	5	688	1.3	18.5	293
Dyce	DY	57.21	-2.20	65	812	1.2	18.1	293
Leuchars	LU	56.38	-2.86	10	709	0.6	19.0	293
Eskdalemuir	ES	55.31	-3.21	242	1747	-0.1	17.8	293
Tynemouth	TY	55.02	-1.42	33	631	2.4	18.2	293
Shap Fell	SF	54.50	-2.68	255	1753	0.5	18.0	293
Whitby	WT	54.48	-0.60	41	561	2.1	18.6	293
Leeming	LE	54.30	-1.53	32	643	1.2	20.7	293
Ringway	RG	53.36	-2.28	33	805	1.7	20.4	293
Holyhead Valley	HV	53.25	-4.54	10	848	4.0	18.3	293
Waddington	WD	53.18	-0.52	68	602	1.5	20.9	293
Shawbury	AW	52.79	-2.66	72	652	1.0	20.7	293
Marham	MA	52.65	0.57	21	644	0.9	21.8	293
Church Lawford	SC	52.36	-1.33	107	676	1.3	21.4	293
Wattisham	WH	52.12	0.96	89	626	1.3	21.3	293
Aberporth	AP	52.14	-4.57	133	857	3.2	17.9	293
Sennybridge	SQ	52.06	-3.61	307	1375	0.9	18.0	293
Rothamsted	RR	51.80	-0.35	128	751	1.2	21.0	293
Bristol	BW	51.45	-2.60	42	855	3.5	21.7	293
East Hamsted	EH	51.38	0.78	75	680	1.6	22.1	293
Boscombe Down	BD	51.16	-1.75	126	751	1.6	21.7	293
North Wyke	NW	50.77	-3.90	177	1065	2.6	19.7	293
Herstmonceux	HX	50.89	0.32	52	787	2.4	20.7	293
Camborne	CB	50.22	-5.33	87	1037	4.7	18.3	293

** In the case of the late cultivar at Eskdalemuir and Wick, maturity was not reached.*

Supplementary Table 2 - Global climate models from the CMIP5 ensemble used in the LARS-WG weather generator. The scenarios are based on RCP4.5 and RCP8.5 for the periods 1981-2010 (baseline) and 2041-2060 and 2081-2100.

Model no.	Research centre	Country	Global climate model	Grid resolution	Reference
1	The Centre for Australian Weather and Climate Research	Australia	ACCESS1-3	1.25° x 1.88°	(Collier and Uhe, 2012)
2	Canadian Centre for Climate Modelling and Analysis	Canada	CanESM2	2.77° x 2.81°	(Chylek et al., 2011)
3	Australia's Commonwealth Scientific and Industrial Research Organisation	Australia	CSIRO-MK36	1.85° x 1.88°	(Jeffrey et al., 2013)
4	EC-EARTH consortium	Europe	EC-EARTH	1.125° x 1.125°	(Hazeleger et al., 2012)
5	Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM3	2° x 2.5°	(Griffies et al., 2011)
6	Goddard Institute for Space Studies National	USA	GISS-E2-R-CC	2.00° x 2.50°	(Chandler et al., 2013)
7	UK Meteorological Office	UK	HadGEM2-ES	1.25° x 1.88°	(Collins et al., 2011; Jones et al., 2011)
8	Institute Pierre Simon Laplace	France	IPSL-CM5A-MR	1.27° x 2.50°	(Dufresne et al., 2013)
9	Institute for Numerical Mathematics	Russia	INM-CM4	1.50° x 20°	(Volodin et al., 2013; Yurova and Volodin, 2011)
10	University of Tokyo, National Institute for Envir. Studies, Japan Agency for Marine-Earth Science & Technology	Japan	MIROC5	1.39° x 1.41°	(Mochizuki et al., 2012; Tatebe et al., 2012; Watanabe et al., 2011)
11			MIROC-ESM	2.77° x 2.81°	(Watanabe et al., 2011)
12	Max-Planck Institute for Meteorology	Germany	MPI-ESM-MR	1.85° x 1.88°	(Brovkin et al., 2013; Schmidt et al., 2013)
13	Meteorological Research Institute	Japan	MRI-CGCM3	1.11° x 1.13°	(Tsujino et al., 2011)
14	National Centre for Atmospheric Research	USA	NCAR-CCSM4	0.94° x 1.25°	(Jahn and Holland, 2013; Meehl et al., 2013)
15			NCAR-CESM1-CAM5	0.94° x 1.25°	(Jahn and Holland, 2013)
16	Norwegian Climate Centre	Norway	NorESM1-M	1.90° x 2.50°	(Bentsen et al., 2013; Iversen et al., 2013)

Supplementary Table 3 – Annual mean temperature for the 1981-2010 baseline and change in annual mean temperature under future climate scenarios (RCP4.5 and RCP8.5).

Minimum and maximum values show the smallest and largest change in temperature (respectively) across all 16 GCMs, from the baseline.

	Annual mean temp, °C	**Change in annual mean temp, from baseline, °C**			
		RCP4.5		**RCP8.5**	
Site	**Baseline**	**Min GCM**	**Max GCM**	**Min GCM**	**Max GCM**
AP	9.9	0.5	2.1	0.5	2.5
AW	9.6	0.6	2.2	0.6	2.7
BD	10.1	0.6	2.3	0.8	2.8
BW	11.2	0.6	2.3	0.7	2.9
CB	10.9	0.4	1.9	0.4	2.4
DY	8.6	0.5	1.9	0.3	2.4
EH	10.2	0.5	2.5	0.8	3.0
ES	7.6	0.6	2.0	0.4	2.4
HV	10.5	0.5	2.0	0.5	2.5
HX	10.6	0.4	2.5	0.8	3.0
KI	8.9	0.5	1.9	0.3	2.3
LE	9.5	0.6	2.1	0.5	2.6
LU	8.8	0.6	2.0	0.4	2.4
MA	10.0	0.6	2.2	0.7	2.7
NW	10.0	0.5	2.2	0.5	2.7
RG	10.0	0.6	2.2	0.6	2.7
RR	9.8	0.6	2.4	0.8	2.9
SC	9.9	0.6	2.2	0.7	2.7
SF	8.0	0.6	2.0	0.5	2.5
SQ	8.4	0.6	2.1	0.6	2.6
TY	9.4	0.6	2.1	0.5	2.6
WD	9.9	0.6	2.2	0.7	2.7
WH	10.0	0.6	2.3	0.7	2.8
WK	8.0	0.4	1.8	0.2	2.2
WT	9.4	0.7	2.2	0.5	2.7

Supplementary Table 4 – Mean precipitation for the 1981-2010 baseline, for summer (JJA) and winter (DJF) and change in precipitation under future climate scenarios (RCP4.5 and RCP8.5).

Minimum and maximum values show the smallest and largest change in precipitation (respectively) across all 16 GCMs, from the baseline.

	Mean precip., summer, mm	**Change in summer precip., from baseline, %**				**Mean precip., winter, mm**	**Change in winter precip., from baseline, %**			
		RCP4.5		**RCP8.5**			**RCP4.5**		**RCP8.5**	
Site	**Baseline**	**Min GCM**	**Max GCM**	**Min GCM**	**Max GCM**	**Baseline**	**Min GCM**	**Max GCM**	**Min GCM**	**Max GCM**
AP	64	-25	12	-26	12	77	-4	35	-6	38
AW	57	-28	13	-26	10	54	-5	34	-5	31
BD	52	-26	16	-25	22	73	-8	26	-3	34
BW	63	-25	19	-26	20	84	-10	28	-6	31
CB	66	-21	13	-23	13	112	-5	31	-4	35
DY	63	-11	9	-11	10	66	-3	32	-7	37
EH	47	-25	27	-25	30	61	-8	28	-4	32
ES	129	-21	10	-19	7	178	-5	36	-3	32
HV	62	-18	14	-20	14	74	-5	39	-5	41
HX	56	-28	23	-28	22	76	-8	27	-5	30
KI	63	-9	5	-15	10	54	-6	24	-10	31
LE	58	-20	16	-20	18	51	-4	34	-6	41
LU	64	-13	6	-11	8	55	-1	33	-4	39
MA	58	-23	20	-26	23	50	-7	34	1	38
NW	63	-23	15	-27	10	118	-6	27	-5	29
RG	65	-25	16	-24	18	71	-5	38	-6	39
RR	60	-31	20	-32	22	62	-8	28	-3	33
SC	64	-27	18	-24	18	49	-1	34	-2	38
SF	99	-21	12	-19	10	204	-9	32	-8	30
SQ	89	-19	14	-23	18	136	-2	35	-3	36
TY	53	-18	10	-20	12	49	-5	37	-8	39
WD	60	-24	12	-28	17	45	-4	30	-5	36
WH	59	-24	24	-26	25	45	-4	37	4	43
WK	60	-13	8	-17	11	66	-2	30	-8	32
WT	46	-21	10	-21	14	48	-1	40	-3	42

References

Bentsen, M., Bethke, I., Debernard, J.B., Iversen, T., Kirkevåg, A., Seland, Ø., Drange, H., Roelandt, C., Seierstad, I.A., Hoose, C., Kristjánsson, J.E., 2013. The Norwegian Earth System Model, NorESM1-M – Part 1: Description and basic evaluation of the physical climate. Geosci. Model Dev. 6, 687–720. https://doi.org/10.5194/gmd-6-687-2013

Brovkin, V., Boysen, L., Raddatz, T., Gayler, V., Loew, A., Claussen, M., 2013. Evaluation of vegetation cover and land-surface albedo in MPI-ESM CMIP5 simulations. J. Adv. Model. Earth Syst. 5, 48–57. https://doi.org/10.1029/2012MS000169

Chandler, M.A., Sohl, L.E., Jonas, J.A., Dowsett, H.J., Kelley, M., 2013. Simulations of the mid-Pliocene Warm Period using two versions of the NASA/GISS ModelE2-R Coupled Model. Geosci. Model Dev. 6, 517–531. https://doi.org/10.5194/gmd-6-517-2013

Chylek, P., Li, J., Dubey, M.K., Wang, M., Lesins, G., 2011. Observed and model simulated 20th century Arctic temperature variability: Canadian Earth System Model CanESM2. Atmos. Chem. Phys. Discuss. 11, 22893–22907. https://doi.org/10.5194/acpd-11-22893-2011

Clarke, D., 2017. Assessing the impacts of drought on UK wheat production. Cranfield University.

Collier, M., Uhe, P., 2012. CMIP5 datasets from the ACCESS1.0 and ACCESS1.3 coupled climate models.

Collins, W.J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C.D., Joshi, M., Liddicoat, S., Martin, G., Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., Woodward, S., 2011. Development and evaluation of an Earth-System model – HadGEM2. Geosci. Model Dev. 4, 1051–1075. https://doi.org/10.5194/gmd-4-1051-2011

Dufresne, J.-L., Foujols, M.-A., Denvil, S., Caubel, A., Marti, O., Aumont, O., Balkanski, Y., Bekki, S., Bellenger, H., Benshila, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., de Noblet, N., Duvel, J.-P., Ethé, C., Fairhead, L., Fichefet, T., Flavoni, S., Friedlingstein, P., Grandpeix, J.-Y., Guez, L., Guilyardi, E., Hauglustaine, D., Hourdin, F., Idelkadi, A., Ghattas, J., Joussaume, S., Kageyama, M., Krinner, G., Labetoulle, S., Lahellec, A., Lefebvre, M.-P., Lefevre, F., Levy, C., Li, Z.X., Lloyd, J., Lott, F., Madec, G., Mancip, M., Marchand, M., Masson, S., Meurdesoif, Y., Mignot, J., Musat, I., Parouty, S., Polcher, J., Rio, C., Schulz, M., Swingedouw, D., Szopa, S., Talandier, C., Terray, P., Viovy, N., Vuichard, N., 2013. Climate change projections using the IPSL-CM5 Earth System Model: from CMIP3 to CMIP5. Clim. Dyn. 40, 2123–2165. https://doi.org/10.1007/s00382-012-1636-1

Griffies, S.M., Winton, M., Donner, L.J., Horowitz, L.W., Downes, S.M., Farneti, R., Gnanadesikan, A., Hurlin, W.J., Lee, H.-C., Liang, Z., Palter, J.B., Samuels, B.L., Wittenberg, A.T., Wyman, B.L., Yin, J., Zadeh, N., 2011. The GFDL CM3 Coupled Climate Model: Characteristics of the Ocean and Sea Ice Simulations. J. Clim. 24, 3520–3544. https://doi.org/10.1175/2011JCLI3964.1

Hallett, S.H., Jones, R.J.A., Keay, C.A., 1996. Environmental information systems developments for planning sustainable land use. Int. J. Geogr. Inf. Syst. 10, 47–64. https://doi.org/10.1080/02693799608902066

Hazeleger, W., Wang, X., Severijns, C., Ştefãnescu, S., Bintanja, R., Sterl, A., Wyser, K., Semmler, T., Yang, S., van den Hurk, B., van Noije, T., van der Linden, E., van der Wiel, K., 2012. EC-Earth V2.2: Description and validation of a new seamless earth system prediction model. Clim. Dyn. 39, 2611–2629. https://doi.org/10.1007/s00382-011-1228-5

Iversen, T., Bentsen, M., Bethke, I., Debernard, J.B., Kirkevåg, A., Seland, Ø., Drange, H., Kristjansson, J.E., Medhaug, I., Sand, M., Seierstad, I.A., 2013. The Norwegian Earth System Model, NorESM1-M – Part 2: Climate response and scenario projections. Geosci. Model Dev. 6, 389–415. https://doi.org/10.5194/gmd-6-389-2013

Jahn, A., Holland, M.M., 2013. Implications of Arctic sea ice changes for North Atlantic deep convection and the meridional overturning circulation in CCSM4-CMIP5 simulations. Geophys. Res. Lett. 40, 1206–1211. https://doi.org/10.1002/grl.50183

Jeffrey, S., Rotstayn, L., Collier, M., Dravitzki, S., Hamalainen, C., Moeseneder, C., Wong, K., Skytus, J., 2013. Australia's CMIP5 submission using the CSIRO-Mk3.6 model. Aust. Meteorol. Oceanogr. J. 63, 1–14. https://doi.org/10.22499/2.6301.001

Jones, C.D., Hughes, J.K., Bellouin, N., Hardiman, S.C., Jones, G.S., Knight, J., Liddicoat, S., O'Connor, F.M., Andres, R.J., Bell, C., Boo, K.-O., Bozzo, A., Butchart, N., Cadule, P., Corbin, K.D., Doutriaux-Boucher, M., Friedlingstein, P., Gornall, J., Gray, L., Halloran, P.R., Hurtt, G., Ingram, W.J., Lamarque, J.-F., Law, R.M., Meinshausen, M., Osprey, S., Palin, E.J., Parsons Chini, L., Raddatz, T., Sanderson, M.G., Sellar, A.A., Schurer, A., Valdes, P., Wood, N., Woodward, S., Yoshioka, M., Zerroukat, M., 2011. The HadGEM2-ES implementation of CMIP5 centennial simulations. Geosci. Model Dev. 4, 543–570. https://doi.org/10.5194/gmd-4-543-2011

Meehl, G.A., Washington, W.M., Arblaster, J.M., Hu, A., Teng, H., Kay, J.E., Gettelman, A., Lawrence, D.M., Sanderson, B.M., Strand, W.G., 2013. Climate change projections in CESM1(CAM5) compared to CCSM4. J. Clim. 26, 6287–6308. https://doi.org/10.1175/JCLI-D-12-00572.1

Mochizuki, T., Chikamoto, Y., Kimoto, M., Ishii, M., Tatebe, H., Komuro, Y., Sakamoto, T.T., Watanabe, M., Mori, M., 2012. Decadal Prediction Using a Recent Series of MIROC Global Climate Models. J. Meteorol. Soc. Japan 90A, 373–383. https://doi.org/10.2151/jmsj.2012-A22

Schmidt, H., Rast, S., Bunzel, F., Esch, M., Giorgetta, M., Kinne, S., Krismer, T., Stenchikov, G., Timmreck, C., Tomassini, L., Walz, M., 2013. Response of the middle atmosphere to anthropogenic and natural forcings in the CMIP5 simulations with the Max Planck Institute Earth system model. J. Adv. Model. Earth Syst. 5, 98–116. https://doi.org/10.1002/jame.20014

Tatebe, H., Ishii, M., Mochizuki, T., Chikamoto, Y., Sakamoto, T.T., Komuro, Y., Mori, M., Yasunaka, S., Watanabe, M., Ogochi, K., Suzuki, T., Nishimura, T., Kimoto, M., 2012. The Initialization of the MIROC Climate Models with Hydrographic Data Assimilation for Decadal Prediction. J. Meteorol. Soc. Japan 90A, 275–294. https://doi.org/10.2151/jmsj.2012-A14

Tsujino, H., Hirabara, M., Nakano, H., Yasuda, T., Motoi, T., Yamanaka, G., 2011. Simulating present climate of the global ocean–ice system using the Meteorological Research Institute Community Ocean Model (MRI.COM): simulation characteristics and variability in the Pacific sector. J. Oceanogr. 67, 449–479.

https://doi.org/10.1007/s10872-011-0050-3

Volodin, E.M., Diansky, N.A., Gusev, A. V., 2013. Simulation and Prediction of Climate Changes in the 19th to 21st Centuries with the Institute of Numerical Mathematics, Russian Academy of Sciences, Model of the Earth's Climate System. Известия Российской академии наук. Физика атмосферы и океана 49, 379–400. https://doi.org/10.7868/S000235151304010X

Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., Nozawa, T., Kawase, H., Abe, M., Yokohata, T., Ise, T., Sato, H., Kato, E., Takata, K., Emori, S., Kawamiya, M., 2011. MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments. Geosci. Model Dev. 4, 845–872. https://doi.org/10.5194/gmd-4-845-2011

Yurova, A.Y., Volodin, E.M., 2011. Coupled simulation of climate and vegetation dynamics. Izv. Atmos. Ocean. Phys. 47, 531–539. https://doi.org/10.1134/S0001433811050124

Chapter 4 - Stability of farm income: the role of agricultural diversity and agri-environment scheme payments

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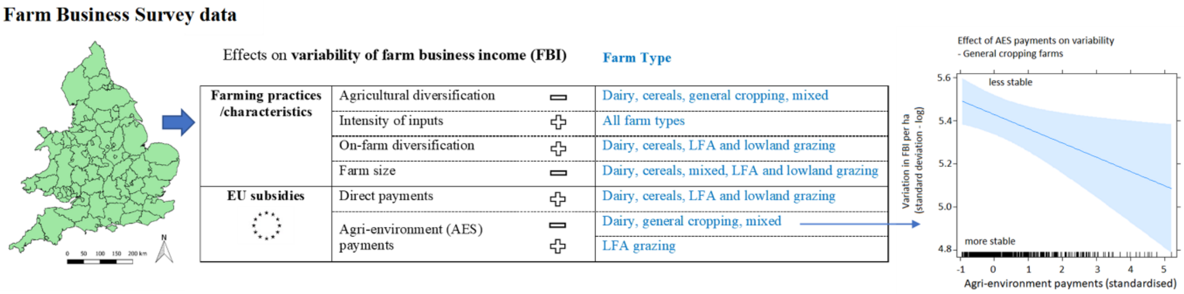
Abstract

Instability (or variability) in farm income represents a significant challenge for farm management and the design of public policies. Identifying farming practices which can increase the stability of farm income may help farms to cope with shocks such as extreme weather events and economic challenges. Farming practices associated with increasing agricultural diversity and agri-environment schemes are considered to improve ecological functions and landscape resilience, however, their effect on the stability of farm income is not well known. Using a multilevel model, we analyse the effect of a range of farming practices and subsidies on the stability of farm income, and their relative importance, using four different measures of stability. We examine data for 2,333 farms in England and Wales, from 2007 to 2015, and use separate multilevel models for a range of different farm types to provide targeted recommendations for farmers. Here we show that greater agricultural diversity (i.e. lower degree of specialisation in different crop and livestock activities) increases the stability of farm income, in dairy, general cropping, cereal and mixed farms. Agricultural diversity is a particularly important factor for general cropping farms; increasing the degree of specialisation by one standard deviation (we use standardised coefficients), increases the variability of income by approximately 20%. Dairy, general cropping and mixed farms that receive more agri-environment payments also have more stable incomes, reducing variability by between 4 and 8%. In contrast, an increase in direct subsidies paid to farmers

based on the area farmed is associated with a relatively large decrease in the stability of farm income, ranging from 6-35% across most farm types. Reducing the intensity of inputs is found to be an important factor increasing the stability of income for all farm types; on average reducing the intensity of inputs reduces variability of income by 20%. Practices associated with increasing agricultural diversity and agri-environment schemes have previously been found to lead to a better provision of ecosystem services and resilience to abiotic stresses, reducing the need for expensive chemical inputs. Engagement in environmentally sustainable farming practices including agri-environment schemes, increasing agricultural diversity, and reducing the intensity of inputs, may increase the stability of many farm businesses whilst at the same time reducing negative impacts of farming on the environment.

Graphical Abstract



1 Introduction

Farm incomes are subject to a variety of threats including unpredictable weather, changes in policy or regulation, variation in the price of outputs and rising input costs (OECD, 2009). Levels of farm income are important, but the stability of income is also a key issue for agricultural businesses. Fluctuating incomes can affect farm decisions and the ability of a farm to sustain its operations year to year (Mishra and Sandretto, 2002; Severini et al., 2016). Instability (or variability) in farm income represents a significant challenge for farm management and the design of public policies. Greater stability of farm income, over a range of conditions, could improve the economic viability and sustainability of farms and therefore help maintain continuity in food production for a growing population with increasing demands for food (FAO, 2009). How we balance the need for food, the stability of farm businesses, as well as the protection of biodiversity and the environment also represents a major challenge.

Research has examined drivers of agricultural system dynamics (i.e. changes over time), however, quantitative assessments remain rare, particularly at the farm level (Dardonville et al., 2020). We summarise a range of farming practices and government payments which may support stability of farm income and the gaps identified in previous research.

One important strategy considered to increase the ability of agricultural systems to cope with shocks and variability, is increasing agricultural diversity (Dardonville et al., 2020; Gaudin et al., 2015; Urruty et al., 2016). Practices associated with increasing agricultural diversity involve harnessing ecological functions to increase the resilience and sustainability of landscapes and tend to have a positive impact on the natural environment (Pretty, 2008; Pretty and Bharucha, 2014; Rockström et al., 2017). Diversification of crop and livestock activities is commonly recognised as an effective tool for managing business and climatic risks, by lessening the effects of variable commodity markets and weather, at the farm level (Bradshaw et al., 2004; Castañeda-Vera and Garrido, 2017; Martin et al., 2017). The effect of agricultural diversification on economic stability has previously been examined using different financial variables. Greater diversification of crop and livestock revenue has been associated with an increase in the stability of gross farm revenue and household income across valley, hill and mountain regions of Switzerland (El Benni et al., 2012). In addition, growing a wider range of crops or using a mixed cropping and livestock system has been found to stabilise return on capital, for lowland and small upland farms in Argentina (Pacín and Oesterheld, 2014). Further empirical studies are warranted to validate the relationship between agricultural diversity (degree of specialisation in different crop and livestock activities) and the stability of agricultural systems in different contexts and at different spatial and temporal scales (Dardonville et al., 2020; Urruty et al., 2016), particularly for a range of farm types.

Previous research examining the effect of farming intensity (based on input or output intensity) on the stability of farm income has found mixed results. Nitrogen fertiliser and pesticides have been found to increase yield but, similarly, their effect on the variability of yields is unclear (Dardonville et al., 2020). Intensification commonly relies upon a greater use of expensive agri-chemicals (Geiger et al., 2010). Higher pesticide and fertiliser costs, used as a proxy for physical quantities, have previously been associated with an increase in crop income by boosting production, but also with an increase in the variability (decrease in stability) of crop income (Enjolras et al., 2014). In contrast, Reidsma et al. (2009) found that variability of farm income was higher on less intensive farms across Europe, measured using total output per hectare (€). However, they did not test whether this varied between farm type, for example cereal or grazing farms, which require different levels of intensity. Further analysis would therefore help understand how increasing intensity, via the use of expensive inputs, affects the stability of farm businesses.

The Common Agricultural Policy (CAP) scheme currently supports producer incomes in the European Union (EU), and a central aim is to reduce income variation by reducing domestic price volatility (El Benni et al., 2012; OECD, 2009). The CAP provides payments to farmers across the EU via two main categories: Pillar 1 provides direct payments to farmers and market support, with the majority dedicated to payments based on the area farmed (namely the Single Payment Scheme (SPS) which was replaced by the Basic Payment Scheme (BPS) in 2015). Pillar 2 pays farmers to implement environmentally friendly actions, e.g. installing hedges, through voluntary agri-environment schemes or to support the wider rural economy. Agricultural subsidies have been argued to play a role in stabilising farm incomes (Castañeda-Vera and Garrido, 2017; Enjolras et al., 2014; OECD, 2009) as the variability in subsidies is potentially lower than other agricultural income (Severini et al., 2016). However, empirical studies have also found the opposite effect; Reidsma et al. (2009) found that variability was higher on farms that received more subsidies per hectare, across regions of Europe. Previous analysis in Italy has also linked direct payments to an increase in crop income variability (from production only), suggesting these payments may encourage farmers to engage in riskier production practices (Enjolras et al., 2014). Further quantitative studies are warranted to evaluate the relationship between direct subsidies across a range of farm types and in different European countries (Castañeda-Vera and Garrido, 2017). In addition, the effect of agri-environment scheme payments (Pillar 2), which compensate farmers for implementing measures to benefit the environment or biodiversity, on the stability of farm income has not been examined previously.

Across Europe and a range of farm types, larger farms have been associated with greater stability of farm income (El Benni et al., 2012; European Commission, 2009; Reidsma et al., 2009; Severini et al., 2016). Larger farms may benefit from greater economies of scale, as well as, a wider range of soils and landscapes and therefore may be better able to cope with extreme or adverse weather across the farm (El Benni et al., 2012; Marra and Schurle, 1994). However, further evidence is needed across a range of farm types, to understand the relative importance of farm size compared to a range of farming practices and subsidies, on the stability of farm income.

On-farm diversification is considered an important strategy to reduce reliance on income from agricultural production which is subject to a wide variety of price fluctuations and climate stresses (McNally, 2001; McNamara and Weiss, 2005). On-farm diversification refers to activities which are fully integrated and derive income for the farm business, for example, income from a farm campsite or letting farm buildings. A greater proportion of income from on-farm diversification has previously been found to increase the economic sustainability of farm businesses in Scotland, by providing an hourly return to the farmer of at least the minimum wage (Barnes et al., 2015). The effect of on-farm diversification on the year-to-year stability of farm business income has been less investigated. A large number of studies have examined how reliance on off-farm income (from off-farm employment outside of the farm business) affects the stability of household or farmer income, with mixed results (e.g. El Benni et al., 2012; Jetté-Nantel et al., 2011; Mishra and Sandretto, 2002). A larger share of household income from off-farm employment has been associated with a decrease in the stability of farm revenue, considered a result of a shift in labour and potentially riskier agricultural production with farmers feeling more protected by alternative income sources (El Benni et al., 2012). Whether income from on-farm diversification has a similar effect on instability of farm income, or conversely increases stability by providing a more stable source of income is not well known.

The stability of farm income has previously been measured using a range of different indices, across different temporal scales (e.g. Barry et al., 2001; El Benni et al., 2012; Loughrey and Hennessy, 2016; Pacín and Oesterheld, 2014; Reidsma et al., 2009; Reidsma and Ewert, 2008). Alternative methods for measuring stability of income may provide different results, affecting the interpretation of a stable farm business. Therefore, we use a range of stability measures to provide a robust and more comprehensive analysis. In this study we use four stability measures to investigate the effect of farming practices and agricultural policy on the stability of farm income in England and Wales between 2007 and 2015, using a multilevel mixed effects model.

This study examines a range of different farm types, based on type of production, which can exhibit very different farm management and characteristics, for example livestock is considered a lower risk production output than crops (Chavas et al., 2019). Farms are often restricted to a type of production due to a substantial machinery investment or landscape characteristics, therefore, we analyse the effect of farming practices and agricultural policy for each farm type separately to provide targeted recommendations for farmers. Previous evidence, in other territories, has either focused on one production or farm type, or used a single measure of stability.

We examine a range of farming practices and subsidies which, as overviewed above, previous literature has indicated may support the stability of farm businesses in different territories, or with mixed results, using different measures of stability. Understanding which management changes are beneficial to agriculture in the current climate, across different scales and a range of environments is important for understanding the adaptation options available in agriculture (Porter et al., 2014). The main aims of the present study are to provide comprehensive analysis of the effect of farming practices and subsidies on the stability of farm income, and their relative importance. Our results are useful in informing farmers which practices may aid in managing income stability and lead to a more robust farm business in the face of increasingly variable weather or future economic shocks.

2 Materials and methods

2.1 Data and study area

The Farm Business Survey (FBS) is a survey conducted in England and Wales, collecting extensive information on the physical and economic performance of approximately 2,500 farm businesses annually (Department for Environment Food and Rural Affairs, 2020).

The population of farms covered by the survey is detailed in the supplementary materials. Farms are classified into farm types according to which crop or livestock production accounts for more than two-thirds of standard gross margin (SGM). We analyse FBS data from 2007 to 2015 for the following six farm types: dairy, cereals, general cropping (arable crops including field scale vegetables account for more than two-thirds of SGM), mixed (no other type accounts for more than two-thirds of SGM), Less Favoured Area (LFA) grazing (grazing livestock accounts for more than two-thirds of SGM and 50 per cent or more of the total land area is in LFA) and lowland grazing farms. Horticulture farms were excluded due their complexity (large diversity in production), as well as, pig and poultry farms due to small sample sizes. The data was examined for outliers and inconsistencies and less than 0.2% of observations, considered to be erroneous, were removed.

Farm business income per hectare is used as the measure of income in this study and is calculated as the sum of: total output from agriculture, on-farm diversification and subsidies, less all fixed and variable costs, including paid labour and depreciation, and profit or loss from the sale of fixed assets. Farm business income represents the financial return to all those invested in the business (farmers, partners, shareholders) and is in essence the same as financial net profit. Farm business income enables the analysis of changes in income over time and is also used by policy makers when assessing the impact of new policies on the individual farm business (Department for Environment Food and Rural Affairs et al., 2018), therefore is the preferred measure of income in our study.

2.2 Measuring the stability of farm income

Stability of agricultural production or income is often measured by examining its variability; high stability of income is associated with low variability. We summarise the key measures of stability (or variability) used in studies that have previously examined the stability of income, using panel data. Stability has been measured over several time periods, to indicate medium-term stability, or as an annual deviation in income from the prior year or years. Stability has also been measured by examining absolute variability, or as a relative measure (ratio) to allow comparison between farms with different means. In this study we use four different measures for the stability of farm income (Table 1): two annual (or short-term) measures of stability (absolute and relative anomaly) and two medium-term measures of stability using the standard deviation and relative standard deviation of farm income.

2.2.1 Annual measures of stability

To measure stability of a given year or season, we use the absolute anomaly calculated as the deviation in income from the expected income. Determining the expected income requires some consideration. Reidsma et al. (2009) considered using the trend in income per farm type over a 14 year period, however since the trend was often not different from zero, the authors used the mean income per farm type as an indicator of expected income. Measuring the absolute deviation from the mean income per farm type indicates the variation in income, for a particular year, from the average performance of farms considered to have similar characteristics. A compromise of this approach is that calculating absolute deviation from the mean for each farm type can result in large absolute anomaly values for those farms with income consistently above (or below) the farm type mean, even though these farms may show low variability in their own income year to year. In this study we calculate the absolute anomaly using the annual deviation from the individual farm mean, over a five-year rolling period. This provides an indication of the deviation in farm income from the average performance at the individual farm. We use a five-year rolling period[1] to calculate the four stability measures in this study, therefore we consider only farms with a minimum of five consecutive years of data in the Farm Business Survey.

Annual stability in farm income and crop yields have also been examined using the relatively anomaly; the ratio of the absolute anomaly and the expected income (Reidsma et al., 2009). Using a relative measure enables stability of farm income to be directly compared across farms (or farm types) with different means. However, relative measures should only be used with ratio data where there is a true or absolute zero. To examine relative stability on an annual basis we calculate the relative anomaly by dividing the absolute anomaly for the individual farm, by the 5-year rolling mean of each farm type (which is always positive) therefore accounting for temporal changes in the mean farm business income over the period

[1] We calculated stability measures over longer (13 years) and shorter time periods (3 years), these measures were highly correlated both with one another and with the 5-year measures (shown in Table 1). We chose a 5-year period to enable us to capture temporal changes over the dataset but also include sufficient data points to calculate the mean income.

2007 to 2015. This gives an indication of the relative deviation from the average performance of farms considered to have more similar characteristics (e.g. as per Reidsma et al. (2009)).

2.2.2 Medium-term measures of stability

A common method of measuring absolute stability of income in the medium or long-term is the standard deviation (SD) (Loughrey and Hennessy, 2016; Pacín and Oesterheld, 2014). This indicates, for an individual farm or farm type, the amount of variation or dispersion around the mean over time. Measuring the SD of income at the farm level enables assessment of differences in stability between individual farms, which is not possible when examining SD for each farm type. Similar to the method used in Barry et al. (2001) and El Benni et al. (2012) we calculate the standard deviation by splitting the full data set (2005-2017) into 13 overlapping time periods, each containing 5 consecutive years of farm business data per farm e.g. the standard deviation for 2007 comprises 5 income records for each farm with data for all years between 2005 and 2009 inclusive.

The coefficient of variation (CV; SD divided by the mean) has also been used to analyse temporal variation in farm income (Barry et al., 2001; El Benni et al., 2012). Using a relative measure such as the CV, enables stability of farm income to be compared directly between farms, or farm types, with different means. However, as above, relative measures should only be used with ratio data where there is a true or absolute zero. Farm business income in this study measures the financial return to farmers or shareholders, therefore can be a positive (profit) or negative (loss) figure. As a result, the CV at the farm level (farm SD divided by the mean farm income) can be very large where the mean is close to zero (due to positive and negative income values) and in such instances does not accurately measure stability. We did not want to restrict the analysis to farms which only made a profit since this would not represent the full range of farms in England and Wales. Equally, we did not want to use an alternative measure of financial performance since Farm Business Income is a key measure of financial performance, widely used by policy makers to assess the impact of new policies on the individual farm business. To examine relative stability in the medium term we calculate a relative (or scaled) standard deviation by dividing the standard deviation for the individual farm by the rolling 5-year mean income of each farm type, therefore accounting for temporal changes in the mean income over the period 2007 to 2015. The rolling 5-year farm type mean income is always positive. This relative standard deviation is calculated using the mean income of farms with similar characteristics. Similar methods (scaling using the mean for each farm type) have been used to calculate relative stability in previous studies (e.g. Reidsma et al., 2009; Reidsma and Ewert, 2008). Table 1 outlines the four measures used to examine stability of farm income in our analysis.

Econometric studies have also examined changes in agricultural production and income by measuring the cost or willingness to pay to reduce risk, and exposure to downside risk (low yields or income) (Antle, 1987; Chavas, 2019; Chavas et al., 2019). Our study does not examine upside or downside risk separately, but instead we examine relative or absolute variation in income around the mean, each year and over 5 years. Large changes in income, particularly over a number of years, can be challenging for farm planning and management and therefore our results hope to inform which farming practices and subsidies are associated with less variable income, using these 4 alternative measures of stability.

Table 1 - Measures of stability of Farm Business Income (FBI) used in this analysis

Stability measure		**Calculation**	**What measure shows?**
Short-term/annual measures			
1	Absolute anomaly: absolute deviation from the rolling 5-year mean* FBI per ha (of individual farm)	$ABS_{it} = \lvert Y_{it} - \bar{Y}_i \rvert$ where $\bar{Y}_i = \frac{1}{5}(\sum_{t-2}^{t+2} Y_i)$	Absolute deviation in FBI per ha at each farm, from the average performance at the farm $\bar{Y}_i$, in year *t*.
2	Relative anomaly: ratio of absolute anomaly from farm mean *(measure 1)* divided by rolling 5-year mean* FBI per ha (per farm type)	$REL_{it} = \frac{ABS_{it}}{\bar{Y}_{m,i}}$ where $\bar{Y}_{m,i} = \underset{\forall\, type\ m}{\text{mean}}\ (\bar{Y}_i)$	Relative deviation in FBI per ha; absolute deviation in FBI per ha from the mean performance at the individual farm, scaled to the 5-year rolling mean FBI per ha of farms of the same type *m* (across England and Wales), in year *t*.
Medium term measures			
3	Standard deviation: Rolling 5-year SD of FBI per farm	$SD_i = \sqrt{\frac{1}{4}\sum_{t-2}^{t+2}(Y_{it} - \bar{Y}_i)^2}$	The amount of variation or dispersion in FBI per ha at the individual farm over a 5-year period.
4	Relative (scaled) standard deviation: Rolling 5-year SD of FBI per farm (*measure 3*) divided by rolling 5-year mean FBI per ha (per farm type)	$REL.SD_i = \frac{SD_i}{\bar{Y}_{m,i}}$	The amount of variation or dispersion in FBI per ha at the individual farm, scaled to the 5-year rolling mean FBI per ha of farms of the same type *m* (across England and Wales), in year *t*.

*We also calculated the absolute anomaly and relative anomaly per farm type using the median FBI per ha, these measures were very strongly positively correlated (Pearson's coefficient >0.98) with the absolute anomaly using the mean income, therefore the mean was used for consistency across all measures.

2.3 Factors associated with the stability of farm income

In this study we analyse the factors affecting the stability of farm income for each farm type, based on the type of production (dairy, cereals, general cropping, mixed, LFA grazing and lowland grazing farms). We are not focused on comparing farm types, however, farm characteristics and practices, e.g. size, intensity and diversity often vary significantly between farm types, therefore, we use separate models to quantify how each covariate affects stability for each farm type. The results of a comparative multilevel model including all farm types and farm type interactions are included in the supplementary material.

The definition and calculation of farming practices and EU subsidy payments examined, are shown in Table 2. To examine farming intensity across a range of farm types we use the IRENA indicator 15, which is calculated as the total cost of fertiliser, crop protection and concentrated animal feed per hectare (European Environment Agency, 2005). This IRENA indicator was developed to identify intensive, high input farms in comparison to extensive farms believed to have a lower environmental impact (European Environment Agency, 2005). The Farm Business Survey (FBS) does not provide a complete record of physical input quantities (e.g. fertilisers and pesticides used), and the IRENA indicator has previously been used to examine farming intensity in the FBS data across a range of farm types (crops and livestock) (Gerrard et al., 2012).

Agricultural diversity (or inversely specialisation) of crop and livestock activities has been examined using the Herfindahl index (El Benni et al., 2012; Poon and Weersink, 2011). The Herfindahl index is calculated based on the proportion of gross farming revenue earned from crops (including wheat, barley, oilseed rape and other key crops) and livestock production (including milk and cattle production and other livestock products). The index ranges from 0 to 1 with lower values indicating a higher degree of agricultural diversity. An alternative measure of agricultural diversity is the Shannon Index, which calculates the diversity of crops grown (number of crops and their proportional representation) (Gerrard et al., 2012). However, we found the Herfindahl index more suitable to identify diversity across a range of different farm types.

To examine agri-environment payments we use total rural development payments (pillar 2) per hectare, which comprise primarily agri-environment schemes, as well as, dedicated support for LFA farmers (refer to the supplementary materials for details of the schemes in operation during the study period).

Summary statistics for the variables used in this study are shown in Table 3. The UK Consumer Price Index is used to deflate all monetary variables, including farm business income, to account for the change in the value of money over time (ONS, 2020).

Table 2 - Definition and calculations of variables (farm characteristics, farming practices and EU subsidy payments) analysed in the study

Independent variable	Calculation
Farm characteristics	
Farm size	Area farmed (hectares) = The utilised agricultural area, plus land let in /minus land rented out
Farming practices	
Intensity of inputs	The total cost of fertiliser, crop protection and concentrated animal feed (£), per hectare (area farmed) (IRENA indicator 15; European Environment Agency, 2005; Gerrard et al., 2012)
Agricultural specialisation (inverse of diversification)	$Herfindahl\ index\ (S) = \sum_{i=1}^{n} (p_i)^2$ Where *n* is the total number of farming activities, p_i is the proportion of revenue earned from the *i*-th farming activity (revenue from farming activity divided by the total farming revenue). Can also be written as sum of revenue for each farming activity squared, divided by total revenue for agriculture squared: (Wheat^2+ barley^2 + other cereals^2 + oilseed rape^2 + peas and beans^2 + potatoes^2 + sugar beet^2 + horticulture^2 + other crops^2 + by-products and forage^2 + milk^2 + cattle^2 + sheep^2 + pigs^2 + eggs^2 + chickens and other poultry^2 + other livestock^2 + other agriculture^2) /total agricultural gross revenue^2
On-farm diversification	Reliance on diversified income (activities integrated into the farm business, in addition to agricultural output) = Gross revenue (output) from on-farm diversification (£) divided by total gross revenue (output) (£)
EU subsidies (Agricultural policy)	
Direct payments per hectare	Total direct payments (£) (Primarily the single payment scheme or basic payment scheme), per hectare (area farmed)
Agri-environment payments per hectare	Total payments under rural development policy (£; pillar 2), per hectare (area farmed)

Table 3 - Summary statistics of FBS data (2007-2015); values deflated using UK Consumer Price Index (2015=100; ONS, 2020).

	All Farms	**Dairy**	**Cereals**	**Gen. cropping**	**Mixed**	**LFA Grazing**	**Lowland Grazing**
Farm Business Income (FBI) per ha (£)	364.95	599.38	387.18	532.18	297.43	200.34	266.83
Dependent variables							
Absolute anomaly of FBI per ha (£)	142.16	209.88	156.99	217.82	131.42	77.73	115.40
Relative anomaly of FBI per ha (£)	0.42	0.36	0.44	0.43	0.43	0.42	0.47
Standard deviation of FBI per ha (£)	195.14	281.13	214.02	291.36	184.12	112.95	160.00
Relative SD of FBI per ha (£)	0.59	0.49	0.61	0.57	0.61	0.61	0.65
Independent variables							
Specialisation (Herfindahl index) (0-1)	0.58	0.71	0.40	0.38	0.49	0.63	0.69
Input intensity per ha (£)	431.07	954.45	330.67	407.19	616.18	173.58	211.11
Direct payments (SPS/BPS) per ha (£)	226.17	227.11	240.58	235.50	221.11	213.40	229.78
Agri-environment payments per ha (£)	53.04	33.30	50.23	40.25	47.56	71.91	58.45
Area farmed (hectares)	188.65	132.03	233.13	277.44	191.88	205.02	120.63
On-farm diversification (reliance) (0-1)	0.04	0.02	0.07	0.04	0.05	0.02	0.06
Number of observations	12,628	2,635	2,367	1,086	1,139	3,687	1,714
Number of farms	2,333*	503	514	268	319	645	390
Number of counties/unitary authorities	78	54	56	39	57	35	53

*Note 283 farms change between farm types during the period, therefore appear in more than one farm type group during the relevant years.

2.4 Multilevel (two-level linear mixed effect) model

The Farm Business survey collects extensive data on farm characteristics of individual farms across England and Wales on an annual basis. Many farms remain in the survey each year, however membership in the survey can change and therefore the data represents an unbalanced panel between 2007 and 2015.

We estimate a multilevel (two-level linear mixed effect) model to examine the effect of a range of farm characteristics, farming practices and EU subsidies on the stability of farm income. This type of model can easily accommodate unbalanced data (Laird and Ware, 1982; Snijders and Bosker, 1999) and has been used previously to examine the influence of management on farm income (Reidsma et al., 2009, 2007). A multilevel model accounts for dependency within the data; observations are likely to be correlated in two ways, firstly because they are from the same farm (level 1), and secondly because farms belong to the same county or unitary authority (level 2) and are therefore likely to have a more similar climate or soil conditions than farms in different locations. A map of county and unitary authority boundaries (hereafter referred to as counties) is included in the supplementary materials (Supplementary Figure 1). We estimate the following two-level mixed model with farms nested within counties, based on restricted maximum likelihood (REML) using each of the four dependent variables measuring the stability of income[2]:

$$\log(Y_{tjk}) = \beta_0 + \beta_1 specialisation_{jk} + \beta_2 intensity_{jk} + \beta_3 direct\ payments_{jk} + \beta_4 direct\ payments_{jk} \cdot year_{jk} + \beta_5 agri\text{-}environment\ payments_{jk} + \beta_6 year_{jk} + \beta_7 area\ farmed_{jk} + \beta_8 on\text{-}farm\ diversification_{jk} + u_k + r_{jk} + e_{tjk} \qquad (1)$$

where Y is the variability of income (instability), for each farm observed at level j=1, …, J, (level 1) nested into k=1, …, K counties (level 2), with also t = 1, ..., T_j periods for each, j, farm, β_0 is the mean intercept across all groups, the regression coefficients $\beta_{1,...,}\beta_p$, are common to all groups, u_k is the random intercept for level 2 (counties), r_{jk} is the random intercept for level 1 (farms) and e_{tjk} is the level 1 residual (error term).

[2] A multilevel model performed significantly better (p value <0.05) than a linear (OLS) model when examining the null hypothesis that the level 1 and 2 groupings are equal to zero.

Multilevel models account for this dependency or nesting structure (farm and county) by splitting the residual into two uncorrelated components (Rabe-Hesketh and Skrondal, 2012); firstly a permanent component, known as the *random intercept* or *random effect* which is specific to the farm (or county) and represents variation between farms (or counties). The random intercept is uncorrelated across farms (or counties) and represents characteristics of variables not included in the model. Secondly there is an idiosyncratic component or within-farm (level 1) residual which is uncorrelated across time and farm. The multilevel model was also run with a further level, region (n=9), nested above county however this resulted in very little change to the model results. In each of the models, independent variables (listed in Table 2 and Table 3) were used as fixed effects and have been standardised (centred around zero, with a SD of 1) to account for the differences in scale between variables and in order to analyse the comparative effect size of each covariate. For models examining stability of income in the medium-term (standard deviation and relative standard deviation of farm business income per ha), the independent variables are averaged over the same five-year time period used to derive the dependent variables (Table 1). Year, *t*, is also included as a continuous fixed effect to examine the trend in income stability over time, as well as, any interaction between time and the value of direct payments per hectare. Model residuals were checked for normality and heteroskedasticity and all measures of income stability were log transformed to account for the non-normal distribution of the income data, to reduce the impact of outliers, and improve model fit based on the Akaike Information Criteria (AIC). To assess the explanatory power of the models, marginal R^2 was calculated following Nakagawa and Schielzeth (2013) using the r2glmm package in R (Jaeger, 2017; R Core Team, 2019). For models examining stability of income in the medium-term we account for temporal autocorrelation in the farm specific error term using the corCAR1 function of the *nlme* R package (Pinheiro et al., 2019) by fitting a continuous first order autoregressive process. Before fitting the models, we checked for outliers and collinearity using pairwise scatterplots, in addition, correlation coefficients between independent variables were all <0.3 (therefore less than the recommended threshold of 0.7; Dormann et al. (2013).

3 Results

3.1 The effects of farming practices and subsidies on the variability of income

Tables 4-7 show the results of the four multilevel (two-level linear mixed effect) models, using four measures of variability (inverse of stability) and include coefficients indicating the relative strength of factors affecting the variability of income by farm type. Models use the log of the dependent variable, therefore the exponent of the coefficient, minus 1 multiplied by 100, provides the percentage change in the variability of income (instability) for every increase in the independent variable by one standard deviation, holding all other predictors constant.

Farming practices and subsidies explained a greater part of the variance when examining the stability of income in the medium term, using the standard deviation and relative standard deviation (marginal R^2 between 0.12 and 0.39). The variance explained by fixed factors examining the effect on annual variability of income was often small (marginal R^2 between 0.02 and 0.15). The Farm Business Survey provides summarised farm data which we use to examine the effect of farming practices and subsidies, however, the stability of income could also be affected more by specific farm management, as well as changing environmental conditions (e.g. climate variability). When comparing results across all measures of variability, we found regression results show the same relationships between farming practices and EU subsidies across all the four measures, however, the significance levels vary in a few instances. In addition, correlations between the measures of variability (Supplementary Table 1) show short-term variability is correlated with medium-term variability indicating farms with larger annual variability are more likely to also show larger variability of income over several years.

3.1.1 Annual variability of farm income

Table 4 and Table 5 show the results of the multilevel model explaining the factors affecting the variability (inverse of stability) of income on an annual basis, using the log of the absolute and relative anomaly respectively.

Greater specialisation (or less diversity in crops and livestock activities) increases variability of absolute and relative income, between 8 and 21% with a significant relationship for dairy, general cropping and mixed farms. For general cropping farms, specialisation of agricultural activities has the largest relative effect on the variability of income in comparison to other covariates; increasing the Herfindahl index by 1 standard deviation increases the variability of income by approximately 20%. Increasing intensity (spending more on fertiliser, pesticide, or concentrated animal feed) is associated with an increase in variability of farm income between 20 and 30% for both absolute and relative income for all farm types, with exception of cereal farms where the effect is smaller (<10%).

An increase in direct payments per hectare of 1 standard deviation increases the variability of income in absolute and relative terms for dairy and LFA grazing farms by 25 and 35% respectively, in addition, greater direct payments increase the variability of relative income for lowland grazing farms (16%). Over time the effect of direct payments decreases (approximately 3% per year), as the value of direct payments per hectare has generally fallen over the period (Supplementary Figure 2). The effect of agri-environment payments is smaller than direct payments and differs between farm types: for dairy, general cropping and mixed farms an increase in agri-environment payments per hectare decreases the variability in absolute and relative income between 5 and 7%, whereas for LFA grazing farms agri-environment payments increase the variability in annual farm business income by 6%.

When considering temporal changes in the mean farm business income per ha, variability in income, using the relative anomaly, increases for dairy, mixed and LFA grazing farms, indicating income for these farm types is becoming increasingly unstable. Increasing farm area is associated with a decrease in the variability in income in both absolute and relative terms. An increase in utilised agricultural area by 1 standard deviation is associated with a decrease in variability between 5 and 20% for all farm types, with exception of general cropping where there is no significant relationship. Increasing reliance on revenue from on-farm diversification (activities integrated into the farm business, in addition to agricultural output) increases the variability of farm business income for dairy and grazing farms, however, the effect (4-8% increase) is smaller than other farming practices examined. Whereas greater reliance on income from on-farm diversification does not significantly affect the variability of income for general cropping, cereal and mixed farms.

Table 4 - Multilevel model results using (log) absolute anomaly of farm business income per hectare as dependent variable. Showing the effect of farming practices and subsidies on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Dairy	Cereals	Gen. cropping	Mixed	LFA Grazing	Lowland Grazing
Random effects						
County SD	0.000	0.000	0.110	0.205	0.126	0.065
Farm SD	0.272	0.210	0.364	0.315	0.248	0.346
Level-1 residual	1.100	1.187	1.072	1.117	1.094	1.115
Fixed effects (Standard Error)						
Intercept	4.591 ***	4.983 ***	5.137 ***	4.336 ***	3.705 ***	4.386 ***
	(0.077)	(0.083)	(0.117)	(0.123)	(0.066)	(0.088)
Specialisation (agricultural)	0.111 ***	0.018	0.192 ***	0.076 *	0.028	0.008
	(0.026)	(0.026)	(0.043)	(0.043)	(0.021)	(0.033)
Input intensity	0.186 ***	0.089 ***	0.186 ***	0.258 ***	0.200 ***	0.201 ***
	(0.028)	(0.028)	(0.041)	(0.042)	(0.023)	(0.034)
Direct payments per ha	0.217 ***	0.064	-0.150	-0.040	0.301 ***	0.108
	(0.065)	(0.072)	(0.110)	(0.118)	(0.057)	(0.074)
Year x direct payments per ha	-0.029 ***	0.011	0.022	0.015	-0.019 **	-0.012
	(0.010)	(0.010)	(0.016)	(0.016)	(0.008)	(0.013)
Agri-environment payments per ha	-0.050 **	-0.037	-0.072 *	-0.078 **	0.054 **	0.030
	(0.025)	(0.029)	(0.041)	(0.040)	(0.022)	(0.033)
Year	0.033 ***	-0.058 ***	-0.038 **	0.004	0.016 **	-0.023 *
	(0.010)	(0.011)	(0.016)	(0.016)	(0.008)	(0.012)
Area farmed	-0.123 ***	-0.054 **	0.016	-0.138 ***	-0.224 ***	-0.190 ***
	(0.026)	(0.027)	(0.045)	(0.043)	(0.024)	(0.035)
On-farm diversification	0.041 *	0.041	0.045	0.060	0.077 ***	0.075 **
	(0.025)	(0.027)	(0.041)	(0.041)	(0.020)	(0.032)
Observations (n)	2,635	2,367	1,086	1,139	3,687	1,714
County (n)	54	56	39	57	35	53
Farm (n)	503	514	268	319	645	390
AIC	8,184	7,666	3,396	3,640	11,375	5,434
BIC	8,254	7,735	3,455	3,700	11,450	5,499
logLik	-4,080	-3,821	-1,686	-1,808	-5,676	-2,705
R^2	0.083	0.043	0.065	0.088	0.138	0.065

Table 5 - Multilevel model results using (log) relative anomaly of farm business income per hectare as dependent variable. Showing the effect of farming practices and subsidies on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Dairy	Cereals	Gen. cropping	Mixed	LFA Grazing	Lowland Grazing
Random effects						
County SD	0.000	0.000	0.105	0.196	0.119	0.036
Farm SD	0.270	0.210	0.363	0.322	0.251	0.354
Level-1 residual	1.101	1.189	1.072	1.119	1.095	1.120
Fixed effects (Standard Error)						
Intercept	-1.883 ***	-1.285 ***	-1.232 ***	-1.794 ***	-1.832 ***	-1.320 ***
	(0.077)	(0.083)	(0.117)	(0.123)	(0.065)	(0.088)
Specialisation (agricultural)	0.118 ***	0.028	0.186 ***	0.077 *	0.025	0.008
	(0.026)	(0.027)	(0.043)	(0.043)	(0.021)	(0.033)
Input intensity	0.185 ***	0.066 **	0.179 ***	0.258 ***	0.207 ***	0.201 ***
	(0.028)	(0.028)	(0.041)	(0.043)	(0.023)	(0.034)
Direct payments per ha	0.231 ***	0.108	-0.132	-0.007	0.302 ***	0.151 **
	(0.066)	(0.072)	(0.110)	(0.119)	(0.057)	(0.074)
Year x direct payments per ha	-0.033 ***	-0.001	0.015	0.007	-0.023 ***	-0.023 *
	(0.010)	(0.010)	(0.016)	(0.016)	(0.008)	(0.013)
Agri-environment payments per ha	-0.050 **	-0.033	-0.072 *	-0.076 *	0.059 ***	0.029
	(0.025)	(0.029)	(0.041)	(0.040)	(0.022)	(0.033)
Year	0.048 ***	-0.004	-0.020	0.059 ***	0.059 ***	0.004
	(0.010)	(0.011)	(0.016)	(0.016)	(0.008)	(0.012)
Area farmed	-0.124 ***	-0.062 **	0.009	-0.141 ***	-0.232 ***	-0.195 ***
	(0.026)	(0.027)	(0.044)	(0.044)	(0.024)	(0.035)
On-farm diversification	0.042 *	0.043	0.049	0.061	0.082 ***	0.081 **
	(0.025)	(0.027)	(0.041)	(0.041)	(0.020)	(0.032)
Observations (n)	2,635	2,367	1,086	1,139	3,687	1,714
County (n)	54	56	39	57	35	53
Farm (n)	503	514	268	319	645	390
AIC	8,187	7,671	3,395	3,644	11,384	5,452
BIC	8,258	7,740	3,455	3,704	11,459	5,517
logLik	-4,082	-3,823	-1,685	-1,810	-5,680	-2,714
R^2	0.092	0.015	0.061	0.101	0.145	0.062

3.2 Medium-term variability of farm income

Table 6 and Table 7 show the results of the multilevel model, explaining the factors affecting the variability of income in the medium-term, using the log of the standard deviation of income and relative standard deviation respectively.

Greater specialisation, or less diversity in crop and livestock activities, also increases variability of absolute and relative income in the medium term with a significant relationship for dairy (12%), cereal (5%) and general cropping farms. As observed using annual measures of stability, specialisation has the largest partial effect on variability of income for general cropping farms of all covariates examined, with results showing a 24% increase in variability is associate with an increase in the Herfindahl index of 1 standard deviation (Figure 1). Input intensity also increases medium-term variability in income for all farm types (by 10 to 28% for an increase in input intensity of 1 standard deviation). Figure 1 shows the partial effect of input intensity on the stability of income for general cropping farms, using the standard deviation of income.

Consistent with the effect on annual variability, an increase in direct payments per hectare is relatively large and increases the medium-term variability of income in absolute and relative terms for dairy and LFA grazing farms (Figure 2) by approximately 20%. In addition, an increase in direct payments is associated with an increase in the variability of relative income in the medium-term, for cereals and lowland grazing farms, however the effect size is smaller (12 and 6% respectively). Over time the effect of direct payments per hectare on the medium-term variability in income decreases for dairy farms, however, it increases for cereals, mixed and lowland grazing farms. The effect of agri-environment payments on medium term variability is smaller than direct payments and differs between farm types: for dairy, general cropping (Figure 1) and mixed farms an increase in agri-environment payments per hectare decreases the variability in absolute and relative income between 5 and 9%. Whereas an increase in agri-environment payments by 1 standard deviation for LFA grazing farms is associated with an increase in variability by 7% (Figure 2).

Variability in relative standard deviation of farm income, which accounts for changes in farm income over time, increases for dairy, cereals, mixed and LFA grazing farms, indicating income for these farm types is becoming increasingly unstable. Consistent with the effect on annual stability measures increasing farm size is associated with a decrease in medium-term variability in income, in both absolute and relative terms. An increase in utilised agricultural area by 1 standard deviation is associated with a decrease in variability between 4 and 19% across all farm types, except for general cropping farms where there is no significant relationship. For most farm types, farm income shows greater variability in the medium-term with an increasing share of revenue coming from on-farm diversification, however, the size of the effect is smaller than most other farming practices (5-8%).

Results of a sensitivity analysis using alternative measures of intensity and on-farm diversification and the impact of changes in farm type are available in the supplementary material.

Table 6 - Multilevel model results using (log) standard deviation of farm business income per hectare as dependent variable. Showing the effect of farming practices and subsidies on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Dairy		Cereals		Gen. cropping		Mixed		LFA Grazing		Lowland Grazing	
Random effects												
County SD	0.060		0.024		0.154		0.101		0.113		0.113	
Farm SD	0.000		0.000		0.000		0.000		0.148		0.137	
Level-1 residual	0.480		0.496		0.564		0.518		0.505		0.509	
Fixed effects (Standard error)												
Intercept	5.272	***	5.311	***	5.509	***	4.908	***	4.471	***	5.043	***
	(0.044)		(0.044)		(0.073)		(0.068)		(0.043)		(0.052)	
Specialisation (agricultural)	0.115	***	0.051	***	0.214	***	0.028		0.022		-0.003	
	(0.017)		(0.017)		(0.033)		(0.026)		(0.016)		(0.022)	
Input intensity	0.185	***	0.122	***	0.141	***	0.247	***	0.203	***	0.191	***
	(0.019)		(0.017)		(0.028)		(0.026)		(0.017)		(0.021)	
Direct payments per ha	0.152	***	-0.026		-0.041		-0.068		0.179	***	0.008	
	(0.034)		(0.036)		(0.056)		(0.054)		(0.033)		(0.035)	
Year x direct payments per ha	-0.017	***	0.016		0.008		0.028	***	0.001		0.012	*
	(0.005)		(0.005)		(0.008)		(0.007)		(0.004)		(0.006)	
Agri-environment payments per ha	-0.050	***	0.003		-0.066	**	-0.051	**	0.063	***	0.027	
	(0.016)		(0.018)		(0.028)		(0.022)		(0.016)		(0.022)	
Year	0.032	***	-0.014	***	-0.011		0.024	***	0.007	*	-0.015	**
	(0.006)		(0.005)		(0.008)		(0.008)		(0.005)		(0.006)	
Area farmed	-0.121	***	-0.045	***	-0.016		-0.120	***	-0.193	***	-0.157	***
	(0.017)		(0.017)		(0.035)		(0.026)		(0.019)		(0.025)	
On-farm diversification	0.045	***	0.062	***	0.019		0.020		0.054	***	0.077	***
	(0.016)		(0.017)		(0.029)		(0.024)		(0.014)		(0.021)	
Observations (n)	2,635		2,367		1,086		1,139		3,687		1,714	
County (n)	54		56		39		57		35		53	
Farm (n)	503		514		268		319		645		390	
AIC	2,012		1,919		909		1,231		3,066		1,541	
BIC	2,088		1,994		974		1,296		3,147		1,612	
logLik	-993		-947		-442		-602		-1,520		-758	
R^2	0.333		0.121		0.191		0.298		0.403		0.227	

Table 7 - Multilevel model results using (log) relative standard deviation of farm business income per hectare as dependent variable. Showing the effect of farming practices and subsidies on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Dairy	Cereals	Gen. cropping	Mixed	LFA Grazing	Lowland Grazing
Random effects						
County SD	0.061	0.031	0.145	0.094	0.104	0.110
Farm SD	0.000	0.000	0.000	0.000	0.150	0.000
Level-1 residual	0.487	0.493	0.570	0.523	0.512	0.535
Fixed effects (Standard error)						
Intercept	-1.148 ***	-0.893 ***	-0.793 ***	-1.169 ***	-0.978 ***	-0.600 ***
	(0.044)	(0.044)	(0.073)	(0.068)	(0.043)	(0.053)
Specialisation (agricultural)	0.111 ***	0.049 ***	0.201 ***	0.027	0.017	-0.002
	(0.017)	(0.017)	(0.033)	(0.027)	(0.016)	(0.022)
Input intensity	0.186 ***	0.091 ***	0.122 ***	0.247 ***	0.208 ***	0.183 ***
	(0.019)	(0.017)	(0.028)	(0.026)	(0.017)	(0.022)
Direct payments per ha	0.176 ***	0.115 ***	0.002	0.026	0.193 ***	0.061 *
	(0.034)	(0.036)	(0.057)	(0.054)	(0.033)	(0.036)
Year x direct payments per ha	-0.023 ***	-0.008	-0.006	0.011	-0.007	-0.002
	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)
Agri-environment payments per ha	-0.053 ***	-0.016	-0.093 ***	-0.051 **	0.064 ***	0.017
	(0.016)	(0.018)	(0.028)	(0.022)	(0.016)	(0.022)
Year	0.039 ***	0.035 ***	-0.001	0.071 ***	0.040 ***	0.006
	(0.006)	(0.005)	(0.008)	(0.008)	(0.005)	(0.006)
Area farmed	-0.127 ***	-0.056 ***	-0.024	-0.125 ***	-0.206 ***	-0.160 ***
	(0.017)	(0.017)	(0.036)	(0.026)	(0.019)	(0.025)
On-farm diversification	0.050 ***	0.083 ***	0.026	0.022	0.060 ***	0.081 ***
	(0.016)	(0.017)	(0.029)	(0.024)	(0.014)	(0.021)
Observations (n)	2,635	2,367	1,086	1,139	3,687	1,714
County (n)	54	56	39	57	35	53
Farm (n)	503	514	268	319	645	390
AIC	2,154	1,931	934	1,251	3,191	1,585
BIC	2,230	2,006	999	1,316	3,272	1,656
logLik	-1,064	-952	-454	-613	-1,583	-780
R^2	0.335	0.119	0.200	0.322	0.390	0.201

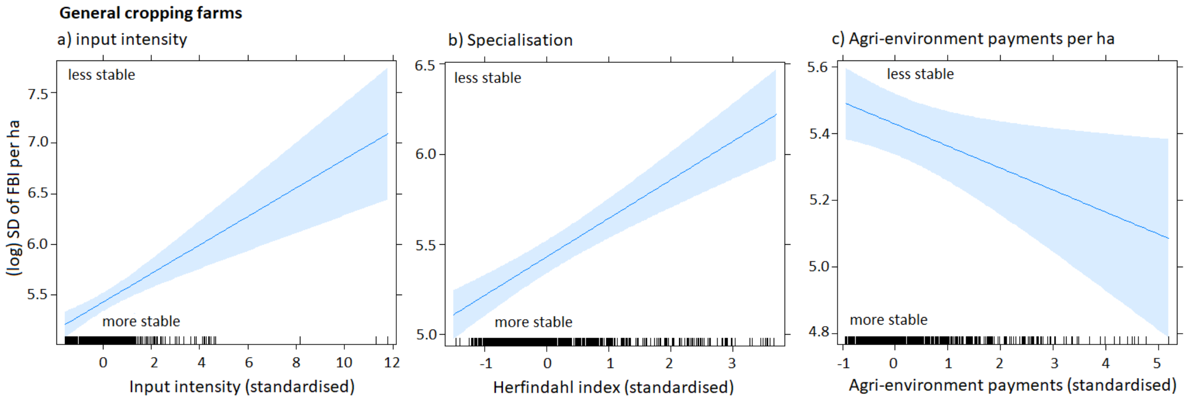


Figure 1 –Effects of input intensity, specialisation of farming activities and agri-environment payments on the standard deviation (SD) of farm business income (FBI) per ha, for general cropping farms. Plots show the partial effects of a) input intensity, b) specialisation and c) agri-environment payments from the multilevel mixed model. The tick marks on the x-axis are the observed data points. The y-axis represents the partial effect of each variable on the (log) standard deviation of farm business income per hectare. The shaded areas indicate the 95 percent confidence intervals.

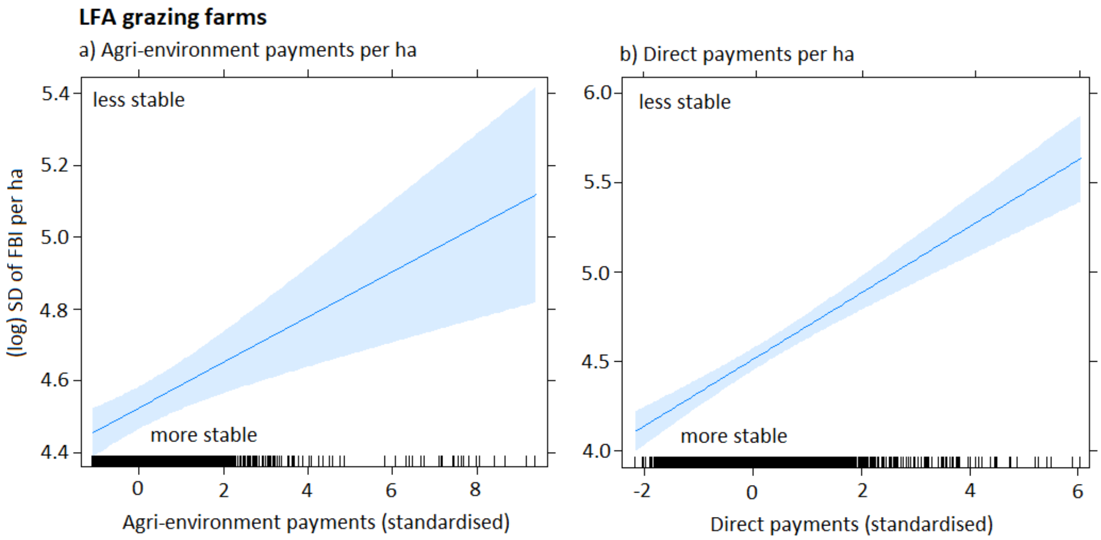


Figure 2 – Effects of agri-environment payments and direct payments on the standard deviation (SD) of farm business income (FBI) per ha, for LFA grazing farms. Plots show the partial effects of a) agri-environment payments and b) Direct payments (t=7) from the multilevel mixed model. The tick marks on the x-axis are the observed data points. The y-axis represents the partial effect of each variable on the (log) standard deviation of farm business income per hectare. The shaded areas indicate the 95 percent confidence intervals.

4 Discussion

4.1 Agricultural diversity, a lower intensity of inputs and agri-environment payments are, for most farm types, associated with greater stability of income

Our study demonstrates that increasing the diversity of agricultural activities and reducing the intensity of inputs, as well as, receiving higher payments from agri-environment schemes are associated with an increase in the stability of farm income. Our results highlight the potential of these farming practices and agri-environment schemes to improve the economic stability of farm businesses, which at the same time may benefit the environment. Greater agricultural diversification (i.e. lower degree of specialisation in different crop and livestock activities) increases the stability of farm income, in dairy, general cropping, cereal and mixed farms, and is a particularly important factor for general cropping farms. Reducing the intensity of inputs is found to be a particularly important factor to increase stability for most farm types, with a large effect size in comparison to other farming practices examined. Agri-environment payments are associated with greater stability at dairy, general cropping and mixed farms, however, the effect size is small in comparison.

4.2 Agricultural diversity associated with greater stability

Prior research has found greater diversity of agricultural activities or crops improves stability of revenue and household income, as well as, return on capital (El Benni et al., 2012; Lawes and Kingwell, 2012; Pacín and Oesterheld, 2014). There was, however, a need to validate the relationship between the diversity of agricultural activities and the stability of farm business income, across a range of different farm types and in other territories. Our analysis shows that greater diversity of agricultural activities also increases the stability of farm business income, in all farm types except for grazing farms. The effect of agricultural diversity is particularly important for general cropping farms who are, on average, the most diverse (Table 3) and may have the opportunity, and structure, to grow a wider range of crops. Increasing agricultural diversity could make farm businesses more resilient to economic shocks with access to a range of markets, therefore, reducing risks from potential price downturns (Bradshaw et al., 2004; Pacín and Oesterheld, 2014). Increased crop diversity has been found to lead to a better provision of ecosystem services, including higher yield, improved soil services and pest regulation (Degani et al., 2019), as well as, a reduction in the risk of crop failure (Gaudin et al., 2015). More diverse farms may be in a better position to adapt to changing environmental conditions, including drought (Degani et al., 2019; Lawes and Kingwell, 2012) or hot and dry years (Gaudin et al., 2015) due to improved soil moisture retention. Whereas, highly specialised farms could be more vulnerable to a given pest or disease and weather events affecting a larger proportion of production and be less able to recoup losses via other crops or livestock activities. Increasing resilience to abiotic and economic stresses by increasing agricultural diversity, may therefore also aid the stability of income. Increasing cropping system diversity has also been found to suppress weeds and improve soil fertility, lessening the need for expensive chemical inputs and reducing input costs, helping to maintain profitability whilst also reducing negative impacts on the environment (Davis et al., 2012).

Whilst we examine agricultural diversity at the farm level, we do not examine the "composition effect" i.e. whether the presence of certain species may influence stability. The presence of productive and drought resistance species in grasslands, and legumes as a cover crop in diverse crop rotations, have been found to improve yield stability and therefore may also effect the stability of farm income (Dardonville et al., 2020). We also consider that farmers may seek to diversify agricultural activities to reduce exposure to the variance in agricultural income (as suggested in Lin et al., 1974), therefore, this relationship may also be reflective of the risk averse attitude of some farmers. However, our finding that increasing agricultural diversity is associated with an increase in economic stability is consistently supported by a number of other studies, which examine a wide range of other farm characteristics, farming practices, insurance and economic variables, in different regions and contexts (e.g. Barry et al. (2001), Dardonville et al. (2020), El Benni et al. (2012), Enjolras et al. (2014), Loughrey and Hennessy (2016))

4.3 Lower input intensity associated with greater stability

Previous research has found mixed results regarding the effect of farming intensity, using different measures, on the stability of farm income (Enjolras et al., 2014; Reidsma et al., 2009). Modelling each farm type separately, we found a decrease in input intensity (lower cost of fertiliser, pesticides and concentrates per hectare) is associated with an increase in the stability of income across all farm types. With rising input prices, a concern of farmers is to control the use of expensive inputs and thereby increase profitability (Firbank et al., 2013). Farms with higher input costs are more likely to have higher gross revenues, however, this does not always translate to a higher farm business income (net profit); input intensity is weakly positively correlated (r<0.3) with farm business income per hectare (Supplementary

Table 2). In crops, when designing fertiliser management practices there is a trade-off between yield, nutrient use efficiency and the environment; as you increase nutrient input, yields typically increase (but at a decreasing rate) and nutrient use efficiency declines (Roberts, 2008). Increasing fertiliser rates has also been previously linked to a decrease in yield stability (Just and Pope, 1979). For livestock farms, intensive grain-fed livestock incurs higher costs for animal feed, as well as, increased water use (Godfray et al., 2010). Farms using more inputs may be taking greater risks; they have the potential for higher outputs, but their larger cost investment could lead to larger financial losses in the event of extreme weather events and production failures. The impact of input intensity on the stability of income during different weather events, for instance wet years where pests or diseases may be prevalent, would be an important interaction to examine further. Our results indicate that reducing the intensity of inputs is an important factor increasing the stability of income, with a large effect on stability, relative to the other farming practices examined. The input intensity indicator used in this study is based on the cost of inputs per hectare and therefore can only provide an approximation for physical quantities, however, reducing synthetic inputs could also improve environmental health by reducing surface runoff and eutrophication (Raun and Johnson, 1999).

4.4 Receiving larger direct payments associated with a decrease in stability

Direct payments provide flat-rate income support to farmers based on the area of land farmed. Direct payments, along with intensity of inputs, are found to be highly influential with models showing large effects on the stability of farm income. An increase in direct payments per hectare is associated with a decrease in the stability of farm income across most farm types. This may seem counterintuitive as one of the goals of the CAP is to support and stabilise farm incomes, however, previous studies have also found similar results. Flat-rate subsidy payments potentially represent a moral hazard to farmers. Farms receiving larger direct payments may be more inclined to engage in riskier production or be less focused on production outputs, with the knowledge they will receive a guaranteed level of income support from the government (Enjolras et al., 2014; Poon and Weersink, 2011; Reidsma et al., 2009).

4.5 The effect of agri-environment payments depends on the farm type

4.5.1 Agri-environment payments improve stability for dairy, general cropping and mixed farms.

In contrast with direct payments, agri-environment payments, for dairy, general cropping and mixed farms, increase stability in income. The contrast between the effect of agri-environment payments and direct payments is particularly interesting and has not been examined previously. The contrast between payments based on land area and payments for environmental activities suggest it could be the impacts of the environmental practices undertaken by the farmer which are associated with the stability of income (rather than just the receipt of money). Voluntary agri-environment schemes compensate farmers for implementing measures to benefit the environment or biodiversity. The CAP focuses on ‘input based systems’ paying farmers and land managers for the ‘cost of inputs’ or ‘income foregone’. The increased stability we see may be due to increase provision of ecosystem services. Maintaining habitats for wildlife, such as wildflower strips, increased flower planting and field diversity through agri-environment schemes may improve the farmed environment for pollinators and natural enemies, supporting crop pollination and natural pest control (Blaauw and Isaacs, 2014; Kennedy et al., 2013; Menalled et al., 2003; Ottoy et al., 2018). This ‘ecological intensification’ (Bommarco et al., 2013; Kleijn et al., 2019; Pywell et al., 2015) may also increase yield and income stability. Insect pollination may increase production stability, for instance by reducing yield losses following heat stress in faba bean (Bishop et al., 2016). Soil management practices under agri-environment schemes, including planting of winter cover crops and minimal cultivation practices, can improve soil fertility and structure and help reduce soil erosion, which could otherwise represent a risk during heavy rainfall events (Büchi et al., 2018; Degani et al., 2019; Natural England, 2013). Increasing soil organic matter has also been found to increase cereal productivity and yield stability (Pan et al., 2009). Agri-environment practices included in agri-environment schemes have been found to help maintain and stabilise yields, increase resilience to pests or disease, as well as reduce the effects of environmental hazards for instance climate shocks. Therefore, it is possible these agri-environment practices could be associated with a greater stability of farm income. The effect of agri-environment payments on stability is smaller than the effect of direct payments, however this remains a new and important finding. Further research to identify which environmental measures may be associated with greater stability of income, across different farm types and landscapes, could be of interest to farmers and policy makers particularly given the UK's transition to a new agricultural policy focusing on environmental land management and productivity measures. We also consider that the type of farmer choosing to participate in agri-environment schemes may be more progressive or adaptable, with prior research suggesting highly educated farmers who are open to innovation may be more willing to engage in agri-environment schemes (Barreiro-Hurlé et al., 2010; Peerlings and Polman, 2009). However, factors and characteristics which influence participation have been found to be varied and wide ranging, including farmer characteristics and attitudes (e.g. previous experience with agri-environment schemes), farm structure, social capital (e.g. influence of neighbouring farms), and economic factors (Lastra-Bravo et al., 2015), which were not considered as part of this study.

4.5.2 Agri-environment payments decrease stability for Less Favoured Area grazing farms

Agri-environment payments have the opposite effect for Less Favoured Area (LFA) grazing farms, reducing the stability of income. LFA grazing farms receive more money from agri-environment schemes per hectare, on average, than any other farm type (Table 3). LFA farmers received additional area-based payments to support the income of farms in challenging environments (refer to the supplementary materials for scheme details). However, the landscapes of LFA farms may not be well-suited for environmental enhancement, in comparison to other farm types, and therefore less able to deliver the ecosystem service benefits associated with a greater stability of production. LFA grazing farms have significantly fewer entry level and higher level options per agri-environment scheme agreement than other farm types in England (Department for Environment Food and Rural Affairs, 2006). In Wales, agri-environment schemes are considered more effective in providing income to support the viability of upland farming lifestyles, rather than providing ecosystem services (Arnott et al., 2019). Government support for LFA farms, via agri-environment schemes, therefore appears to have a similar effect as direct payments and does not support the stability of income.

4.6 Larger farms have a greater stability of income

Farm size is associated with an increase in the stability of farm income, in line with prior research and is a moderately important factor in stabilising income. Larger farms may be more adept at coping with income and price variation; larger farms are associated with economies of scale, greater wealth, stability of land control and a larger asset base therefore may have a better capacity to adapt to changing economic conditions or prices (El Benni et al., 2012; Velandia et al., 2009). In addition, a larger area of land may benefit from a wider range of topography and soil conditions and therefore yield responses across the farm. As a result larger farms may be better able to adapt to changing or extreme weather conditions (Marra and Schurle, 1994) which could aid in increasing the stability of income.

4.7 Greater reliance on on-farm diversification decreases stability of income

On-farm diversification into other activities (in addition to agricultural output) is often considered advantageous by providing an additional income source (McNally, 2001) and a viable financial return to farmers (Barnes et al., 2015). However, our results show that greater reliance on on-farm diversification decreases the stability of income, although the effect is relatively small. The effect of reliance on income from on-farm diversification has been less investigated in the literature, however, previous research found reliance on income from off-farm employment had a similar effect, reducing the stability of household income (El Benni et al., 2012). Farms may be branching into other activities they are not specialised in. Importantly income from on-farm diversification is also, on average, not a consistent or stable source of income for farmers in England and Wales; farms may dip in and out of diversified activities with revenue from on-farm diversification showing high variability (mean CV of revenue from on-farm diversification is 0.82 across all farm types, over a five-year rolling period), and therefore does not support income stability. Our results provide an initial indication of the relationship between on-farm diversification and the stability of income, however, farms can seek to diversify farm income in a variety of ways. Further analysis on the effect of reliance on on-farm diversification from different activities would help to provide a greater understanding of the relationship with the stability of farm income.

4.8 Stability measures and moving beyond stability

We use four stability measures to provide a robust analysis of overall income stability. The alternative measures of stability are correlated and provide similar results in our study, however, this may not be replicated in other regions, or when examining the effects of other farming practices or covariates. The choice of stability measure should depend upon the specific research question, and how stability is to be interpreted.

Our study focuses on the stability of farm income, which is a key issue for agricultural businesses. However, total levels of farm income are also important to ensure viable businesses for farmers. With a growing population more food will also need to be produced from existing agricultural land, by increasing output intensity using sustainable practices. Prior research identifies practices which strengthen sustainability to produce more food with less environmental impact (Campbell et al., 2014; Charles et al., 2014; Rockström et al., 2017). Examples of sustainable production systems include using conservation techniques such as no-till farming and sophisticated crop rotations, requiring less chemical inputs, which aim to preserve ecosystem services and harness ecological functions to increase productivity, as well as, improve livelihoods (Pretty, 2008; Pretty and Bharucha, 2014; Rockström et al., 2017). Our results show greater agricultural diversity and participation in agri-environment schemes may also reduce the variability of farm income. Therefore, whilst not the focus of our study, there appears to be some compatibility with these results and farming practices advocated to increase agricultural output and total farm income in a sustainable manner.

5 Conclusions

Our study provides knowledge on the effect of agricultural diversity on the stability of farm income in a new territory and across a range of different farm types. Results show that increasing the diversity of agricultural activities is associated with an increase in the stability of farm income, for dairy, general cropping, cereal and mixed farms. Agricultural diversity is an important farming practice associated with stability, particularly for general cropping farms. Prior research indicates farms with greater agricultural diversity may be in a better position to cope with climate and economic shocks, with crops and livestock exhibiting different responses to environmental conditions and by providing access to a wider range of markets. In addition, increasing crop diversity can also improve soil services and pest regulation reducing the need for expensive chemical inputs.

Our results also show that reducing the intensity of inputs is associated with greater stability of income across all farm types. Reducing the intensity of inputs is found to be an important factor increasing the stability of income, with a large effect on stability, relative to the other farming practices examined. Current farming techniques tend to rely upon increasing the intensity of inputs to obtain higher outputs, however, farms using more increasingly expensive inputs may also be exposed to greater variability of income, in the event of extreme weather events and production failures. We did not consider how intensity of farming may increase total income or total production, which is also important to ensure viable businesses for farmers and to feed a growing population. However, increasing the production of food should be done in a sustainable manner, with greater stability, whilst contributing to the health of ecosystems.

Direct subsidies paid to farmers based on the area farmed are associated with a relatively large decrease in the stability of farm income, across most farm types. In contrast, we show that higher agri-environment payments increase the stability of farm income, for dairy, general cropping and mixed farms. Agri-environment schemes may help to reduce the effects of environmental hazards for instance climate shocks, as well as provide a higher and more stable provision of natural pest control, by adopting practices to benefit the environment or biodiversity. LFA grazing farms receive additional dedicated area payments via agri-environment schemes to support farms in challenging environments. This flat rate income support for LFA farms appears to have a similar effect as direct payments and does not support income stability. The effect of agri-environment payments on stability is smaller than the effect of direct payments, however this remains a new and important finding. Further analysis to identify which environmental practices, undertaken through agri-environment schemes, may lead to greater stability of income is an area of research which could be of interest to farmers and policy makers, particularly given the current transition from direct payments to a new agricultural policy in the UK focusing on environmental land management and productivity measures.

Our results suggest that engagement in environmentally sustainable farming practices, including increasing agricultural diversity, engagement in agri-environment schemes and reducing the intensity of inputs, can increase the stability of many farm businesses whilst also reducing negative impacts of farming on the environment.

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References

Antle, J.M., 1987. Econometric Estimation of Producers' Risk Attitudes. Am. J. Agric. Econ. 69, 509–522. https://doi.org/10.2307/1241687

Arnott, D., Chadwick, D., Harris, I., Koj, A., Jones, D.L., 2019. What can management option uptake tell us about ecosystem services delivery through agri-environment schemes? Land use policy 81, 194–208. https://doi.org/10.1016/j.landusepol.2018.10.039

Barnes, A.P., Hansson, H., Manevska-Tasevska, G., Shrestha, S.S., Thomson, S.G., 2015. The influence of diversification on long-term viability of the agricultural sector. Land use policy. https://doi.org/10.1016/j.landusepol.2015.08.023

Barreiro-Hurlé, J., Espinosa-Goded, M., Dupraz, P., 2010. Does intensity of change matter? Factors affecting adoption of agri-environmental schemes in Spain. J. Environ. Plan. Manag. 53, 891–905. https://doi.org/10.1080/09640568.2010.490058

Barry, P.J., Escalante, C.L., Bard, S.K., 2001. Economic risk and the structural characteristics of farm businesses. Agric. Financ. Rev. 61, 73–86. https://doi.org/10.1108/00214760180001117

Bishop, J., Jones, H.E., Lukac, M., Potts, S.G., 2016. Insect pollination reduces yield loss following heat stress in faba bean (Vicia faba L.). Agric. Ecosyst. Environ. 220, 89–96. https://doi.org/10.1016/j.agee.2015.12.007

Blaauw, B.R., Isaacs, R., 2014. Flower plantings increase wild bee abundance and the pollination services provided to a pollination-dependent crop. J. Appl. Ecol. 51, 890–898. https://doi.org/10.1111/1365-2664.12257

Bommarco, R., Kleijn, D., Potts, S.G., 2013. Ecological intensification: Harnessing ecosystem services for food security. Trends Ecol. Evol. 28, 230–238. https://doi.org/10.1016/j.tree.2012.10.012

Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: Crop diversification in the Canadian prairies. Clim. Change 67, 119–141. https://doi.org/10.1007/s10584-004-0710-z

Büchi, L., Wendling, M., Amossé, C., Necpalova, M., Charles, R., 2018. Importance of cover crops in alleviating negative effects of reduced soil tillage and promoting soil fertility in a winter wheat cropping system. Agric. Ecosyst. Environ. 256, 92–104. https://doi.org/10.1016/j.agee.2018.01.005

Campbell, B.M., Thornton, P., Zougmoré, R., van Asten, P., Lipper, L., 2014. Sustainable intensification: What is its role in climate smart agriculture? Curr. Opin. Environ. Sustain. 8, 39–43. https://doi.org/10.1016/j.cosust.2014.07.002

Castañeda-Vera, A., Garrido, A., 2017. Evaluation of risk management tools for stabilising farm income under CAP 2014-2020. Econ. Agrar. y Recur. Nat. 17, 3–23. https://doi.org/10.7201/earn.2017.01.01

Charles, H., Godfray, H., Garnett, T., 2014. Food security and sustainable intensification. Philos. Trans. R. Soc. B Biol. Sci. 369, 6–11. https://doi.org/10.1098/rstb.2012.0273

Chavas, J.P., 2019. Adverse Shocks in Agriculture: The Assessment and Management of

Downside Risk. J. Agric. Econ. 70, 731–748. https://doi.org/10.1111/1477-9552.12312

Chavas, J.P., Cooper, J., Wallander, S., 2019. The impact of input and output decisions on agricultural production risk. J. Agric. Resour. Econ. 44, 513–535. https://doi.org/10.22004/ag.econ.292329

Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184. https://doi.org/10.1016/j.agsy.2020.102913

Davis, A.S., Hill, J.D., Chase, C.A., Johanns, A.M., Liebman, M., 2012. Increasing Cropping System Diversity Balances Productivity, Profitability and Environmental Health. PLoS One 7, 1–8. https://doi.org/10.1371/journal.pone.0047149

Degani, E., Leigh, S.G., Barber, H.M., Jones, H.E., Lukac, M., Sutton, P., Potts, S.G., 2019. Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought. Agric. Ecosyst. Environ. 285, 106625. https://doi.org/10.1016/j.agee.2019.106625

Department for Environment Food and Rural Affairs, 2020. Farm Business Survey [WWW Document]. URL https://www.gov.uk/government/collections/farm-business-survey (accessed 3.20.20).

Department for Environment Food and Rural Affairs, 2006. Evaluation of the introduction and operation of Environmental Stewardship - MA01028, Science and Research Projects.

Department for Environment Food and Rural Affairs, Department of Agriculture Environment Food and Rural Affairs, Welsh Assembly, The Scottish Government, 2018. Agriculture in the United Kingdom 2017, National Statistics.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., Mcclean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography (Cop.). 36, 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

El Benni, N., Finger, R., Mann, S., 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. Agric. Financ. Rev. 72, 301–324. https://doi.org/10.1108/00021461211277204

Enjolras, G., Capitanio, F., Aubert, M., Adinolfi, F., 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. New Medit 13, 31–40.

European Commission, 2009. Income variability and potential cost of income insurance for EU, Note to the file. https://doi.org/10.1016/S0140-6736(09)62056-0

European Environment Agency, 2005. Agriculture and environment in EU-15 — the IRENA indicator report. Copenhagen, Denmark.

FAO, 2009. FAO's Director-general on how to feed the world in 2050. Popul. Dev. Rev. 35, 837–839. https://doi.org/10.1111/j.1728-4457.2009.00312.x

Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification among British farms. Agric. Ecosyst. Environ. 173, 58–65. https://doi.org/10.1016/j.agee.2013.04.010

Gaudin, A.C.M., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C., Deen, W., 2015. Increasing crop diversity mitigates weather variations and improves yield stability. PLoS One 10, 1–20. https://doi.org/10.1371/journal.pone.0113261

Geiger, F., Bengtsson, J., Berendse, F., Weisser, W.W., Emmerson, M., Morales, M.B., Ceryngier, P., Liira, J., Tscharntke, T., Winqvist, C., Eggers, S., Bommarco, R., Pärt, T., Bretagnolle, V., Plantegenest, M., Clement, L.W., Dennis, C., Palmer, C., Oñate, J.J., Guerrero, I., Hawro, V., Aavik, T., Thies, C., Flohre, A., Hänke, S., Fischer, C., Goedhart, P.W., Inchausti, P., 2010. Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland. Basic Appl. Ecol. 11, 97–105. https://doi.org/10.1016/j.baae.2009.12.001

Gerrard, C.L., Padel, S., Moakes, S., 2012. The use of Farm Business Survey data to compare the environmental performance of organic and conventional farms. Int. J. Agric. Manag. 2, 5–16. https://doi.org/10.5836/ijam/2013-01-02

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science (80-.). 327, 812–818. https://doi.org/10.1126/science.1185383

Jaeger, B., 2017. r2glmm: Computes R Squared for Mixed (Multilevel) Models.

Jetté-Nantel, S., Freshwater, D., Katchova, A.L., Beaulieu, M., 2011. Farm income variability and off-farm diversification among Canadian farm operators. Agric. Financ. Rev. 71, 329–346. https://doi.org/10.1108/00021461111177602

Just, R.E., Pope, R.D., 1979. Production Function Estimation and Related Risk Considerations. Am. J. Agric. Econ. 61, 276–284. https://doi.org/10.2307/1239732

Kennedy, C.M., Lonsdorf, E., Neel, M.C., Williams, N.M., Ricketts, T.H., Winfree, R., Bommarco, R., Brittain, C., Burley, A.L., Cariveau, D., Carvalheiro, L.G., Chacoff, N.P., Cunningham, S.A., Danforth, B.N., Dudenhöffer, J.H., Elle, E., Gaines, H.R., Garibaldi, L.A., Gratton, C., Holzschuh, A., Isaacs, R., Javorek, S.K., Jha, S., Klein, A.M., Krewenka, K., Mandelik, Y., Mayfield, M.M., Morandin, L., Neame, L.A., Otieno, M., Park, M., Potts, S.G., Rundlöf, M., Saez, A., Steffan-Dewenter, I., Taki, H., Viana, B.F., Westphal, C., Wilson, J.K., Greenleaf, S.S., Kremen, C., 2013. A global quantitative synthesis of local and landscape effects on wild bee pollinators in agroecosystems. Ecol. Lett. 16, 584–599. https://doi.org/10.1111/ele.12082

Kleijn, D., Bommarco, R., Fijen, T.P.M., Garibaldi, L.A., Potts, S.G., van der Putten, W.H., 2019. Ecological Intensification: Bridging the Gap between Science and Practice. Trends Ecol. Evol. 34, 154–166. https://doi.org/10.1016/j.tree.2018.11.002

Laird, N.M., Ware, J.H., 1982. Random-Effects Models for Longitudinal Data. Biometrics 38, 963. https://doi.org/10.2307/2529876

Lastra-Bravo, X.B., Hubbard, C., Garrod, G., Tolón-Becerra, A., 2015. What drives farmers' participation in EU agri-environmental schemes?: Results from a qualitative meta-analysis. Environ. Sci. Policy 54, 1–9. https://doi.org/10.1016/j.envsci.2015.06.002

Lawes, R.A., Kingwell, R.S., 2012. A longitudinal examination of business performance indicators for drought-affected farms. Agric. Syst. 106, 94–101. https://doi.org/10.1016/j.agsy.2011.10.006

Lin, W., Dean, G.W., Moore, C. V, 1974. An Empirical Test of Utility vs. Profit Maximization in Agricultural Production. Am. J. Agric. Econ. 56, 497–508. https://doi.org/10.2307/1238602

Loughrey, J., Hennessy, T., 2016. Farm income variability and off-farm employment in Ireland. Agric. Financ. Rev. 76, 378–401. https://doi.org/10.1108/AFR-10-2015-0043

Marra, M.C., Schurle, B.W., 1994. Kansas Wheat Yield Risk Measures and Aggregation: A Meta-Analysis Approach. J. Agric. Resour. Econ. 19, 69–77.

Martin, G., Magne, M.A., Cristobal, M.S., 2017. An integrated method to analyze farm vulnerability to climatic and economic variability according to farm configurations and farmers’ adaptations. Front. Plant Sci. 8, 1–16. https://doi.org/10.3389/fpls.2017.01483

McNally, S., 2001. Farm diversification in England and Wales — what can we learn from the farm business survey? J. Rural Stud. 17, 247–257. https://doi.org/10.1016/S0743-0167(00)00050-4

McNamara, K.T., Weiss, C., 2005. Farm Household Income and On-and-Off Farm Diversification. J. Agric. Appl. Econ. 37, 37–48. https://doi.org/10.1017/S1074070800007082

Menalled, F.D., Costamagna, A.C., Marino, P.C., Landis, D.A., 2003. Temporal variation in the response of parasitoids to agricultural landscape structure. Agric. Ecosyst. Environ. 96, 29–35. https://doi.org/10.1016/S0167-8809(03)00018-5

Mishra, A.K., Sandretto, C.L., 2002. Stability of Farm Income and the Role of Nonfarm Income. Rev. Agric. Econ. 24, 208–221.

Nakagawa, S., Schielzeth, H., 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. Methods Ecol. Evol. 4, 133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x

Natural England, 2013. Entry Level Stewardship, Environmental Stewardship Handbook.

OECD, 2009. Managing risk in agriculture: A holistic approach, Managing Risk in Agriculture: A Holistic Approach. https://doi.org/10.1787/9789264075313-en

ONS, 2020. Consumer price inflation time series (MM23) [WWW Document]. URL https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bt/mm23 (accessed 3.20.20).

Ottoy, S., Angileri, V., Gibert, C., Paracchini, M.L., Pointereau, P., Terres, J.M., Van Orshoven, J., Vranken, L., Dicks, L. V., 2018. Impacts of selected Ecological Focus Area options in European farmed landscapes on climate regulation and pollination services: A systematic map protocol. Environ. Evid. 7, 1–10. https://doi.org/10.1186/s13750-018-0122-6

Pacín, F., Oesterheld, M., 2014. In-farm diversity stabilizes return on capital in Argentine agro-ecosystems. Agric. Syst. 124, 51–59. https://doi.org/10.1016/j.agsy.2013.10.008

Pan, G., Smith, P., Pan, W., 2009. The role of soil organic matter in maintaining the productivity and yield stability of cereals in China. Agric. Ecosyst. Environ. 129, 344–348. https://doi.org/10.1016/j.agee.2008.10.008

Peerlings, J., Polman, N., 2009. Farm choice between agri-environmental contracts in the European Union. J. Environ. Plan. Manag. 52, 593–612. https://doi.org/10.1080/09640560902958131

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team, 2019. nlme: Linear and Nonlinear Mixed Effects Models.

Poon, K., Weersink, A., 2011. Factors affecting variability in farm and off-farm income. Agric. Financ. Rev. 71, 379–397. https://doi.org/10.1108/00021461111177639

Porter, J.R., Xie, L., Challinor, A.J., Cochrane, K., Howden, S.M., Iqbal, M.M., Lobell, D.B., Travasso, M.I., 2014. Food security and food production systems. Clim. Chang. 2014 Impacts, Adapt. Vulnerability. Part A Glob. Sect. Asp. Contrib. Work. Gr. II to Fifth Assess. Rep. Intergov. Panel Clim. Chang. 485–533. https://doi.org/10.1111/j.1728-4457.2009.00312.x

Pretty, J., 2008. Agricultural sustainability: Concepts, principles and evidence. Philos. Trans. R. Soc. B Biol. Sci. 363, 447–465. https://doi.org/10.1098/rstb.2007.2163

Pretty, J., Bharucha, Z.P., 2014. Sustainable intensification in agricultural systems. Ann. Bot. 114, 1571–1596. https://doi.org/10.1093/aob/mcu205

Pywell, R.F., Heard, M.S., Woodcock, B.A., Hinsley, S., Ridding, L., Nowakowski, M., Bullock, J.M., 2015. Wildlife-friendly farming increases crop yield: Evidence for ecological intensification. Proc. R. Soc. B Biol. Sci. 282. https://doi.org/10.1098/rspb.2015.1740

R Core Team, 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rabe-Hesketh, S., Skrondal, A., 2012. Multilevel and longitudinal modeling using Stata Third Edition: Volume I: Continuous Responses, Third Edit. ed. A Stata Press Publication, StataCorp LP, College Station, Texas.

Raun, W.R., Johnson, G. V., 1999. Improving nitrogen use efficiency for cereal production. Agron. J. 91, 357–363. https://doi.org/10.2134/agronj1999.00021962009100030001x

Reidsma, P., Ewert, F., 2008. Regional Farm Diversity Can Reduce Vulnerability of Food Production to Climate Change. Ecol. Soc. 13. https://doi.org/10.5751/ES-02476-130138

Reidsma, P., Ewert, F., Oude Lansink, A., 2007. Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity. Clim. Change 84, 403–422. https://doi.org/10.1007/s10584-007-9242-7

Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: A multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/s10113-008-0059-3

Roberts, T.L., 2008. Improving nutrient use efficiency. Turkish J. Agric. For. 32, 177–182. https://doi.org/10.3906/tar-0801-9

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., Smith, J., 2017. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio 46, 4–17. https://doi.org/10.1007/s13280-016-0793-6

Severini, S., Tantari, A., Di Tommaso, G., 2016. Do CAP direct payments stabilise farm income? Empirical evidences from a constant sample of Italian farms. Agric. Food Econ. 4. https://doi.org/10.1186/s40100-016-0050-0

Snijders, T.A.B., Bosker, R.J., 1999. Multilevel Analysis An Introduction to Basic and Advanced Multilevel Modeling. SAGE Publications Ltd, London, UK.

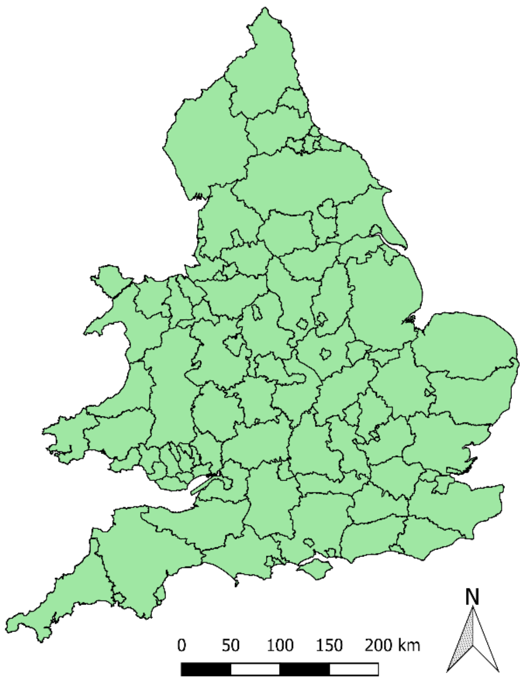
Urruty, N., Tailliez-Lefebvre, D., Huyghe, C., 2016. Stability, robustness, vulnerability and resilience of agricultural systems. A review. Agron. Sustain. Dev. 36, 1–15. https://doi.org/10.1007/s13593-015-0347-5

Velandia, M., Rejesus, R.M., Knight, T.O., Sherrick, B.J., 2009. Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales. J. Agric. Appl. Econ. 41, 107–123. https://doi.org/10.1017/s1074070800002583

Supplementary material

Stability of farm income: the role of agricultural diversity and agri-environment scheme payments

1. County and Unitary Authority boundaries used in the analysis



Supplementary Figure 1 – County and Unitary Authority boundaries of England and Wales, used in the multilevel model analysis.

2. Population of farms included in the Farm Business Survey

The Farm Business Survey (FBS) is an annual survey conducted in England and Wales, collecting business information for approximately 2,500 farms each year (Defra, 2020). The FBS population includes farms which meet a minimum size criteria: from 2005 to 2009 it includes full-time farms and part-time farms which occupy a farmer for half their time or more (>0.5 standard labour requirements) and from 2010 it includes farms with at least €25,000 of output (Defra, 2020). Small farms excluded from the survey only account for approximately 4% of agricultural production (Rural Business Research, 2020).

3. Overview of changes in common agricultural policy during study period, in England and Wales

Pillar 1 of the CAP provides direct payments to farmers, based on area farmed. Pillar 2 “Rural Development Regulation” (RDR) includes support for agri-environment schemes (AES) and the wider rural economy. Agri-environment schemes represent a significant proportion of pillar 2 Rural Development Regulation (RDR) in the UK (Reed et al., 2014). The key AES in England operating during the period of this study was Environmental Stewardship (Natural England, 2009), which either paid farmers a flat rate for straightforward environmental management across the entire farm landscape (Entry Level Stewardship) or followed a more demanding level (Higher level stewardship) requiring more complex and targeted environmental management in return for larger payments. In Wales, a similar tiered agri-environment scheme, namely Tir Cynnal (entry level scheme) and Tir Gofal (higher level), was in operation until 2012. In 2012 these schemes were merged into a single scheme called Glastir (National Assembly for Wales, 2011) which, similar to Environmental Stewardship, paid farmers a flat rate per hectare under the ‘All Wales’ element of the scheme. The upper level element of the scheme targets specific areas of environmental concern and pays farmers depending on the specific management taken.

Part of pillar 2 also provides additional dedicated support for farms in Less Favoured Areas (LFAs), for example those in mountainous or upland areas, to support these farms whilst preserving the environment and cultural landscape in Europe’s rural areas (Bonn et al., 2008; DEFRA, 2006). From 2001, farmers in the English LFAs could receive area-based payments (under the Hill Farm Allowance) and optional payments for environmental enhancement (DEFRA, 2006). The HFA scheme closed in 2010 and farmers were offered Upland Entry Level Stewardship agreements as part of the Environmental Stewardship scheme, with an elevated standard payment rate (Natural England, 2013). Until 2012, Farms in the Welsh LFAs could also receive area-based payments (under “Tir Mynydd” hill support scheme). In 2012, LFA farmers receiving Tir Mynydd were offered Glastir agreements with elevated standard payment rates for LFAs (National Assembly for Wales, 2011).

4. Correlation between the four measures of the stability of farm income

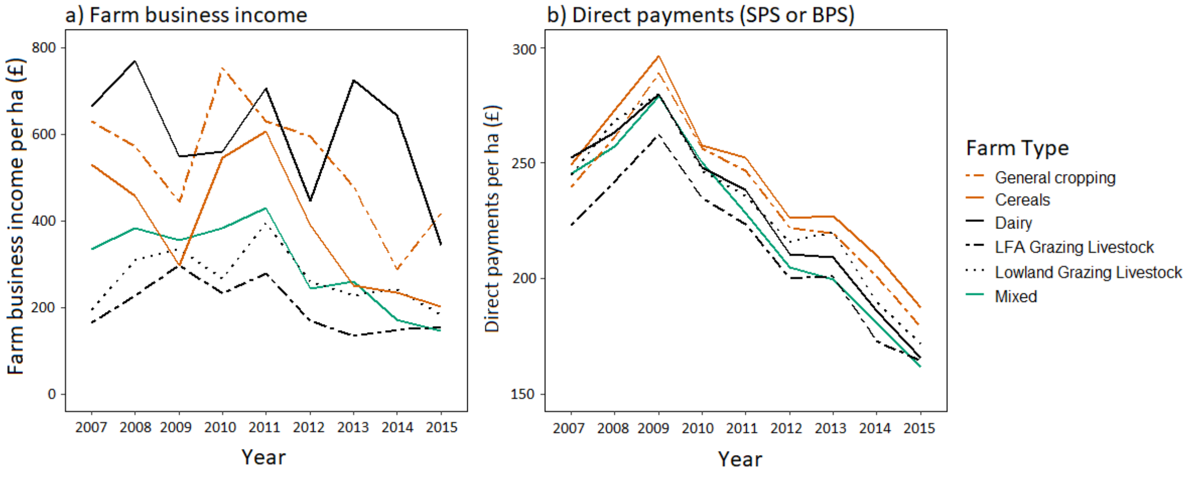
Commonalities in their calculation leads to the annual measures of stability, absolute and relative anomaly, being strongly positively correlated (Supplementary Table 1). Equally, medium-term stability measures, the standard deviation and relative standard deviation of farm income are also strongly positively correlated (r>0.7). Both absolute measures (absolute anomaly and standard deviation) and relative measures (relative anomaly and relative standard deviation) are moderately correlated with one another (Supplementary Table 1), therefore farms with larger variability in the annual terms are more likely to show larger variability over several years. Similar results are seen when calculating the Pearson's correlation coefficients for each farm type separately.

Supplementary Table 1 - Pearson's correlation coefficient (r) of dependent variables used in the analysis

	Relative anomaly	Standard deviation	Relative SD
Absolute anomaly	0.830	0.689	0.480
Relative anomaly		0.509	0.655
Standard deviation			0.738

5. Changes in Farm business income and direct payments over time

Between 2007 and 2015 farm business income (a net figure incorporating all income, government payments, as well as, all fixed and variable costs) in England and Wales was highly changeable for all farm types, with large variability in mean income over time (Supplementary Figure 1). Since 2011, mean farm income has shown a downward trend across most farm types (Supplementary Figure 1Supplementary Figure). Over the same period, direct payments (primarily Single Payment Scheme (SPS) and Basic Payment Scheme (BPS)) show a downward trend since 2009 across all farm types. Since direct payments are calculated in Euros, strengthening of the pound between 2009 and 2015 led to a reduction in the pound equivalent paid to farmers during this period. In addition, the value of single farm payments has not kept up with the rate of inflation, causing a reduction subsidies per ha in 'real' monetary terms.



Supplementary Figure 2 - Farm business income and direct payments (primarily Single Payment Scheme or Basic Payment Scheme) per ha (2007-2015). Figures use data from the Farm Business Survey; values deflated using UK Consumer Price Index (2015=100; ONS, 2020)

6. Correlation between input and output intensity and farm business income (FBI) per hectare

There is a strong positive correlation (*r*>0.7) between the intensity of inputs (Cost of fertiliser, crop protection and concentrated animal feed divided by the area farmed in hectares) and output intensity (economic value of agricultural products produced per hectare). However, there is only a weak positive correlation (*r*<0.3) between input intensity and farm business income per hectare. Similar results are seen when calculating the Pearson's correlation coefficients for each farm type separately.

Supplementary Table 2 - Pearson's correlation coefficient (r) of farm business income (FBI) and intensity variables used in the analysis

	Input intensity	Output intensity
FBI per ha	0.298	0.535
Input intensity		0.856

7. Multilevel model, all farm types combined

Using the same methods outlined in the main text, we ran multilevel models for the effect of farming practices and government payments on the stability of farm income with all farm types included in each model. Model were run using the two relative measures of income stability to account for the variation in mean income for each farm type. An interaction was included between each farm type and the independent variables to examine if the effect of farming practices and government payments differ between farm types.

The models indicate the effects of independent variables show relationships which are consistent with the farm type models included in the paper; for most farm types size and agri-environment payments decrease the variability of income, while increasing input intensity, specialisation of farming activities, direct payments and greater reliance on income from on-farm diversification increases the variability of income. The effects observed for each farm type are, in many cases, significantly different from the effects seen in dairy farms (used as the reference level). As seen in the paper, the effect of agri-environment payments for LFA grazing farms is significantly different from dairy farms and increases the variability of income. This same effect is found for lowland grazing farms in the model results below.

Supplementary Table 3 - Multilevel model results for the effect of farming practices and government payments on the stability of farm income, including all farm types, using (log) relative anomaly of farm business income per hectare as dependent variable. Significant at: *10, **5 and ***1 percent levels.

	All farms		
Random effects			
County SD	0.029		
Farm SD	0.298		
Level-1 residual	1.117		
Fixed effects			Standard error
Intercept	-1.895	***	(0.079)
LFA Grazing Livestock	0.067		(0.100)
Cereals	0.607	***	(0.113)
Mixed	0.138		(0.140)
General cropping	0.680	***	(0.140)
Lowland Grazing Livestock	0.568	***	(0.116)
Area farmed	-0.121	***	(0.027)
Input intensity	0.184	***	(0.029)
Specialisation (agricultural)	0.118	***	(0.027)
On-farm diversification	0.041		(0.025)
Direct payments per ha	0.227	***	(0.067)
Year	0.049	***	(0.011)
Agri-environment payments per ha	-0.050	*	(0.026)
Direct payments per ha × year	-0.033	***	(0.010)
Area farmed × LFA Grazing Livestock	-0.118	***	(0.037)
Area farmed × Cereals	0.064	*	(0.038)
Area farmed × Mixed	-0.005		(0.048)
Area farmed × General cropping	0.125	**	(0.050)
Area farmed × Lowland Grazing Livestock	-0.071	*	(0.042)
Input intensity × LFA Grazing Livestock	0.027		(0.038)

Input intensity × Cereals	-0.128	***	(0.040)
Input intensity × Mixed	0.079		(0.050)
Input intensity × General cropping	0.000		(0.049)
Input intensity × Lowland Grazing Livestock	0.019		(0.044)
Specialisation × LFA Grazing Livestock	-0.094	***	(0.035)
Specialisation × Cereals	-0.090	**	(0.038)
Specialisation × Mixed	-0.048		(0.049)
Specialisation × General cropping	0.085	*	(0.049)
Specialisation × Lowland Grazing Livestock	-0.109	***	(0.042)
On-farm diversification × LFA Grazing Livestock	0.041		(0.033)
On-farm diversification × Cereals	0.000		(0.038)
On-farm diversification × Mixed	0.008		(0.046)
On-farm diversification × General cropping	0.008		(0.047)
On-farm diversification × Lowland Grazing Livestock	0.039		(0.040)
Direct payments per ha × LFA Grazing Livestock	0.065		(0.088)
Direct payments per ha × Cereals	-0.115		(0.096)
Direct payments per ha × Mixed	-0.215		(0.134)
Direct payments per ha × General cropping	-0.373	***	(0.130)
Direct payments per ha × Lowland Grazing Livestock	-0.081		(0.099)
Year × LFA Grazing Livestock	0.008		(0.013)
Year × Cereals	-0.054	***	(0.015)
Year × Mixed	0.004		(0.019)
Year × General cropping	-0.072	***	(0.019)
Year × Lowland Grazing Livestock	-0.046	***	(0.016)
Agri-environment payments per ha × LFA Grazing Livestock	0.110	***	(0.034)
Agri-environment payments per ha × Cereals	0.023		(0.039)
Agri-environment payments per ha × Mixed	-0.019		(0.046)
Agri-environment payments per ha × General cropping	-0.029		(0.048)
Agri-environment payments per ha × Lowland Grazing Livestock	0.077	*	(0.041)
Direct payments per ha × year × LFA Grazing Livestock	0.010		(0.013)
Direct payments per ha × year × Cereals	0.030	**	(0.014)
Direct payments per ha × year × Mixed	0.034	*	(0.019)
Direct payments per ha × year × General cropping	0.048	**	(0.019)
Direct payments per ha × year × Lowland Grazing Livestock	0.011	***	(0.016)
Observations (n)	12,628		
County (n)	78		
Farm (n)	2,333		
AIC	39,727		
BIC	40,151		
logLik	-19,807		
R^2	0.091		

Supplementary Table 4 - Multilevel model results for the effect of farming practices and government payments on the stability of farm income, including all farm types, using (log) relative standard deviation of farm business income per hectare as dependent variable. Significant at: *10, **5 and ***1 percent levels.

	All farms		
Random effects			
County SD	0.074		
Farm SD	0.000		
Level-1 residual	0.525		
Fixed effects			Standard error
Intercept	-1.140	***	(0.046)
LFA Grazing Livestock	0.192	***	(0.056)
Cereals	0.233	***	(0.061)
Mixed	0.129	*	(0.070)
General cropping	0.256	***	(0.072)
Lowland Grazing Livestock	0.543	***	(0.063)
Area farmed	-0.118	***	(0.017)
Input intensity	0.205	***	(0.020)
Specialisation (agricultural)	0.091	***	(0.017)
On-farm diversification	0.048	***	(0.016)
Direct payments per ha	0.181	***	(0.035)
Year	0.037	***	(0.006)
Agri-environment payments per ha	-0.047	***	(0.017)
Direct payments per ha × year	-0.024	***	(0.005)
Area farmed × LFA Grazing Livestock	-0.087	***	(0.025)
Area farmed × Cereals	0.079	***	(0.023)
Area farmed × Mixed	0.025		(0.026)
Area farmed × General cropping	0.089	***	(0.031)
Area farmed × Lowland Grazing Livestock	-0.044	*	(0.026)
Input intensity × LFA Grazing Livestock	-0.007		(0.024)
Input intensity × Cereals	-0.145	***	(0.024)
Input intensity × Mixed	0.072	**	(0.032)
Input intensity × General cropping	-0.081	***	(0.029)
Input intensity × Lowland Grazing Livestock	-0.028		(0.027)
Specialisation × LFA Grazing Livestock	-0.077	***	(0.022)
Specialisation × Cereals	-0.045	*	(0.023)
Specialisation × Mixed	-0.106	***	(0.027)
Specialisation × General cropping	0.102	***	(0.030)
Specialisation × Lowland Grazing Livestock	-0.097	***	(0.025)
On-farm diversification × LFA Grazing Livestock	0.011		(0.021)
On-farm diversification × Cereals	0.045	**	(0.023)
On-farm diversification × Mixed	-0.046	*	(0.025)
On-farm diversification × General cropping	-0.012		(0.024)
On-farm diversification × Lowland Grazing Livestock	0.030		(0.023)
Direct payments per ha × LFA Grazing Livestock	0.021		(0.048)
Direct payments per ha × Cereals	-0.090	*	(0.048)

Direct payments per ha × Mixed	-0.172	***	(0.058)
Direct payments per ha × General cropping	-0.141	**	(0.062)
Direct payments per ha × Lowland Grazing Livestock	-0.116	**	(0.049)
Year × LFA Grazing Livestock	0.004		(0.007)
Year × Cereals	0.000		(0.008)
Year × Mixed	0.020	**	(0.009)
Year × General cropping	-0.043	***	(0.009)
Year × Lowland Grazing Livestock	-0.028	***	(0.008)
Agri-environment payments per ha × LFA Grazing Livestock	0.105	***	(0.023)
Agri-environment payments per ha × Cereals	0.020		(0.025)
Agri-environment payments per ha × Mixed	-0.001		(0.024)
Agri-environment payments per ha × General cropping	-0.031		(0.027)
Agri-environment payments per ha × Lowland Grazing Livestock	0.055	**	(0.026)
Direct payments per ha × year × LFA Grazing Livestock	0.017	**	(0.007)
Direct payments per ha × year × Cereals	0.018	***	(0.007)
Direct payments per ha × year × Mixed	0.034	***	(0.008)
Direct payments per ha × year × General cropping	0.015	*	(0.009)
Direct payments per ha × year × Lowland Grazing Livestock	0.022	***	(0.008)
Observations (n)	12,628		
County (n)	78		
Farm (n)	2,333		
AIC	10,838		
BIC	11,269		
logLik	-5,361		
R^2	0.309		

8. Sensitivity analysis of multilevel model

A small proportion of farms (n=283) change farm type across the time series, and therefore appeared in more than one model, albeit in different years. To consider how this may have affected the results we repeated the model analysis using farms classified as only one farm type across the data series (n=2049). The results of these models showed very little change to the models presented in this paper; the direction and relationships of the independent variables remained consistent and there was little change in the significance of variables in the models. Therefore, we can conclude a small subset of farms changing farm type across the time series does not impact the conclusions drawn from the study.

We also examined the model results using alternative measures of intensity and on-farm diversification. We ran the models using output intensity (economic value of agricultural products produced per hectare (£)) as a measure of agricultural intensity. Output intensity was strongly positively correlated with input intensity (*r*>0.7; Supplementary Table 2). The effect of output intensity on the stability of income revealed the same relationship as input intensity, increasing the variability of farm income across all models, with little change in the magnitude or significance of coefficients. We also examined the effect of on-farm diversification using different independent variables, including the total value of revenue from diversified activities per hectare (£) and a dummy variable capturing farms which do not engage in on-farm diversification (1) versus those who do (0), which was included in the model alongside the ratio of revenue from on-farm diversification. All variables showed similar relationships; farms who engage in on-farm diversification or increase revenue from diversified activities have more variable income.

References

Bonn, A., Allott, T., Hubacek, K., Stewart, J., 2008. Drivers of environmental change in uplands, Drivers of Environmental Change in Uplands. https://doi.org/10.4324/9780203886724

Defra, 2020. Farm Business Survey [WWW Document]. URL https://www.gov.uk/government/collections/farm-business-survey (accessed 3.20.20).

DEFRA, 2006. Hill Farm Allowance Explanatory booklet 2006.

National Assembly for Wales, 2011. An introduction to Glastir and other UK agri-environment schemes.

Natural England, 2013. Entry Level Stewardship, Environmental Stewardship Handbook.

Natural England, 2009. Agri-environment schemes in England 2009.

ONS, 2020. Consumer price inflation time series (MM23) [WWW Document]. URL https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bt/mm23 (accessed 3.20.20).

Reed, M.S., Moxey, A., Prager, K., Hanley, N., Skates, J., Bonn, A., Evans, C.D., Glenk, K., Thomson, K., 2014. Improving the link between payments and the provision of ecosystem services in agri-environment schemes. Ecosyst. Serv. 9, 44–53. https://doi.org/10.1016/j.ecoser.2014.06.008

Rural Business Research, 2020. FBS data builder - coverage [WWW Document]. URL http://www.farmbusinesssurvey.co.uk/DataBuilder/UserDocumentation/CoverageOfSurvey.htm (accessed 3.20.20).

Chapter 5 - Towards stability of food production and farm income in a variable climate

This chapter is under review as a research article with Ecological Economics (on 3rd July 2021), with Harkness, C as lead author, and Areal, F. J., Semenov, M. A., Senapati, N., Shield, I. F. and Bishop, J as co-authors.

Author contribution: CH obtained and cleaned the data, performed the data analysis and interpretation of the results, and wrote the paper. FA and JB provided comments on the models and analysis. All co-authors provided comments on the paper.

Abstract

Stable food production is vital for food security. Stability of farm income is also necessary to ensure the sustainability of food production and to protect livelihoods, in a changing climate. We analyse the relative effects of climate variability, subsidies and farming practices on the stability of food production and farm income. We examine farms in England and Wales between 2005 and 2017, and link farms to climate data at a sub-regional scale. Our results show that variability in temperature and rainfall reduces the stability of farm income and food production, however, their importance varies between farm type. While variability in climate can be largely outside of the farmers control, our findings indicate that, under current conditions, farm management can have a comparatively large effect on stability. Greater agricultural diversity can have multiple benefits improving both the stability of food production and farm income. More controlled or precise use of agrochemicals may also help improve stability of income, whilst maintaining production. Future climate impacts and adaptation are likely to vary between farm types, therefore agricultural policy targeting the stability of farm performance should be flexible enough to be tailored to different types of production.

1 Introduction

Stable food production is essential for food security (FAO, 2006). Likewise, stability of farm income is necessary to ensure the sustainability of farm businesses that can continue to produce food, and protect livelihoods, in a changing climate. Agriculture is subject to a wide range of risks and uncertainties, including climatic, economic, biotic (pests and disease) and environmental, many of which will intensify with climate change. The capacity of the agricultural system to cope with shocks and maintain stability of food production is vital to attaining the UN Sustainable Development Goals of eradicating hunger and securing food for an increasing global population (Griggs et al., 2013).

Agricultural production, and therefore farm income, is highly dependent upon weather conditions. Climate change and associated increases in weather variability therefore pose many challenges to farmers. Climate variability and extremes (e.g. heat waves, flooding and drought) can severely reduce crop yields (e.g. Deryng et al., 2014; Powell and Reinhard, 2015) and livestock productivity, influencing both the direct health of the animal and feed availability (Kipling et al., 2016). Farm incomes are also impacted by production losses due to adverse weather, in addition to other factors including changes in commodity prices and policy (Reidsma et al., 2009).

Alongside climate impacts, the magnitude and stability of agricultural production and farm income are strongly associated with farm characteristics (e.g. farm type and size), farming practices (e.g. diversity, input intensity) and government subsidies (Harkness et al., 2021; Reidsma et al., 2009). Understanding the effects of these farming practices and subsidies alongside, and in comparison to, the influence of climate could help farms adapt to more variable conditions. To effectively guide adaptation, it is important to understand the relative importance of government policy in comparison to farm-level management practices. However, quantitative assessments on agricultural system dynamics (i.e. changes over time) remain rare at the farm level (Dardonville et al., 2020).

At the farm-level, changes in management can have dramatic impacts on the stability of food production and income. Increased diversity in crop rotations has been found to enhance yield stability in certain crops and reduce the risk of crop failure (Dardonville et al., 2020; Gaudin et al., 2015). Greater use of fertiliser and pesticides is associated with greater yield, however the effect of agrochemicals on the variability of yields is unclear (Dardonville et al., 2020). Management strategies to enhance yield and its stability do not necessarily have complementary benefits for farm income, which requires expenditure to be considered.

Reducing input intensity, engaging in government agri-environment schemes and increasing agricultural diversity, as well as larger farm size have previously been found to increase the stability of income for many farm businesses (El Benni et al., 2012; Enjolras et al., 2014; Harkness et al., 2021; Pacín and Oesterheld, 2014).

To effectively target adaptation, it is necessary to integrate climate, farm characteristics, farming practices and subsidies and assess their relative importance. However, the impacts of these factors are typically examined separately, in different disciplines, and at different spatial scales. The stability of agricultural production is usually assessed via the variability of yield over a given time period (e.g. Ceglar et al., 2016; Reidsma et al., 2009). Few studies have considered the impacts of a range of farming practices, subsidies and climate on the stability of both food production and farm income. Reidsma et al. (2009) found that increasing farm size and output intensity increased crop yield and income stability, while variability in direct payments decreased yield and income stability across regions of Europe. In addition, variability in precipitation decreased yield stability in many crops (Reidsma et al., 2009). In contrast to previous studies, our analysis here also considers the effect of agricultural diversity and agri-environment scheme payments, on the stability of food production and farm income. The production type can also influence the stability of income and food produced (e.g. Chavas, Cooper and Wallander, 2019; Harkness *et al.*, 2021), therefore we consider differences within and between farm types, which can exhibit very different farm management and characteristics.

The key aim of our research is to examine the relative effect of climate variability in combination with subsidies and farming practices on the temporal stability of food production and farm income, at the farm level. Here, we expand upon our previous work (Harkness et al., 2021) to incorporate the effects of climate variability and additionally examine factors affecting the stability of total food production at the farm level. This provides insight into how policy, and management at the farm-level, can improve the resilience and sustainability of farming in a changing climate. We use a cohort of 929 farms across counties of England and Wales over the period between 2005 and 2017, during which the UK experienced a diverse range of adverse weather conditions including flooding, drought, and heatwaves (e.g. Kendon, Marsh and Parry, 2013). We examine the stability of food produced at the farm level using a common unit of calories, which has not been examined previously. This enables us to compare productivity across different crop and livestock products. We examine the stability of farm income using the measure of farm business income, which is in essence the same as net profit and integrates both income and expenditure. Our approach also enables us to evaluate trade-offs between enhancing the stability of food production and of farm income, and where potential adaptations may differ between farm types.

2 Materials and methods

2.1 Data and study area

We examine data from the Farm Business Survey (FBS) between 2005 and 2017, which is a survey conducted in England and Wales collecting information from approximately 2,500 farm businesses annually (Defra, 2020). The FBS records farm level data on financial performance and food production, as well as subsidies received and other farm characteristics, including the county (or unitary authority) location of each farm. Farms are classified in the survey into farm types according to which type of production accounts for more than two-thirds of standard gross margin (SGM). We focus our analysis on cereals, general cropping (arable crops including field scale vegetables account for more than two-thirds of SGM) and mixed farms (no other type accounts for more than two-thirds of SGM).

Climate variability, and averages, have been calculated using the HadUK-Grid gridded climate observations produced by the Met Office (Hollis et al., 2019). The HadUK-grid dataset includes a wide set of climate variables, including temperature and precipitation, for daily, monthly, seasonal and annual timescales, as well as long term averages and at different spatial resolutions. We average 5km HadUK-Grid gridded climate observations for each county or unitary authority to provide an estimate of the climate at each farm, and link climatic conditions to farm data at a smaller spatial scale than used in previous studies (e.g. across regions of Europe in Reidsma et al. (2009)). Figure 1 shows the climate variables (described in section 2.3) for an example 5-year period included in the analysis, which illustrates the spatial differences between the county and unitary authorities (spatial units used in the analysis) in England and Wales.

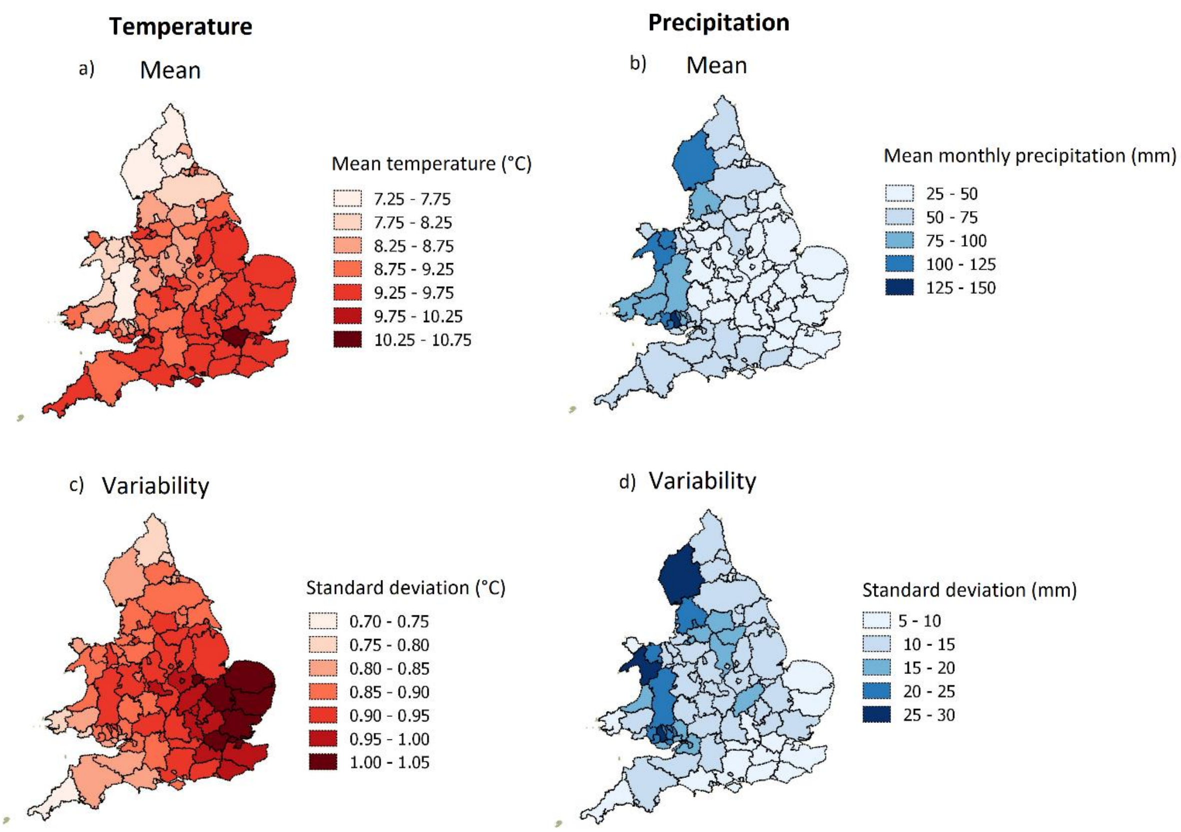


Figure 1 – Spatial distribution of climate variables for an example 5-year period (2009-2013): a) mean temperature b) mean monthly precipitation c) standard deviation of mean temperature d) standard deviation of mean monthly precipitation, during the main growing season (January-June) and across county and unitary authorities of England and Wales

2.2 Measuring the stability of food production and farm income

We examine the effect of climate variability in combination with subsidies and farming practices on medium-term stability of food production and farm income. We calculate medium-term stability (changes over time) using the standard deviation over a 5-year rolling period, as used in previous studies (Barry et al., 2001; Harkness et al., 2021). This measure indicates the amount of variation or dispersion of farm business income or calories at the individual farm over a 5-year period.

To examine the stability of farm income we use farm business income per hectare (£/ha) which is calculated as the sum of: total output from agriculture, on-farm diversification and subsidies, less all fixed and variable costs, including paid labour and depreciation, and profit or loss from the sale of fixed assets (Harkness et al., 2021). Farm business income is in essence the same as net profit and is the preferred measure of income used by policy makers to examine the impact of policies at the farm level (Department for Environment Food and Rural Affairs et al., 2018).

The Farm Business Survey also records annual food production. To examine the stability of food produced at each farm, we calculate the total calories (kcal/ha) available for direct human consumption. Calories represents a common unit of production (analogous to £/ha for income) and therefore no weighting for different products is required. To calculate calories we use the FAO Food Balance Sheet (FAO, 2021) which derives calories per 100g for each agricultural commodity. We use these factors to convert the units of food produced in the Farm Business Survey (tonnes (crops), hectolitres (milk), dozen (eggs) and number (livestock)) into calories. Further details on the calculation of calories per food product is provided in the supplementary materials. As this study focuses on the stability of food production, using a consistent measure of food production over the period examined allows us to analyse how much total food production has varied for the main food products, as listed in Supplementary Table 1. The stability of calories per hectare has been calculated in the same way as for income; using the standard deviation over a 5-year rolling period.

2.3 The factors affecting farm stability

We use the same methods from Harkness et al. (2021) to calculate the farming practices: farm size, input intensity (cost of chemical inputs per hectare), agricultural diversification (degree of specialisation in different crop and livestock products), and value of subsidies: direct (area-based) payments and agri-environment scheme payments per hectare. To examine their relative effects on farm stability, these variables are averaged over the same 5-year rolling period used to derive the dependent variables (standard deviation of farm income and calories). The calculations of independent variables are provided in supplementary table 2.

To examine the effect of climate variability on the stability of food production and farm income, we calculate the standard deviation in temperature and rainfall over a 5-year rolling period. This involves firstly calculating the mean temperature and monthly precipitation for the first 6 months of the year (January – June) in each county to provide an indication of temperature and rainfall in the main growing period (similar to the approach used by Reidsma et al. (2009)). These county level climate conditions are then used to calculate the standard deviation in temperature and precipitation over a rolling 5-year period to examine the effect of climate variability at the farm level. Crops are affected by adverse weather conditions which occur at specific stages of development, however, we wanted to examine how variability in climate conditions can affect total food production at the farm level (across all agricultural products), therefore we measured climate variability across the main part of the growing season for crops in the UK. The stability of performance may also be influenced by average climate conditions (or base temperatures), as well as variability, therefore we include variables capturing the mean temperature and precipitation for each 5-year period, to reduce the risk of confounding these relationships.

The standard deviation is an absolute measure of dispersion, therefore we also control for the level of income and calories produced by each farm (using total farm business income and calories per hectare), which may also affect the level of stability.

Summary statistics for the variables used in this study are shown in table 1. The UK Consumer Price Index is used to deflate all monetary variables, including farm business income, to account for the change in the value of money over time (ONS, 2020).

Table 1 - Summary statistics of FBS data (2005-2017); values deflated using UK Consumer Price Index (2015=100; ONS, 2020).

	Mean (2005-2017)				**Standard deviation (SD) (2005-2017)**			
	All Farms	**Cereals**	**Gen. cropping**	**Mixed**	**All Farms**	**Cereals**	**Gen. cropping**	**Mixed**
Dependent variables								
SD of Farm Business Income (FBI) per ha (£)	219.57	213.77	271.13	183.97	144.05	116.84	192.72	129.06
SD of calories per ha (kcal)	2,537,320	2,864,774	2,736,539	1,668,707	1,557,537	1,340,314	1,655,014	1,562,107
Independent variables								
Farming practices and subsidies								
Specialisation (Herfindahl index) (0-1)	0.41	0.40	0.37	0.49	0.16	0.14	0.14	0.18
Input intensity per ha (£)	413.59	327.26	399.05	607.44	533.25	137.37	243.86	997.30
Direct payments (SPS/BPS) per ha (£)	237.57	244.15	237.49	223.87	62.36	59.95	57.06	69.42
Agri-environment payments per ha (£)	45.70	48.54	39.81	45.22	50.47	56.62	41.19	43.74
Area farmed (hectares)	234.97	233.52	284.21	192.41	246.33	218.59	358.33	144.99
Climate (Jan-Jun)								
Mean temperature (°C)	8.29	8.31	8.40	8.14	0.66	0.66	0.51	0.74
SD of mean temperature (°C)	0.90	0.91	0.91	0.88	0.21	0.21	0.22	0.19
Mean monthly precipitation (mm)	60.07	58.18	55.95	67.84	16.08	13.79	14.72	18.88
SD of mean monthly precipitation (mm)	15.48	15.27	14.42	16.90	4.53	4.35	3.87	5.09
Control variables								
Farm Business Income (FBI) per ha (£)	390.96	387.20	495.80	301.80	393.09	357.27	460.26	373.88
Calories per ha (kcal)	15,929,805	17,651,252	19,406,013	9,115,433	8,110,153	6,608,759	8,087,139	6,968,904
Number of observations	4,529	2,357	1,044	1,128				
Number of farms	929*	512	261	318				
Number of counties/unitary authorities	65	56	38	57				

*Note 162 farms change between farm types during the period, therefore appear in more than one farm type group during the relevant years.

2.4 Multilevel (two-level linear mixed effect) model

We use a multilevel model to examine the relative effects of climate variability, farming practice and subsidies on the stability of food production and farm income. Multilevel models allow us to account for dependencies within the data: Farms belonging to the same county or unitary authority (level 2) have the same estimated climate and may also have more similar environmental conditions (e.g. soil) than farm in different counties. Farms are also surveyed in the data over multiple years (we consider farms in the survey for a minimum of 5 years) therefore the multilevel model controls for the correlation between observations from the same farm (level 1). This type of model can easily accommodate the unbalanced panel data used in this study (Snijders and Bosker, 1999) and has been used previously to examine the influence of management and climate on farm level performance (Harkness et al., 2021; Reidsma et al., 2009, 2007).

We estimate a varying-intercept Bayesian two-level mixed model with farms nested within counties. The empirical specification of the model is:

$$
\begin{aligned}
Y_{tjk} &\sim \text{Log-normal}(u_{tjk}, \sigma_e) \\
u_{tjk} &= \alpha + \alpha_{\text{county}[k]} + \alpha_{\text{farm}[jk]} + \textstyle\sum \beta_p X_{jk} \\
\alpha &\sim \text{Normal}(0, 10) \\
\alpha_{\text{county}} &\sim \text{Normal}(0, \sigma_{\text{county}}) \\
\alpha_{\text{farm}} &\sim \text{Normal}(0, \sigma_{\text{farm}}) \\
\beta_p &\sim \text{Normal}(0, 10) \\
\sigma_{\text{e}} &\sim \text{HalfCauchy}(10) \\
\sigma_{\text{county}} &\sim \text{HalfCauchy}(10) \\
\sigma_{\text{farm}} &\sim \text{HalfCauchy}(10)
\end{aligned}
\qquad (1)
$$

We fit a log-normal model to account for the non-normal distribution of the dependent variable, Y_{tjk} (the standard deviation of income and calories), in each model and reduce the impact of outliers. In the linear model, α is the mean intercept across all groups, α_{county} is the county level intercept (level 2), α_{farm} is the farm level intercept (level 1). β_p denotes the coefficients for each predictor variable, X_{jk}, which are listed in table 1. α and β are given a vague (weakly informative) Gaussian prior centred on 0, and the residual variation (σ_{e}) is given a Half-Cauchy prior (Gelman, 2006; Nalborczyk et al., 2019), thus restricting the range of possible values to positive ones. The same Half-Cauchy prior is specified for the two varying intercepts[1].

In each of the models, predictor variables have been standardised (centred around zero, with a SD of 1) to account for the differences in scale and to examine the relative effect size of each independent variable. Year, *t*, is also included as a continuous variable to control for the trend in income stability and calories over time, as well as examine the interaction between time and direct payments per hectare, which was significant for mixed farms. Before fitting the models, we checked for outliers and collinearity using pairwise scatterplots. In addition, correlation coefficients between independent variables were all less than the recommended threshold of 0.7 (Dormann et al. (2013).

We fitted a Bayesian multilevel model in the *brms* package in R (Bürkner, 2018, 2017; R Core Team, 2019). To generate the posterior samples of the parameter estimates *brms* makes use of the computationally efficient Hamiltonian Monte-Carlo (HMC) Sampler (Neal, 2011) and its extension the no-U-turn Sampler by Hoffman and Gelman (2014) implemented in the Stan software package (Stan Development Team, 2020). Each model was fitted with 4 chains of 10,000 per chain of which 2,000 were used for the warm-up. Visual model diagnostics showed adequate mixing of chains for each parameter, with the Rhat value (Gelman and Rubin test statistic; Gelman and Rubin, (1992)) less than 1.003, providing strong evidence of convergence. A Bayesian version of the marginal R^2 was obtained using the *bayes_R2* method available in *brms* (Nalborczyk et al., 2019), with calculations based on Gelman *et al.*, (2019). Due to the temporal nature of the variables we considered the presence of temporal autocorrelation. We inspected the residual variance (σ_e), which showed no significant autocorrelation. For comparison, we also estimated the same models using frequentist methods and incorporated a AR(1) residual autocorrelation structure[2]. The frequentist results are provided in the supplementary materials and show relationships which are consistent with the Bayesian results provided in section 3.

[1] We also ran the models using the default priors set in the *brms* package (weakly informative Student-t distributions), which resulted in little change to the model results.

[2] At the time of writing, the package used for applying MCMC does not allow for an AR(1) residual autocorrelation structure for unevenly spaced data (longitudinal data with gaps).

3 Results

3.1 The effects of farming practices and subsidies on the variability of income

Figures 2 and 3 show the posterior means, and 95% credible intervals (CIs), of the multilevel models. These figures indicate the relative effect of farming practices, subsidies and climate conditions on the variability (inverse of stability) of food production and farm income, by farm type. The model results are also provided in table annex 1 and 2. Models use the log of the dependent variable, therefore the exponent of the posterior mean, minus 1 multiplied by 100, provides the percentage change in the variability of income for every increase in the independent variable by one standard deviation, holding all other predictors constant.

3.1.1 Factors affecting the variability of farm income

Farming practices are important factors influencing the variability of farm income per hectare (figure 2). Farms which spend more on chemical inputs (fertiliser, pesticide and concentrated animal feed) have more variable income. Increasing input intensity by 1 standard deviation increases the variability of income between 10 and 21% across the 3 farm types, which represents a large increase relative to other factors examined. More specialised cereal and general cropping farms (i.e. those with less diversity of crop and livestock activities) also have more variable income, however, this was not an important factor for mixed farms. For general cropping farms (which are on average the most diverse; Table 1) specialisation has a large relative effect; increasing specialisation by 1 standard deviation increases the variability of income by 13% (95% CI [7%, 20%]). Larger cereal and mixed farms have more stable incomes. Increasing the area farmed by 1 standard deviation reduces the variability of income by 6% (95% CI [-9%, -3%]) for cereal farms, and for mixed farms the decrease is larger (-11%, (95% CI [-15%, -6%]).

The value of direct payments per hectare is an important factor for cereal farms. An increase in direct payments increases the variability of income by 4% (95% CI [1%, 7%]). While the effect of agri-environment scheme payments differs between farm types. An increase in agri-environment payments per hectare decreases the variability of income for mixed farms by 6% (95% CI [-10%, -3%]), whereas increases the variability income by 3% for cereal farms, although the lower bound of the credible interval is close to zero (95% CI [0%, 6%]). Subsidies therefore have a smaller relative effect on the variability of income, in comparison to the farming practices examined in this study.

Climatic conditions are also estimated to be an important factor influencing the variability of income. The variability of income for cereal farms are particularly sensitive to changes in both prevailing (mean) temperatures and precipitation and its variability. Larger variability of temperature increases the variability of income for cereal farms by 5% on average, while increasing the variability of precipitation also has the same effect (5% increase). Increasing warmth (mean temperatures) and average precipitation has the opposite effect and are both associated with a decrease in the variability of income of 9%, while holding all other factors constant. Changes in precipitation have a larger effect for mixed farms and are found to be more important than changes in temperature. An increase in mean rainfall reduces the variability of income by 11%, whereas greater variability in precipitation, over a 5-year period, increases the variability of income by 7% on average, for mixed farms.

Generally, the relative effects of climatic factors associated with the variability of income were similar in size to the effects of the farming practices examined (Figure 2). With exception of general cropping farms, where the effect of input intensity and specialisation were found to be more important than the climatic conditions examined (Figure 2).

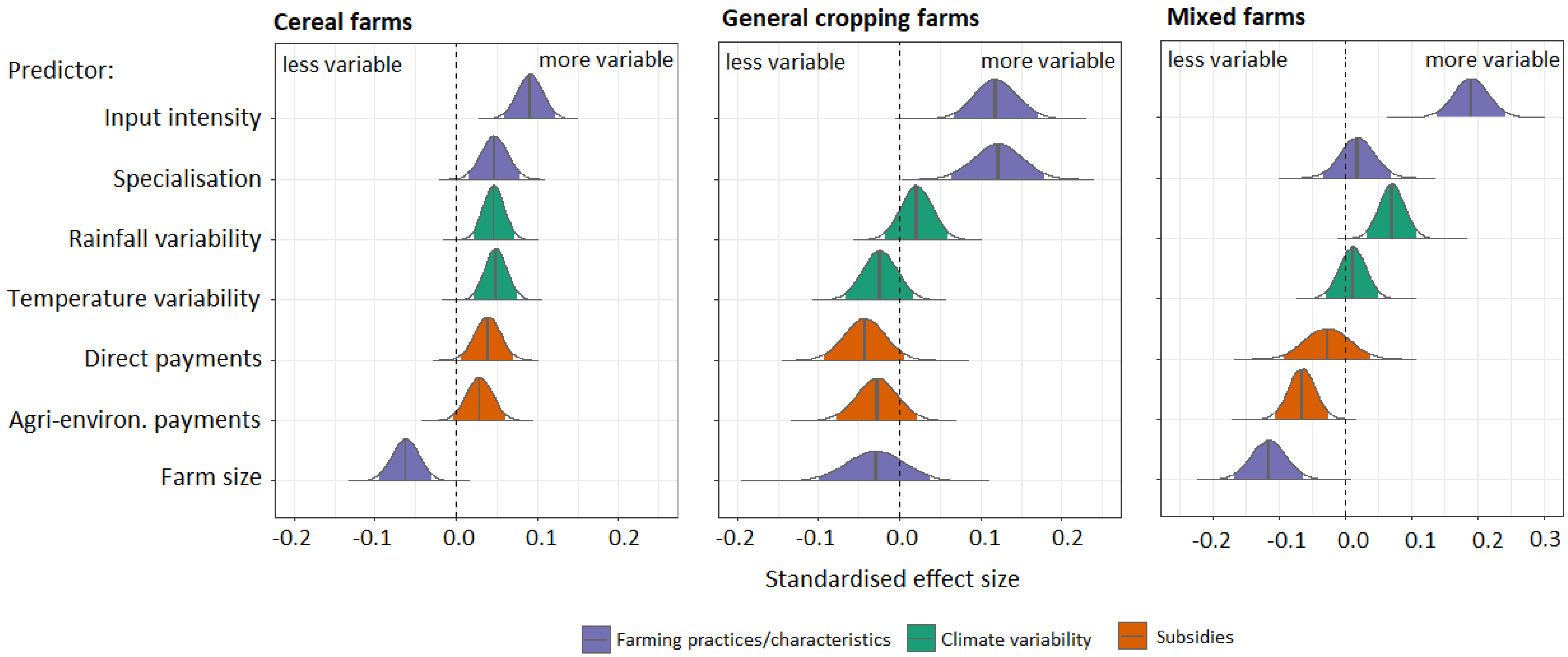


Figure 2 – Posterior distribution of the standardised relative effects of farming practices, subsidies and climate variability on the variability (standard deviation) of farm business income per ha. Shaded areas represent the 95% credible intervals.

3.1.2 Factors affecting the variability of food production

Farming practices examined also affect the stability of food production, however, the relative size of these effects differ between farm types (figure 3). For general cropping and mixed farms, increasing input intensity is associated with an average decrease in the variability of calories by 4% and 10% respectively. Spending more on chemical inputs therefore helps improve the stability of food production but increases the variability of farmers income. Increasing specialisation of crop and livestock activities is associated with an increase in the variability of calories for general cropping and cereal farms, however, this was not an important factor for mixed farms. The effect of specialisation is relatively large compared to other factors and is largest for cereal farms. Increasing specialisation by 1 standard deviation increases the variability of calories by 10% for cereal farms (95% CI [7%, 14%]), and by 5% (95% CI [1%, 10%]), for general cropping farms. Larger farms are associated with less variability in calories produced. Increasing the area farmed by 1 standard deviation reduces the variability in calories between 4% and 9% across the 3 farm types.

The value of direct payments is an important factor for mixed farms. Receiving more direct payments per hectare is associated with an increase in the variability of calories produced by approximately 3% over the period examined, and this effect increases over time. The effect of agri-environment scheme payments on the variability of calories differs between farm types, which is consistent with the effects on farm income. An increase in agri-environment scheme payments per hectare decreases the variability of calories for mixed farms by 5% (95% CI [-10%, 0%]), whereas increases the variability of calories for cereal farms by 3% (95% CI [0%, 6%]), although one bound of the 95% credible interval is close to zero. The relative effects of agri-environment scheme payments are therefore smaller than the farming practices we examined.

Climatic conditions are also estimated to be an important factor influencing the variability of calories, however fewer important effects were found compared to those associated with the variability of income. Changes to both the prevailing (mean) temperature, and variability in temperatures, were important factors affecting the variability of calories for cereal farms; Increasing the temperature variability by 1 standard deviation was associated with an increase in the variability of calories of 3% (95% CI [0%, 5%]). While, increasing warmth (mean temperatures) decreased the variability of calories by 4% (95% CI [-7%, 0%]), while holding all other factors constant. An increase in mean rainfall was also associated with a reduction in the variability of calories produced by mixed farms of 11% (95% CI [-17%, -2%]).

In general, the farming practices employed by farms are therefore associated with a larger relative effect on the stability of calories produced, compared to the effects of more variable climate conditions (figure 3). For general cropping farms in particular, farming practices and characteristics were more important than subsidies or climate variability in influencing the variability of calories produced (figure 3).

In this study we estimate the relative effects of climate variability using variability in average temperature and monthly precipitation for the main part of the growing season, between January and June. We also estimate models using climate conditions over a 12-month period, using all months in the agricultural season (October to September). Including all months in the analysis does not have a large impact on the results. Results of this sensitivity analysis are available in the supplementary material.

We also examine results using a different calculation of diversity. In the main results we calculate diversity using revenue from different crop and livestock products. We also calculated the equivalent diversity index using the calories produced for each product type per farm (see supplementary table 2). Models using diversity in calories provided very similar results to the models using diversity based on revenues; also showing that specialisation of calories resulted in a large increase in the variability of farm business income and calories.

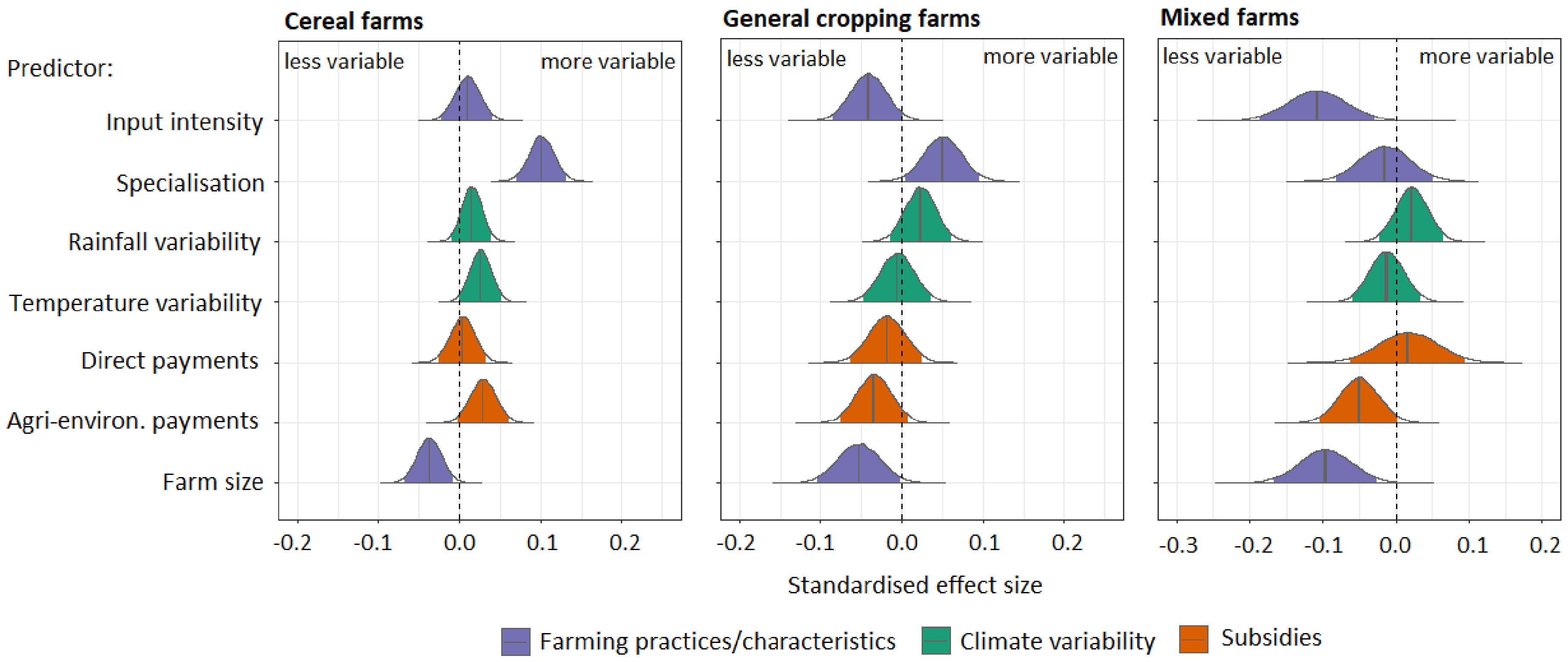


Figure 3 – Posterior distribution of the standardised relative effects of farming practices, subsidies and climate variability on the variability (standard deviation) of calories per ha. Shaded areas represent the 95% credible intervals.

4 Discussion

Our study provides knowledge on the relative importance of farming practices, subsidies and climate variability on the stability of food production and farm income. Our results highlight the importance of agricultural diversity to increase the stability of both food production and farm incomes. We identified a potential trade-off in the use of agrochemicals between the stability of food production and farm incomes. More precise use of chemicals may help to increase the stability of income, whilst maintaining outputs. Subsidies paid to farmers through the Common Agricultural Policy have a small effect on the stability compared to farm management. Direct (area based) payments reduce stability of income and food production, whereas agri-environment schemes improve stability, for general cropping and mixed farms. Climate conditions also affect both the stability of food production and farm income, however, the importance and relative size of these effects vary between farm type.

4.1 Diversity benefits both the stability of food production and farm income.

Our results show that greater agricultural diversity is associated with greater stability of farm income and total calories produced at the farm level. The relative strength of these associations, in comparison to other farming practices and climate conditions, indicates that maintaining and/or increasing agricultural diversity is highly important for the future sustainability of farming systems and food security. More diverse agricultural systems, with a broader range of traits and functions, are associated with a range of benefits which could improve stability of farm performance in a changing climate (Dardonville et al., 2020; Lin, 2011). More diverse agroecological systems, for example with greater crop diversity, have been found to improve pest and disease suppression and soil services (Degani et al., 2019; Lin et al., 2011). In addition, greater diversity may provide buffering and mitigation to the effects of climate variability and adverse conditions, including drought (Degani et al., 2019; Lawes and Kingwell, 2012) and high temperatures (Gaudin et al., 2015). The income of more diverse farms is also less affected by the price of single commodities on global markets, therefore reducing the potential impact of price downturns (Bradshaw et al., 2004; Pacín and Oesterheld, 2014).

We also found that farm size is an important factor affecting stability. Larger farms were associated with greater stability of both food production and farm incomes across most farm types. The effect of farm size was particularly large for mixed farms. Larger farms may benefit from greater economies of scale (El Benni et al., 2012). Larger farms may also encompass a more diverse range of topography or soils, which could result in different exposure and responses to weather conditions across the farm in similarity to agricultural diversity.

4.2 Increasing inputs results in a potential trade-off between stability of food production and income

Our results show that more intensive farms (those spending more on fertiliser, pesticide and concentrated animal feed) have less stable income. In contrast, we find that greater input intensity is also associated with more stability of calories produced at the farm level, for general cropping and mixed farms. Spending more on increasingly expensive chemical inputs has previously been associated with a reduction in the stability of farm income (Enjolras et al., 2014; Harkness et al., 2021). However, the effects of fertiliser and pesticides on the stability of yield are less clear (Dardonville et al., 2020). We find that the negative effect of input intensity reducing the stability of income is relatively large compared to other factors, including climate variability, for all farm types examined. The beneficial effect of chemical inputs stabilising food production is largest for mixed farms, where increased use of concentrated animal feed may protect livestock production from the effects of weather variability. For general cropping farms, higher input intensity may also help stabilise calories produced by preventing large crop losses (Popp et al., 2013). Despite the benefits to production, our results indicate that greater input intensity is not economically sustainable for farm businesses, with higher input costs reducing the stability of income. This suggests a potential trade-off in the use of chemical inputs between the stability of food production and farm incomes. Agrochemicals are often used in excess which has limited economic benefit, through declining nutrient efficiency and resistance (Roberts, 2008; Varah et al., 2020), as well as, leading to the contamination of ecosystems. Greater precision and more controlled use of chemicals may therefore offer an important solution to sufficiently support sustainable food production whilst at the same time reducing inputs costs and increasing income stability. Improved crop rotation and other practices of integrated pest management may also offer opportunities to reduce pesticide use without significant losses in crop yields (e.g. Barzman et al., 2015; Lechenet et al., 2017).

4.3 The effect of subsidies are relatively small and vary between farm type

We find that the value of government subsidies affects both the stability of food production and farm income. However, the effects of subsidies on stability are relatively small compared to farming practices (i.e., diversification and input intensity), and vary between farm types. Our results generally indicate a positive association between agri-environment payments and the stability of both farm income and food production, though the strength of this relationship varies between farm types. Agri-environment schemes compensate farmers for engaging in practices to benefit the environment or biodiversity and include options to maintain habitats for wildlife as well as soil management practices, which can help enhance ecosystem services and increase the resilience of the farm landscape (e.g. Degani et al., 2019; Kennedy et al., 2013; Ottoy et al., 2018). Farms receiving larger agri-environment payments may be benefitting from the direct source of income and indirect benefits of ecosystem services to food production. Agri-environment schemes do not seem to have the same stabilising effect for cereal farms. Agri-environment scheme options may not provide the same benefits for cereal crops, or these farms may engage differently with the scheme. Our results indicate that direct payments, based on area alone, reduce the stability of income and food production for certain farm types. A guaranteed level of income support from the government has been considered to represent a moral hazard to farmers, who may be more inclined to engage in riskier production, leading to greater variability in farm performance (Enjolras et al., 2014; Harkness et al., 2021; Reidsma et al., 2009). Direct payments per hectare are also variable; strengthening of the pound against the Euro between 2009 and 2015 led to a reduction in the pound equivalent, which alongside inflation, has reduced the value of direct payments paid to UK farmers over this period (Harkness et al., 2021). In general, the effects of subsidies on stability are relatively small in comparison to the farming practices examined. Greater emphasis could be given in future schemes to support agricultural diversification, as well as more precise chemical application, which appear to offer the most important solutions to improve the stability and sustainability of food production and farm incomes.

4.4 The effect of climate variability on farm stability differs between farms types

Climate variability affects both the stability of farm income and food production. However, the importance and relative size of these effects can vary depending on the production type, as well as the measure of farm performance being examined. Climate conditions are particularly important for cereal farms; variability in both temperature and rainfall reduce the stability of income, while deviations in temperature are more influential in reducing the stability of food production. For mixed farms, changes in precipitation have a larger effect on the stability of income and are found to be more important than changes in temperature. Reidsma *et al.* (2009) also found high variability in precipitation has a large effect on agricultural stability across Europe, however, they did not examine the effects between different types of production and examined climate at a larger regional scale. Grass productivity is particularly dependent upon rainfall and limited by more extreme conditions including dry periods in spring and summer (van den Pol-van Dasselaar et al., 2020). Therefore, mixed farms may incur additional costs for feeding livestock during periods of adverse weather leading to greater variability of income. General cropping farms do not appear as sensitive to variability in temperature and precipitation, while the effect of input intensity and specialisation were found to be more important. General cropping farms are, on average, the most diverse farm type (table 1), which may provide greater resilience to climate variability and adverse weather (Dardonville et al., 2020; Gaudin et al., 2015) and would be an interesting interaction to examine in future research.

An increase in mean temperatures and rainfall are found to be generally associated with greater stability of income and food production. We suggest this is due to crops benefiting from warming, up to their optimum temperature thresholds, over the period of our study. An increase in growing degree days (warmth) has previously been found to increase crop yields and yield stability reflecting greater yields from longer maturing varieties (Butler and Huybers, 2015).

Climate thresholds (cardinal temperatures and rainfall requirements/tolerances) and the timing of sensitive stages differ between crops. Our measures of climate variability were not specific, as we wanted to compare the effects of climate across different agricultural products and farm types. Climate indices specific to single crops (e.g. Harkness et al., 2020) may detect stronger responses for individual crop yields. Our analysis considers changes in county level mean temperatures and rainfall, and their variability, however we do not consider the effects of mean temperatures exceeding optimum thresholds, i.e., under future climates, or the effects of short-term extremes for example heatwaves or heavy rainfall events. The period examined in this study between 2005 and 2017 is not long enough to obtain signals from climate change. Interannual climate variability is driven by a range of different factors and modelling future climate variability is complex. Recent research has found interannual variability (σ) in precipitation is generally expected to increase under global warming, which has implications for the occurrence of droughts and flooding (He and Li, 2019), as well as a projected increase in summer temperature variability and heatwaves (Fischer et al., 2012; Fischer and Schär, 2009). Without adaptation the effects of climate variability could have an increasingly large effect on the stability of future food production and farm incomes, and strategies to reduce this instability should be prioritised.

5 Conclusions

Our results highlight the importance of considering both farming practices and climate conditions when examining stability of farm performance at the farm level. While variability in climate can be largely outside of the farmers control our findings indicates that, under current conditions, farm management can have a comparatively large effect on stability which may provide opportunities for farmers, supported by policy makers, to tackle instability in farm performance. Our results suggest greater agricultural diversity and more controlled or precise use of agrochemicals may help improve the stability farm businesses and the sustainability of food production. In a changing climate the effects of climate variability could have an increasingly large effect on the stability of future food production and farm incomes, and therefore strategies to address instability should be prioritised. Future climate impacts and adaptation are also likely to vary between farm types, therefore agricultural policy targeting stability should be flexible enough to be tailored to different types of production.

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References

Barry, P.J., Escalante, C.L., Bard, S.K., 2001. Economic risk and the structural characteristics of farm businesses. Agric. Financ. Rev. 61, 73–86. https://doi.org/10.1108/00214760180001117

Barzman, M., Bàrberi, P., Birch, A.N.E., Boonekamp, P., Dachbrodt-Saaydeh, S., Graf, B., Hommel, B., Jensen, J.E., Kiss, J., Kudsk, P., Lamichhane, J.R., Messéan, A., Moonen, A.C., Ratnadass, A., Ricci, P., Sarah, J.L., Sattin, M., 2015. Eight principles of integrated pest management. Agron. Sustain. Dev. 35, 1199–1215. https://doi.org/10.1007/s13593-015-0327-9

Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: Crop diversification in the Canadian prairies. Clim. Change 67, 119–141. https://doi.org/10.1007/s10584-004-0710-z

Bürkner, P.C., 2018. Advanced Bayesian multilevel modeling with the R package brms. R J. 10, 395–411. https://doi.org/10.32614/rj-2018-017

Bürkner, P.C., 2017. brms: An R package for Bayesian multilevel models using Stan. J. Stat. Softw. 80, 1–28.

Butler, E.E., Huybers, P., 2015. Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase. Environ. Res. Lett. 10. https://doi.org/10.1088/1748-9326/10/3/034009

Ceglar, A., Toreti, A., Lecerf, R., Van der Velde, M., Dentener, F., 2016. Impact of meteorological drivers on regional inter-annual crop yield variability in France. Agric. For. Meteorol. 216, 58–67. https://doi.org/10.1016/j.agrformet.2015.10.004

Chavas, J.P., Cooper, J., Wallander, S., 2019. The impact of input and output decisions on agricultural production risk. J. Agric. Resour. Econ. 44, 513–535. https://doi.org/10.22004/ag.econ.292329

Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184. https://doi.org/10.1016/j.agsy.2020.102913

Defra, 2020. Farm Business Survey [WWW Document]. URL https://www.gov.uk/government/collections/farm-business-survey (accessed 3.20.20).

Degani, E., Leigh, S.G., Barber, H.M., Jones, H.E., Lukac, M., Sutton, P., Potts, S.G., 2019. Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought. Agric. Ecosyst. Environ. 285, 106625. https://doi.org/10.1016/j.agee.2019.106625

Department for Environment Food and Rural Affairs, Department of Agriculture Environment Food and Rural Affairs, Welsh Assembly, The Scottish Government, 2018. Agriculture in the United Kingdom 2017, National Statistics.

Deryng, D., Conway, D., Ramankutty, N., Price, J., Warren, R., 2014. Global crop yield response to extreme heat stress under multiple climate change futures. Environ. Res. Lett. 9. https://doi.org/10.1088/1748-9326/9/3/034011

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., Mcclean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography (Cop.). 36, 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

El Benni, N., Finger, R., Mann, S., 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. Agric. Financ. Rev. 72, 301–324. https://doi.org/10.1108/00021461211277204

Enjolras, G., Capitanio, F., Aubert, M., Adinolfi, F., 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. New Medit 13, 31–40.

FAO, 2021. FAO Food Balance Sheet [WWW Document]. FAOSTAT. URL http://www.fao.org/faostat/en/#data/FBS (accessed 2.26.21).

FAO, 2006. Food Security (No. Issue 2).

Fischer, E.M., Rajczak, J., Schär, C., 2012. Changes in European summer temperature variability revisited. Geophys. Res. Lett. 39, 1–8. https://doi.org/10.1029/2012GL052730

Fischer, E.M., Schär, C., 2009. Future changes in daily summer temperature variability: Driving processes and role for temperature extremes. Clim. Dyn. 33, 917–935. https://doi.org/10.1007/s00382-008-0473-8

Gaudin, A.C.M., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C., Deen, W., 2015. Increasing crop diversity mitigates weather variations and improves yield stability. PLoS One 10, 1–20. https://doi.org/10.1371/journal.pone.0113261

Gelman, A., 2006. Prior distributions for variance parameters in hierarchical models. Bayesian Anal. 1, 515–534.

Gelman, A., Goodrich, B., Gabry, J., Vehtari, A., 2019. R-squared for Bayesian Regression Models. Am. Stat. 73, 307–309. https://doi.org/10.1080/00031305.2018.1549100

Gelman, A., Rubin, D.B., 1992. Inference from Iterative Simulation Using Multiple Sequences. Stat. Sci. 7, 457–472. https://doi.org/10.1214/ss/1177011136

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M.C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., Noble, I., 2013. Sustainable development goals for people and planet. Nature 495, 305–307. https://doi.org/10.1038/495305a

Harkness, C., Areal, F.J., Semenov, M.A., Senapati, N., Shield, I.F., Bishop, J., 2021. Stability of farm income: The role of agricultural diversity and agri-environment scheme payments. Agric. Syst. 187, 103009. https://doi.org/10.1016/j.agsy.2020.103009

Harkness, C., Semenov, M.A., Areal, F., Senapati, N., Trnka, M., Balek, J., Bishop, J., 2020. Adverse weather conditions for UK wheat production under climate change. Agric. For. Meteorol. 282–283, 107862. https://doi.org/10.1016/j.agrformet.2019.107862

He, C., Li, T., 2019. Does global warming amplify interannual climate variability? Clim. Dyn. 52, 2667–2684. https://doi.org/10.1007/s00382-018-4286-0

Hoffman, M.D., Gelman, A., 2014. The no-U-turn sampler: Adaptively setting path lengths in

Hamiltonian Monte Carlo. J. Mach. Learn. Res.

Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I., 2019. HadUK-Grid—A new UK dataset of gridded climate observations. Geosci. Data J. 6, 151–159. https://doi.org/10.1002/gdj3.78

Kendon, M., Marsh, T., Parry, S., 2013. The 2010-2012 drought in England and Wales. Weather 68, 88–95. https://doi.org/10.1002/wea.2101

Kennedy, C.M., Lonsdorf, E., Neel, M.C., Williams, N.M., Ricketts, T.H., Winfree, R., Bommarco, R., Brittain, C., Burley, A.L., Cariveau, D., Carvalheiro, L.G., Chacoff, N.P., Cunningham, S.A., Danforth, B.N., Dudenhöffer, J.H., Elle, E., Gaines, H.R., Garibaldi, L.A., Gratton, C., Holzschuh, A., Isaacs, R., Javorek, S.K., Jha, S., Klein, A.M., Krewenka, K., Mandelik, Y., Mayfield, M.M., Morandin, L., Neame, L.A., Otieno, M., Park, M., Potts, S.G., Rundlöf, M., Saez, A., Steffan-Dewenter, I., Taki, H., Viana, B.F., Westphal, C., Wilson, J.K., Greenleaf, S.S., Kremen, C., 2013. A global quantitative synthesis of local and landscape effects on wild bee pollinators in agroecosystems. Ecol. Lett. 16, 584–599. https://doi.org/10.1111/ele.12082

Kipling, R.P., Bannink, A., Bellocchi, G., Dalgaard, T., Fox, N.J., Hutchings, N.J., Kjeldsen, C., Lacetera, N., Sinabell, F., Topp, C.F.E., van Oijen, M., Virkajärvi, P., Scollan, N.D., 2016. Modeling European ruminant production systems: Facing the challenges of climate change. Agric. Syst. 147, 24–37. https://doi.org/10.1016/j.agsy.2016.05.007

Lawes, R.A., Kingwell, R.S., 2012. A longitudinal examination of business performance indicators for drought-affected farms. Agric. Syst. 106, 94–101. https://doi.org/10.1016/j.agsy.2011.10.006

Lechenet, M., Dessaint, F., Py, G., Makowski, D., Munier-Jolain, N., 2017. Reducing pesticide use while preserving crop productivity and profitability on arable farms. Nat. Plants 3. https://doi.org/10.1038/nplants.2017.8

Lin, B.B., 2011. Resilience in agriculture through crop diversification: Adaptive management for environmental change. Bioscience 61, 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Lin, B.B., Flynn, D.F.B., Bunker, D.E., Uriarte, M., Naeem, S., 2011. The effect of agricultural diversity and crop choice on functional capacity change in grassland conversions. J. Appl. Ecol. 48, 609–618. https://doi.org/10.1111/j.1365-2664.2010.01944.x

Nalborczyk, L., Batailler, C., Loevenbruck, H., Vilain, A., Bürkner, P.C., 2019. An introduction to bayesian multilevel models using brms: A case study of gender effects on vowel variability in standard Indonesian. J. Speech, Lang. Hear. Res. 62, 1225–1242. https://doi.org/10.1044/2018_JSLHR-S-18-0006

Neal, R.M., 2011. MCMC using hamiltonian dynamics, in: Handbook of Markov Chain Monte Carlo. https://doi.org/10.1201/b10905-6

ONS, 2020. Consumer price inflation time series (MM23) [WWW Document]. URL https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bt/mm23 (accessed 3.20.20).

Ottoy, S., Angileri, V., Gibert, C., Paracchini, M.L., Pointereau, P., Terres, J.M., Van

Orshoven, J., Vranken, L., Dicks, L. V., 2018. Impacts of selected Ecological Focus Area options in European farmed landscapes on climate regulation and pollination services: A systematic map protocol. Environ. Evid. 7, 1–10. https://doi.org/10.1186/s13750-018-0122-6

Pacín, F., Oesterheld, M., 2014. In-farm diversity stabilizes return on capital in Argentine agro-ecosystems. Agric. Syst. 124, 51–59. https://doi.org/10.1016/j.agsy.2013.10.008

Popp, J., Peto, K., Nagy, J., 2013. Pesticide productivity and food security. A review. Agron. Sustain. Dev. 33, 243–255. https://doi.org/10.1007/s13593-012-0105-x

Powell, J.P., Reinhard, S., 2015. Measuring the effects of extreme weather events on yields. Weather Clim. Extrem. 12, 69–79. https://doi.org/10.1016/j.wace.2016.02.003

R Core Team, 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Reidsma, P., Ewert, F., Oude Lansink, A., 2007. Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity. Clim. Change 84, 403–422. https://doi.org/10.1007/s10584-007-9242-7

Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: A multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/s10113-008-0059-3

Roberts, T.L., 2008. Improving nutrient use efficiency. Turkish J. Agric. For. 32, 177–182. https://doi.org/10.3906/tar-0801-9

Snijders, T.A.B., Bosker, R.J., 1999. Multilevel Analysis An Introduction to Basic and Advanced Multilevel Modeling. SAGE Publications Ltd, London, UK.

Stan Development Team, 2020. Stan Reference Manual [WWW Document]. URL https://mc-stan.org/

van den Pol-van Dasselaar, A., Hennessy, D., Isselstein, J., 2020. Grazing of dairy cows in europe-an in-depth analysis based on the perception of grassland experts. Sustain. 12. https://doi.org/10.3390/su12031098

Varah, A., Ahodo, K., Coutts, S.R., Hicks, H.L., Comont, D., Crook, L., Hull, R., Neve, P., Childs, D.Z., Freckleton, R.P., Norris, K., 2020. The costs of human-induced evolution in an agricultural system. Nat. Sustain. 3, 63–71. https://doi.org/10.1038/s41893-019-0450-8

Appendix A – Annex (model results tables)

Table A.1 - Multilevel model results examining the effect of farming practices, subsidies and climate on the variability of farm business income, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*"

	Cereals				General Cropping				Mixed			
Parameter	**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**	
σ_{county} (county SD)	**0.05***	0.04	0.00	0.13	**0.15***	0.06	0.03	0.26	**0.09***	0.05	0.01	0.19
σ_{farm} (farm SD)	**0.35***	0.02	0.32	0.38	**0.44***	0.03	0.39	0.49	**0.38***	0.02	0.34	0.424
σ_e (SD of residuals)	**0.34***	0.01	0.33	0.35	**0.33***	0.01	0.32	0.35	**0.35***	0.01	0.34	0.372
α (Intercept)	**5.34***	0.04	5.27	5.42	**5.39***	0.06	5.26	5.51	**4.88***	0.06	4.77	4.99
β (Independent vars):												
Input intensity	**0.09***	0.02	0.06	0.12	**0.12***	0.03	0.07	0.17	**0.19***	0.03	0.14	0.24
Specialisation	**0.05***	0.02	0.02	0.08	**0.12***	0.03	0.06	0.18	0.02	0.03	-0.03	0.07
Area Farmed	**-0.06***	0.02	-0.10	-0.03	-0.03	0.04	-0.10	0.04	**-0.12***	0.03	-0.17	-0.06
Direct payments	**0.04***	0.02	0.01	0.07	-0.04	0.03	-0.09	0.01	-0.03	0.03	-0.09	0.04
Direct payments x year									**0.03***	0.01	0.02	0.04
AES payments	**0.03***	0.02	0.00	0.06	-0.03	0.03	-0.08	0.02	**-0.07***	0.02	-0.11	-0.03
SD temperature	**0.05***	0.01	0.02	0.08	-0.02	0.02	-0.07	0.02	0.01	0.02	-0.03	0.05
SD precipitation	**0.05***	0.01	0.02	0.07	0.02	0.02	-0.02	0.06	**0.07***	0.02	0.03	0.11
Mean temperature	**-0.10***	0.02	-0.14	-0.06	-0.02	0.03	-0.07	0.03	-0.02	0.03	-0.07	0.04
Mean precipitation	**-0.09***	0.02	-0.14	-0.05	-0.02	0.04	-0.09	0.06	**-0.11***	0.03	-0.17	-0.05
Total Income per ha	**0.13***	0.02	0.10	0.16	**0.14***	0.02	0.09	0.18	**0.11***	0.03	0.06	0.16
Year (t)	**-0.02***	0.01	-0.04	-0.01	0.00	0.01	-0.02	0.02	**0.04***	0.01	0.02	0.06
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.187				0.222				0.519			
WAIC	26704.05				12183.29				12435.64			

Table A.2 - Multilevel model results examining the effect of farming practices, subsidies and climate on the variability of calories, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*"

	Cereals				**General Cropping**				**Mixed**			
Parameter	**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**	
σ_{county} (county SD)	**0.08***	0.03	0.03	0.13	**0.08***	0.05	0.01	0.18	**0.13***	0.06	0.01	0.26
σ_{farm} (farm SD)	**0.31***	0.01	0.28	0.34	**0.31***	0.02	0.27	0.36	**0.56***	0.03	0.50	0.62
σ_e (SD of residuals)	**0.33***	0.01	0.32	0.34	**0.34***	0.01	0.33	0.36	**0.40***	0.01	0.38	0.42
α (Intercept)	**14.65***	0.04	14.58	14.72	**14.66***	0.06	14.54	14.76	**13.80***	0.07	13.67	13.94
***β* (Independent vars):**												
Input intensity	0.01	0.02	-0.02	0.04	**-0.04***	0.02	-0.09	0.00	**-0.11***	0.04	-0.19	-0.03
Specialisation	**0.10***	0.02	0.07	0.13	**0.05***	0.02	0.01	0.10	-0.02	0.03	-0.08	0.05
Area Farmed	**-0.04***	0.02	-0.07	-0.01	**-0.05***	0.03	-0.11	0.00	**-0.10***	0.04	-0.17	-0.03
Direct payments	0.00	0.02	-0.03	0.03	-0.02	0.02	-0.06	0.03	0.02	0.04	-0.06	0.09
Direct payments x year									**0.01***	0.01	0.00	0.03
AES payments	**0.03***	0.02	0.00	0.06	-0.03	0.02	-0.08	0.01	**-0.05***	0.03	-0.10	0.00
SD temperature	**0.03***	0.01	0.00	0.05	-0.01	0.02	-0.05	0.04	-0.01	0.02	-0.06	0.03
SD rainfall	0.02	0.01	-0.01	0.04	0.02	0.02	-0.01	0.06	0.02	0.02	-0.02	0.07
Mean temperature	**-0.04***	0.02	-0.08	0.00	-0.04	0.02	-0.08	0.01	0.02	0.04	-0.05	0.10
Mean rainfall	0.03	0.02	-0.01	0.07	-0.04	0.03	-0.11	0.03	**-0.11***	0.04	-0.19	-0.02
Total Calories per ha	**0.17***	0.02	0.13	0.20	**0.28***	0.03	0.22	0.33	**0.47***	0.04	0.39	0.55
Year (t)	**0.02***	0.01	0.01	0.03	0.01	0.01	-0.01	0.03	**0.05***	0.01	0.03	0.07
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.196				0.227				0.379			
WAIC	71403.22				31578.63				33092.48			

Supplementary materials

Towards stability of food production and farm income in a variable climate

1 Calculating total food production

The Farm Business Survey (Department for Environment Food and Rural Affairs, 2020a) records food produced annually at each farm in the relevant units for each food group i.e. tonnes (crops), hectolitres (milk), dozen (eggs) and number (livestock). To enable comparison of total food produced at each farm, and its variability, we calculate the number of calories (kcal) produced available for direct human consumption. To calculate calories we use the FAO Food Balance Sheet (FAO, 2021a) which provides country level production, imports, exports and stock variations for 98 food commodities for human consumption and derives calories/energy (kcal), fat and protein per capita. The FAO food balance sheet has been used in previous studies examining food supplies and the resulting adequacy to meet energy requirements (e.g. Macdiarmid et al., 2018). Calories, fat and protein per 100g for each commodity is derived in the food balance sheet data, which are termed “nutritive factors”. These nutritive factors are calculated in terms of their primary equivalents, which represent the weight of the original commodity, e.g., farm, carcass or fresh catch weight (Smith et al., 2016). We use the Food Balance Sheet nutritive factors to calculate the total calories produced at each farm, by converting the units of food produced in the Farm Business Survey e.g. tonnes of wheat, into calories. Please see supplementary table 1 for the calculation of kcal per unit of production in the Farm Business Survey, derived from the kcal/100g from the FAO food balance sheet.

We exclude food products which are not available for direct human consumption (i.e. animal feed and seeds), as well as, rearing or breeding animals which are not primarily sold for slaughter. As this study focuses on the stability (or inversely variability) of food production, using a consistent measure of food production over the period (2005-2017) allows us to examine how much total food production has varied over the period in main food products listed in supplementary table 1.

Within the Farm Business Survey, livestock production, or more specifically meat, is recorded using the number of animals sold. To calculate calories of meat produced at each farm we converted the quantity of livestock sold into weight (grams), and ultimately calories, using the average UK dressed carcass weights and liveweights per bird between 2005 and 2017 (Department for Environment Food and Rural Affairs, 2020b). Supplementary table 1 provides the weight used for each livestock category in the Farm Business Survey. Using average weights in the calculation of calories from meat in livestock production limits our ability to examine variability in the weight of livestock sold for slaughter, and therefore calories, on a temporal basis, i.e., livestock may have been affected by climate stresses or disease in a particular year. However, to enable analysis of food production at the farm level, using a common unit of production, it was necessary to make these assumptions. We limit our analysis to cereals, general cropping and mixed farms therefore livestock production was not the sole or key focus of our study. Milk production is provided in hectolitres in the Farm Business Survey, so volumes produced and therefore calories could be easily calculated.

Farm Business Survey data		FAO Food balance sheet [a]				
FBS product	Unit	FAO commodity	Kcal/100 grams	Average carcass weight/ liveweight (grams) [b]	Kcal per unit in FBS	Comments
Winter wheat	tonnes	WHEAT	334		3,340,000	
Spring wheat	tonnes	WHEAT	334		3,340,000	
Mixed wheat	tonnes	WHEAT	334		3,340,000	
Durum wheat	tonnes	WHEAT	334		3,340,000	
Triticale	tonnes	TRITICALE	327		3,270,000	
Winter barley	tonnes	BARLEY	332		3,320,000	
Spring barley	tonnes	BARLEY	332		3,320,000	
Mixed barley	tonnes	BARLEY	332		3,320,000	
Winter oats	tonnes	OATS	385		3,850,000	
Spring oats	tonnes	OATS	385		3,850,000	
Mixed oats	tonnes	OATS	385		3,850,000	
Rye	tonnes	RYE	319		3,190,000	
Mixed cereals	tonnes	*Cereals average*	339		3,394,000	Used average of cereal crops: Wheat, triticale, barley, oats, rye.
Grain maize	tonnes	MAIZE	356		3,560,000	
Beans for stockfeed	tonnes				-	Excluded: crop not for human food consumption
Peas for stockfeed	tonnes				-	Excluded: crop not for human food consumption
Peas harvested dry for human consumption	tonnes	PEAS DRY	346		3,460,000	
Lupins	tonnes	LUPINS	390		3,900,000	
Soya beans	tonnes	SOYBEANS	335		3,350,000	
Other protein crops	tonnes	*Legumes average*	354		3,535,000	Used average of legume crops in FAO: Peas, lupins, soybeans, beans
Spring beans	tonnes	BROAD BEANS DRY	343		3,430,000	
Winter beans	tonnes	BROAD BEANS DRY	343		3,430,000	
Potatoes - first early (i.e. wholly or mainly harvested by 31st. July)	tonnes	POTATOES	67		670,000	
Processing potatoes	tonnes	POTATOES	67		670,000	
Ware potatoes	tonnes	POTATOES	67		670,000	

Seed potatoes	tonnes				-	Excluded: crop not for human food consumption
Sugar beet (1)	tonnes	SUGAR BEETS	70		700,000	
Flax (1)	tonnes	LINSEED	498		4,980,000	
Linseed	tonnes	LINSEED	498		4,980,000	
Winter oilseed rape - not double low varieties	tonnes	RAPESEED	494		4,940,000	
Spring oilseed rape - not double low varieties	tonnes	RAPESEED	494		4,940,000	
Winter oilseed rape - double low varieties	tonnes	RAPESEED	494		4,940,000	
Spring oilseed rape - double low varieties	tonnes	RAPESEED	494		4,940,000	
Other oilseed rape - double low varieties	tonnes	RAPESEED	494		4,940,000	
Other herbaceous oilseed crops (e.g. poppy seed, sunflower)	tonnes	*Other oilseed average*	421		4,205,000	Used average of other oilseed crops: poppy seed and sunflower
Hemp	tonnes				-	Excluded: crop not for human food consumption
Hops (1)	tonnes				-	Excluded: crop not included in FAO balance sheet (N.B. only 4 farms in FBS which produce hops between 2005-2017)
Medicinal plants, aromatics and spices (mustard, caraway, canary seed, saffron, borage, evening primrose etc.)	tonnes	MUSTARD SEED	469		4,690,000	Used mustard seed as a proxy. (No other food crops available in FAO balance sheet)
Herbage seed (grass and clover)	tonnes				-	Excluded: crop not for human food consumption
Other arable crops (2)	tonnes	*Arable crops average*	327		3,265,000	Used average of all the above arable crops
Vegetable seeds, seedlings and young plants for sale	tonnes				-	Excluded: crop not for human food consumption
Cabbage - summer and autumn	tonnes	CABBAGES	19		190,000	
Cabbage - winter and winter storage	tonnes	CABBAGES	19		190,000	
Brussels sprouts - fresh market	tonnes	CABBAGES	19		190,000	Brussels sprouts not included in FAO balance sheet therefore used cabbages as a proxy

Brussels sprouts - processing	tonnes	CABBAGES	19		190,000	Brussels sprouts not included in FAO balance sheet therefore used cabbages as a proxy
Cauliflower	tonnes	CAULIFLOWER	9		90,000	
Winter hardy cauliflowers (broccoli)	tonnes	CAULIFLOWER	9		90,000	
Beetroot	tonnes	ROOTS AND TUBERS DRY	282		2,820,000	
Carrots - fresh market	tonnes	CARROTS	38		380,000	
Carrots - processing	tonnes	CARROTS	38		380,000	
Parsnips	tonnes	ROOTS AND TUBERS DRY	282		2,820,000	Brussels sprouts not included in FAO balance sheet therefore used roots and tubers as a proxy
Parsley	tonnes				-	Excluded: crop not included in FAO balance sheet (N.B. only 5 farms in FBS which produce parsley between 2005-2017)
Leeks	tonnes	LEEKS AND OTHER ALLIACEOUS	37		370,000	
Onions - bulb	tonnes	ONIONS DRY	31		310,000	
Onions - salad or bunch	tonnes	ONIONS GREEN	24		240,000	
Lettuce - crisp / iceberg	tonnes	LETTUCE	12		120,000	
Spinach	tonnes	SPINACH	16		160,000	
Green peas - market	tonnes	PEAS GREEN	31		310,000	
Green peas - processing	tonnes	PEAS GREEN	31		310,000	
Broad beans - market	tonnes	BROAD BEANS DRY	343		3,430,000	
Broad beans - processing	tonnes	BROAD BEANS DRY	343		3,430,000	
Runner and french beans - market	tonnes	STRING BEANS	27		270,000	
Runner and french beans - processing	tonnes	STRING BEANS	27		270,000	
Asparagus	tonnes	ASPARAGUS	12		120,000	
Marrows and courgettes	tonnes	PUMPKINS SQUASH GROUDS	19		190,000	
Turnips and swedes, mainly for human consumption	tonnes	ROOTS AND TUBERS DRY	282		2,820,000	
Other / mixed fresh vegetables (celeriac, globe and Jerusalem artichokes, chicory)	tonnes	VEGETABLES FRESH NES	22		220,000	

Calabrese	tonnes	CABBAGES	19		190,000	Calabrese not included in FAO balance sheet therefore cabbages used as a proxy
Strawberries - fresh market	tonnes	STRAWBERRIES	28		280,000	
Sweetcorn	tonnes	SWEET CORN PREPARED	77		770,000	
Christmas trees	tonnes				-	Excluded: crop not for human food consumption
Flower bulbs and tubers	tonnes				-	Excluded: crop not for human food consumption
Flower seeds, cuttings etc.	tonnes				-	Excluded: crop not for human food consumption
All other and mixed cut flowers	tonnes				-	Excluded: crop not for human food consumption
Apples - culinary	tonnes	APPLES	48		480,000	
Apples - dessert less than 1,200 trees per hectare	tonnes	APPLES	48		480,000	
Apples - dessert over 1,200 trees per hectare	tonnes	APPLES	48		480,000	
Apples - mixed dessert	tonnes	APPLES	48		480,000	
Apples - cider	tonnes	APPLES	48		480,000	
Pears - less than 1,200 trees per hectare	tonnes	PEARS	54		540,000	
Pears - over 1,200 trees per hectare	tonnes	PEARS	54		540,000	
Perry pears	tonnes	PEARS	54		540,000	
Cherries	tonnes	CHERRIES	65		650,000	
Plums - Victorias	tonnes	PLUMS	52		520,000	
Other / mixed top fruit including peaches and apricots	tonnes	*peaches and apricot average*	39		390,000	Used average of peaches and apricots
Red and white currants	tonnes	CURRANTS	59		590,000	
Blackcurrants - fresh - market and processing	tonnes	CURRANTS	59		590,000	
Raspberries	tonnes	RASPBERRIES	47		470,000	
Gooseberries	tonnes	GOOSEBERRIES	44		440,000	
Other / mixed soft fruit including blackberries	tonnes	BERRIES NES	49		490,000	
Mixed top and soft fruit	tonnes	FRUIT NES	45		450,000	

Vineyard selling wine grapes	tonnes	GRAPES	53		530,000	
Miscanthus	tonnes				-	Excluded: crop not for human food consumption
Short rotation coppice	tonnes				-	Excluded: crop not for human food consumption
Whole milk	hectolitre (100 litres)	COW MILK	61		63,013	
Milk Products (cheese, cream, butter etc.)	hectolitre (100 litres)	*Milk products average*	433		34,463	Used average of milk products: cheese, butter, cream
Breeding bulls for use with the dairy herd (one year and over)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Dairy cows	Quantity (no.)	BEEF VEAL	225	3,112	700,120	
Dairy calves	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Breeding bulls for use with the beef herd (one year and over)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Beef cows - LFA	Quantity (no.)	BEEF VEAL	225	3,630	816,689	
Beef cows - Lowland	Quantity (no.)	BEEF VEAL	225	3,630	816,689	
Heifers in calf (rearing) - Dairy	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Heifers in calf (rearing) - Beef	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Fat cattle excluding veal calves	Quantity (no.)	BEEF VEAL	225	3,112	700,120	
Other cattle 2 yrs and over - Male (excluding bulls)	Quantity (no.)	BEEF VEAL	225	3,630	816,689	
Other cattle 2 yrs and over - Female (excluding bulls)	Quantity (no.)	BEEF VEAL	225	3,112	700,120	
Other cattle 1 to 2 years - Male (including bull beef)	Quantity (no.)	BEEF VEAL	225	3,398	764,661	
Other cattle 1 to 2 years - Female	Quantity (no.)	BEEF VEAL	225	3,183	716,100	
Other cattle under 1 year - For slaughter as calves	Quantity (no.)	BEEF VEAL	225	423	95,231	
Other cattle under 1 year - Other cattle and bull calves	Quantity (no.)	BEEF VEAL	225	423	95,231	

Rams and ram hoggs (6 months and over)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Ewes and shearlings (one year and older) - LFA	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Ewes and shearlings (one year and older) - Lowland	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Ewe hoggs (6 months and less than 1 year to be used for breeding)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Fat lambs and hoggets under 1 year	Quantity (no.)	LAMB MEAT	119	191	22,747	
Store lambs under 1 year	Quantity (no.)	LAMB MEAT	119	191	22,747	
Other sheep 1 year and over	Quantity (no.)	MUTTON LAMB	263	191	50,272	
Boars (includes boars sent for slaughter)	Quantity (no.)	PORK	220	1,485	326,765	
Breeding sows (including gilts which have farrowed)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Sows for slaughter	Quantity (no.)	PORK	220	1,485	326,765	
Gilts in pig	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Maiden gilts	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Fat pigs / finished pigs	Quantity (no.)	PORK	220	787	173,074	
Store pigs 20 kgs and over (All pigs being reared for the breeding herd)	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Piglets / weaners (under 20 kgs)	Quantity (no.)	PORK	220	787	173,074	
Eggs production	dozen	HEN EGGS	139	65*	1,084	
Hens and pullets in lay, cocks and cull hens	Quantity (no.)	CHICKEN MEAT	122	21	2,622	
Pullets one week to point of lay	Quantity (no.)			-	-	Excluded, animal used for breeding or rearing, not primarily sold for slaughter.
Broilers	Quantity (no.)	CHICKEN MEAT	122	22	2,692	

Other table chickens	Quantity (no.)	CHICKEN MEAT	122	21	2,622	
Turkeys	Quantity (no.)	TURKEY MEAT	126	126	15,938	
Ducks, geese and other poultry	Quantity (no.)	MEAT POULTRY	185	35**	6,383	

[a] Calories data obtained from FAO "nutritive factors" used in the Food Balance Sheets (FAO, 2001)

[b] Average UK dressed carcass weights and liveweights per bird between 2005 and 2017 (Department for Environment Food and Rural Affairs, 2020b).

*An average egg weight of 65g has been used which represents a medium egg size.

**Duck and geese liveweights are taken from the FAO technical conversion factors used in the Food Balance Sheets (FAO, 2021b)

Supplementary Table 1 - Conversion table to calculate calories for each food product in the Farm Business Survey

2 Calculation of independent variables (farming practices, subsidies and climate)

We use the same methods from Harkness et al. (2021) to calculate the farming practices and value of subsidies for each farm: farm size, input intensity (cost of chemical inputs per hectare), agricultural diversification (degree of specialisation in different crop and livestock products), as well as the value of direct (area-based) payments and agri-environment scheme payments per hectare. The calculations of each variable are provided in supplementary table 2. The calculation of climate variables (variability and averages) are described in the main text and detailed in supplementary table 2.

Supplementary Table 2 - Definition and calculations of farming practices, EU subsidy payments and climate variables analysed in the study

Independent variable	**Calculation**
Farming practices and subsidies [a]	
Farm size	Area farmed (hectares) = The utilised agricultural area, plus land let in or minus land rented out
Intensity of inputs	The total cost of fertiliser, crop protection and concentrated animal feed (£), per hectare (area farmed) (IRENA indicator 15; European Environment Agency, 2005; Gerrard et al., 2012)
Agricultural specialisation (inverse of diversification)	$Herfindahl\ index\ (S) = \sum_{i=1}^{n} (p_i)^2$ Where *n* is the total number of farming activities, p_i is the proportion of revenue earned from the *i*-th farming activity (revenue from farming activity divided by the total farming revenue). Can also be written as sum of revenue for each farming activity squared, divided by total revenue for agriculture squared: (Wheat^2+ barley^2 + other cereals^2 + oilseed rape^2 + peas and beans^2 + potatoes^2 + sugar beet^2 + horticulture^2 + other crops^2 + by-products and forage^2 + milk^2 + cattle^2 + sheep^2 + pigs^2 + eggs^2 + chickens and other poultry^2 + other livestock^2 + other agriculture^2) /total agricultural gross revenue^2
Direct payments per hectare	Total direct payments (£) (Primarily the single payment scheme or basic payment scheme), per hectare (area farmed)
Agri-environment payments per hectare	Total payments under rural development policy (£; pillar 2), per hectare (area farmed)
Climate variables [b]	

Mean temperature (°C)	Mean temperature (°C) for first half of year (Jan to June)
SD of mean temperature (°C)	SD of mean temperature (°C) for first half of year (Jan to June)
Mean monthly precipitation (mm)	Mean monthly rainfall for first half of year (mm) (Jan to June)
SD of mean monthly precipitation (mm)	SD of mean monthly rainfall (mm) for first half of year (mm) (Jan to June)

[a] Farming practices and subsidies are averaged over the same rolling five-year time period used to derive the dependent variables

[b] Climate variables (standard deviation (SD) and mean temperature and monthly rainfall) are calculated over the same rolling five-year period.

3 Multilevel model using frequentist methods

Using the same models outlined in the main text we estimate the multilevel models for the 3 farm types using frequentist methods. We fit the models using the *nlme* R package, and fit a continuous first order autoregressive process using the corCAR1 function to account for temporal autocorrelation in the farm specific error term, and which allows for an irregularly sampled dataset (Pinheiro et al., 2019).

The results from the frequentist models are shown in supplementary tables 3 and 4. These models show relationships which are consistent with the Bayesian results shown in the main text; The direction of each coefficient is consistent with the posterior distributions and the size of the relative effects are similar. The significance of the coefficients vary in a few instances, where one bound of the Bayesian credible intervals shown in the main text were also close to zero.

Supplementary Table 3 - Multilevel model results using (log) standard deviation of farm business income per hectare as dependent variable. Showing the effect of farming practices, subsidies and climate on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Cereals		General cropping		Mixed	
Random effects						
County SD	0.04		0.12		0.01	
Farm SD	0.00		0.00		0.00	
Level-1 residual	0.48		0.55		0.50	
Fixed effects (Standard Error)						
Intercept	5.282***	(0.04)	5.392***	(0.06)	4.925***	(0.06)
Input intensity	0.09***	(0.02)	0.11***	(0.03)	0.19***	(0.03)
Specialisation	0.03**	(0.02)	0.10***	(0.03)	0.02	(0.03)
Area Farmed	-0.06***	(0.02)	-0.02	(0.03)	-0.12***	(0.02)
Direct payments	0.05***	(0.02)	-0.03	(0.03)	0.00	(0.04)
Direct payments x year		(0.02)			0.02***	(0.01)
AES payments	0.02	(0.02)	-0.05*	(0.03)	-0.05***	(0.02)
SD temperature	0.02*	(0.01)	-0.03	(0.02)	0.01	(0.02)
SD precipitation	0.07***	(0.01)	0.03*	(0.02)	0.06***	(0.02)
Mean temperature	-0.06***	(0.02)	-0.02	(0.02)	0.00	(0.03)
Mean precipitation	-0.11***	(0.02)	0.00	(0.03)	-0.11***	(0.03)
Total Income per ha	0.14***	(0.02)	0.15***	(0.03)	0.13***	(0.02)
Year (t)	-0.01**	(0.01)	0.00	(0.01)	0.03***	(0.01)
Observations (n)	2357		1044		1128	
County (n)	56		38		57	
Farm (n)	512		261		318	
AIC	1798		857		1209	
BIC	1891		936		1295	
logLik	-883		-413		-588	
R^2	0.195		0.190		0.345	

Supplementary Table 4 - Multilevel model results using (log) standard deviation of calories per hectare as dependent variable. Showing the effect of farming practices, subsidies and climate on the variability of farm income. Significant at: *10, **5 and ***1 percent levels.

	Cereals		**General cropping**		**Mixed**	
Random effects						
County SD	0.08		0.09		0.14	
Farm SD	0.00		0.00		0.00	
Level-1 residual	0.45		0.46		0.68	
Fixed effects (Standard Error)						
Intercept	14.667***	(0.04)	14.696***	(0.06)	13.897***	(0.08)
Input intensity	0.01	(0.02)	-0.03	(0.02)	-0.12***	(0.04)
Specialisation	0.09***	(0.02)	0.07***	(0.02)	-0.02	(0.04)
Area Farmed	-0.04***	(0.02)	-0.06**	(0.03)	-0.11***	(0.04)
Direct payments	0.01	(0.02)	-0.01	(0.03)	-0.01	(0.05)
Direct payments x year					0.02*	(0.01)
AES payments	0.01	(0.02)	-0.02	(0.02)	-0.03	(0.03)
SD temperature	0.02*	(0.01)	0.00	(0.02)	-0.01	(0.02)
SD precipitation	0.01	(0.01)	0.03	(0.02)	0.01	(0.02)
Mean temperature	-0.02	(0.02)	-0.03	(0.02)	0.02	(0.03)
Mean precipitation	0.03	(0.02)	-0.04	(0.03)	-0.11***	(0.04)
Total Calories per ha	0.15***	(0.02)	0.26***	(0.03)	0.49***	(0.04)
Year (t)	0.02**	(0.01)	0.00	(0.01)	0.03***	(0.01)
Observations (n)	2357		1044		1128	
County (n)	56		38		57	
Farm (n)	512		261		318	
AIC	1585		864		1467	
BIC	1677		943		1552	
logLik	-777		-416		-716	
R^2	0.151		0.242		0.342	

4 Sensitivity analysis of climate variables included in the multilevel models

The models estimated in the main text examine the effect of climate variability on the stability of food production and farm income using average temperatures and monthly precipitation for the main part of the growing season (January to June.) Here we consider how including all months of the agricultural season may affect these results. As we focus our study on cereal, general cropping and mixed farms the agricultural season for each harvest year is considered to start on the 1st October and finish on 30th September the following year.

Using the Bayesian methods outlined in the main text we estimate the same multilevel models, except here climate variables are calculated using the mean temperature and mean monthly rainfall between 1st October and 30th September, as well as standard deviations over a five-year period. The results of these models are shown in the supplementary tables 5 and 6. These models show the same relationships identified in the main text. There is very little change in the posterior distributions of each farming practice; the relative effects on the stability of income and food production is very similar and the importance of each variable remains consistent. The relationships between climate variability (and averages) and farm stability are also the same; The direction of each climate variable remains consistent, while there are some small changes in the relative effect size. For general cropping farms the standard deviation of temperature is found to be an important factor increasing the variability of calories when using temperatures across the season, as shown in supplementary table 6. In summary, this sensitivity shows that, in our models, using data for the entire agricultural season to calculate temperature and rainfall variability, and averages over 5-year periods, leads to very little change compared to using climate conditions between January and June only.

	Cereals				General Cropping				Mixed			
Parameter	**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**	
σ_{county} (county SD)	**0.08***	0.04	0.01	0.17	**0.15***	0.06	0.05	0.27	**0.10***	0.05	0.01	0.20
σ_{farm} (farm SD)	**0.35***	0.02	0.32	0.38	**0.44***	0.03	0.39	0.49	**0.38***	0.02	0.34	0.43
σ_e (SD of residuals)	**0.34***	0.01	0.33	0.35	**0.33***	0.01	0.32	0.35	**0.36***	0.01	0.34	0.37
α (Intercept)	**5.25***	0.04	5.18	5.33	**5.42***	0.06	5.30	5.54	**4.86***	0.05	4.76	4.97
β (Independent vars):												
Input intensity	**0.09***	0.02	0.05	0.12	**0.12***	0.03	0.07	0.17	**0.19***	0.03	0.14	0.24
Specialisation	**0.05***	0.02	0.02	0.09	**0.12***	0.03	0.07	0.18	0.02	0.03	-0.03	0.07
Area Farmed	**-0.06***	0.02	-0.09	-0.03	-0.03	0.04	-0.10	0.04	**-0.12***	0.03	-0.17	-0.07
Direct payments	**0.03***	0.02	0.00	0.07	-0.04	0.03	-0.09	0.01	-0.03	0.03	-0.09	0.04
Direct payments x year									**0.03***	0.01	0.02	0.04
AES payments	0.03	0.02	-0.01	0.06	-0.03	0.03	-0.08	0.02	**-0.07***	0.02	-0.11	-0.03
SD temperature (Oct-Sep)	**0.02***	0.01	0.00	0.05	-0.01	0.02	-0.04	0.03	0.01	0.02	-0.03	0.04
SD precipitation (Oct-Sep)	**0.06***	0.01	0.04	0.08	-0.03	0.02	-0.07	0.01	**0.04***	0.02	0.01	0.08
Mean temperature (Oct-Sep)	**-0.16***	0.03	-0.22	-0.12	-0.02	0.03	-0.09	0.04	-0.04	0.03	-0.10	0.02
Mean precipitation (Oct-Sep)	**-0.11***	0.02	-0.16	-0.07	0.04	0.04	-0.04	0.13	**-0.11***	0.04	-0.18	-0.04
Total Income per ha	**0.12***	0.02	0.09	0.15	**0.13***	0.03	0.09	0.18	**0.11***	0.03	0.06	0.16
Year (t)	-0.01	0.01	-0.02	0.01	-0.01	0.01	-0.02	0.01	**0.04***	0.01	0.03	0.06
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.201				0.223				0.517			
WAIC	26680.55				12180.80				12444.28			

Supplementary Table 5 - Multilevel model results examining the effect of farming practices, subsidies and climate for the agricultural season (Oct-Sep) on the variability of farm business income, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*".

	Cereals				General Cropping				Mixed			
Parameter	**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**		**Posterior mean**	**SD**	**95% CI**	
σ_{county} (county SD)	**0.08***	0.03	0.02	0.13	**0.09***	0.05	0.01	0.18	**0.12***	0.06	0.01	0.24
σ_{farm} (farm SD)	**0.31***	0.01	0.28	0.34	**0.31***	0.02	0.27	0.36	**0.55***	0.03	0.50	0.62
σ_e (SD of residuals)	**0.33***	0.01	0.32	0.34	**0.34***	0.01	0.32	0.36	**0.40***	0.01	0.38	0.42
α (Intercept)	**14.66***	0.03	14.59	14.72	**14.71***	0.05	14.61	14.81	13.86	0.07	13.73	13.98
***β* (Independent vars):**												
Input intensity	0.01	0.02	-0.02	0.04	-0.03	0.02	-0.08	0.01	**-0.10***	0.04	-0.18	-0.02
Specialisation	**0.10***	0.02	0.07	0.13	**0.05***	0.02	0.01	0.10	-0.01	0.03	-0.08	0.06
Area Farmed	**-0.04***	0.02	-0.07	-0.01	**-0.05***	0.03	-0.11	0.00	**-0.09***	0.04	-0.16	-0.02
Direct payments	0.01	0.02	-0.02	0.04	-0.01	0.02	-0.06	0.04	0.02	0.04	-0.06	0.10
Direct payments x year									**0.02***	0.01	0.00	0.03
AES payments	0.03	0.02	-0.01	0.06	-0.04	0.02	-0.08	0.01	**-0.05***	0.03	-0.11	0.00
SD temperature (Oct-Sep)	**0.05***	0.01	0.02	0.07	**0.04***	0.02	0.01	0.08	0.03	0.02	-0.02	0.07
SD precipitation (Oct-Sep)	-0.01	0.01	-0.03	0.02	-0.01	0.02	-0.04	0.03	0.02	0.02	-0.02	0.06
Mean temperature (Oct-Sep)	**-0.06***	0.02	-0.10	-0.03	-0.04	0.03	-0.09	0.01	0.01	0.04	-0.07	0.09
Mean precipitation (Oct-Sep)	0.00	0.02	-0.04	0.05	-0.05	0.03	-0.11	0.02	**-0.15***	0.05	-0.24	-0.06
Total Income per ha	**0.16***	0.02	0.12	0.20	**0.27***	0.03	0.21	0.32	**0.45***	0.04	0.37	0.54
Year (t)	**0.02***	0.01	0.01	0.03	0.00	0.01	-0.02	0.01	**0.04***	0.01	0.02	0.06
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.202				0.231				0.376			
WAIC	71398.09				31573.80				33086.68			

Supplementary Table 6 - Multilevel model results examining the effect of farming practices, subsidies and climate for the agricultural season (Oct-Sep) on the variability of calories, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*".

References

Department for Environment Food and Rural Affairs, 2020a. Farm Business Survey [WWW Document]. URL https://www.gov.uk/government/collections/farm-business-survey (accessed 3.20.20).

Department for Environment Food and Rural Affairs, 2020b. Latest cattle, sheep and pig slaughter statistics [WWW Document]. Natl. Stat. URL https://www.gov.uk/government/statistics/cattle-sheep-and-pig-slaughter (accessed 10.21.20).

European Environment Agency, 2005. Agriculture and environment in EU-15 — the IRENA indicator report. Copenhagen, Denmark.

FAO, 2021a. FAO Food Balance Sheet [WWW Document]. FAOSTAT. URL http://www.fao.org/faostat/en/#data/FBS (accessed 2.26.21).

FAO, 2021b. Technical Conversion Factors for Agricultural Commodities. 1–782.

FAO, 2001. Food balance sheets A handbook, World Health Organization Regional Publications - European Series. Rome.

Gerrard, C.L., Padel, S., Moakes, S., 2012. The use of Farm Business Survey data to compare the environmental performance of organic and conventional farms. Int. J. Agric. Manag. 2, 5–16. https://doi.org/10.5836/ijam/2013-01-02

Macdiarmid, J.I., Clark, H., Whybrow, S., de Ruiter, H., McNeill, G., 2018. Assessing national nutrition security: The UK reliance on imports to meet population energy and nutrient recommendations. PLoS One 13, 1–16. https://doi.org/10.1371/journal.pone.0192649

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team, 2019. nlme: Linear and Nonlinear Mixed Effects Models.

Smith, M.R., Micha, R., Golden, C.D., Mozaffarian, D., Myers, S.S., 2016. Global Expanded Nutrient Supply (GENuS) Model: A New Method for Estimating the Global Dietary Supply of Nutrients. PLoS One 11, e0146976. https://doi.org/10.1371/journal.pone.0146976

Appendix C – Exploratory multilevel models (tried and tested as part of Chapter 5)

As discussed in chapter 2 other climate variables and model specifications were considered when developing the methods used in chapter 5. The correlation matrix (Table C.1) and models shown below (in tables C.2 and C.3) were produced when developing the methodology for Chapter 5. The variables or subsequent results from these models, were either not considered robust or appropriate to answer the research questions being examined.

Table C.1 - Pearson's correlation coefficient (r) of other climate variables considered for the analysis.

Correlations between seasonal climate variables considered in the analysis (mean and standard deviation (SD) of the climatic water balance (CWB), growing degree days (GDD), killing degree days (KDD).

	Autumn CWB mean	Spring CWB mean	Summer CWB mean	Winter CWB mean	GDD mean	KDD mean	Autumn CWB SD	Spring CWB SD	Summer CWB SD	Winter CWB SD	GDD SD	KDD SD
Autumn.CWB.mean	1.000											
Spring.CWB.mean	0.907	1.000										
Summer.CWB.mean	0.913	0.836	1.000									
Winter.CWB.mean	0.903	0.882	0.776	1.000								
GDD.mean	-0.401	-0.435	-0.438	-0.341	1.000							
KDD.mean	-0.370	-0.354	-0.460	-0.309	0.278	1.000						
Autumn.CWB.sd	0.585	0.538	0.577	0.478	-0.238	-0.379	1.000					
Spring.CWB.sd	0.137	-0.017	0.134	0.054	0.037	-0.118	0.250	1.000				
Summer.CWB.sd	0.634	0.619	0.619	0.574	-0.227	-0.432	0.454	0.310	1.000			
Winter.CWB.sd	0.707	0.717	0.500	0.856	-0.194	-0.177	0.421	0.128	0.494	1.000		
GDD.sd	-0.066	-0.086	-0.281	0.118	-0.009	0.114	-0.095	-0.158	-0.191	0.218	1.000	
KDD.sd	-0.382	-0.359	-0.471	-0.315	0.266	0.969	-0.388	-0.137	-0.461	-0.177	0.145	1.000

Table C.2 – Multilevel model results examining how farming practices and subsidies affect the stability of farm income and moderate the effects of climate variability (with interaction terms)

Linear mixed-effects model fit by REML in lme
Autocorrelation corrected using corCAR1

	Cereals		General cropping		Mixed	
County SD	0.054		0.121		0.100	
Farm SD	0.000		0.000		0.000	
Level-1 residual	0.482		0.547		0.518	
Fixed effects (Standard errors in brackets)	**Cereals**		**General cropping**		**Mixed**	
(Intercept)	5.274 ***	(0.040)	5.429 ***	(0.065)	4.956 ***	(0.059)
Area Farmed	-0.064 ***	(0.016)	-0.016	(0.034)	-0.140 ***	(0.026)
Total Income per ha	0.166 ***	(0.016)	0.133 ***	(0.026)	0.145 ***	(0.026)
Year (t)	-0.012 *	(0.007)	-0.005	(0.010)	0.020 **	(0.010)
Climate						
Variability in CWB - Winter	0.048 ***	(0.016)	0.020	(0.023)	0.020	(0.023)
Variability in CWB - Summer	0.017 *	(0.009)	0.018	(0.014)	0.023	(0.014)
Variability in GDD - Season	-0.017 *	(0.009)	-0.003	(0.012)	-0.022	(0.016)
Variability in KDD - Summer	0.001	(0.011)	0.009	(0.018)	0.014	(0.016)
Farming practices						
Input intensity	0.092 ***	(0.017)	0.123 ***	(0.029)	0.205 ***	(0.029)
Specialisation	0.045 ***	(0.017)	0.106 ***	(0.031)	0.023	(0.026)
AES payments	0.015	(0.017)	-0.056 **	(0.028)	-0.029	(0.022)
Interactions						
Input intensity x Variability in CWB - Winter	0.005	(0.014)	-0.018	(0.022)	-0.007	(0.023)
Input intensity x Variability in CWB - Summer	-0.004	(0.009)	-0.021 *	(0.011)	-0.036 ***	(0.011)
Input intensity x Variability in GDD	-0.007	(0.010)	0.010	(0.015)	-0.006	(0.016)
Input intensity x Variability in KDD	0.006	(0.013)	-0.002	(0.030)	-0.030 *	(0.018)
Specialisation x Variability in CWB - Winter	0.005	(0.015)	-0.001	(0.017)	0.016	(0.022)
Specialisation x Variability in CWB - Summer	-0.006	(0.009)	-0.004	(0.010)	0.019	(0.013)
Specialisation x Variability in GDD	0.012	(0.009)	0.024 *	(0.013)	-0.007	(0.016)
Specialisation x Variability in KDD	0.017 *	(0.009)	-0.025	(0.016)	0.004	(0.018)
AES payments x Variability in CWB - Winter	-0.007	(0.013)	-0.013	(0.018)	-0.009	(0.019)
AES payments x Variability in CWB - Summer	-0.019 **	(0.010)	-0.015	(0.016)	-0.008	(0.013)
AES payments x Variability in GDD	0.000	(0.010)	-0.001	(0.013)	0.016	(0.015)
AES payments x Variability in KDD	0.000	(0.010)	-0.010	(0.013)	-0.012	(0.017)
Observations (n)	2357		1047		1128	
County (n)	56		38		57	
Farm (n)	512		262		318	
AIC	1931		941		1320	
BIC	2086		1075		1455	
logLik	-939		-444		-633	

Table C.2 – Multilevel model results examining how farming practices and subsidies affect the stability of food production and moderate the effects of climate variability (with interaction terms)

Linear mixed-effects model fit by REML in lme
Autocorrelation corrected using corCAR1

	Cereals		General cropping		Mixed	
County SD	0.101		0.093		0.181	
Farm SD	0.000		0.000		0.000	
Level-1 residual	0.446		0.463		0.684	
Fixed effects (Standard errors in brackets)	**Cereals**		**General cropping**		**Mixed**	
(Intercept)	14.621 ***	(0.040)	14.657 ***	(0.058)	13.934 ***	0.074
Area Farmed	-0.047 ***	(0.016)	-0.062 **	(0.027)	-0.129 ***	0.037
Total Calories per ha	0.161 ***	(0.019)	0.332 ***	(0.026)	0.555 ***	0.041
Year (t)	0.027 ***	(0.006)	0.007	(0.010)	0.022 **	0.011
Variability in CWB - Winter	0.010	(0.016)	-0.023	(0.023)	-0.015	0.026
Variability in CWB - Summer	0.043 ***	(0.009)	0.065 ***	(0.014)	0.039 ***	0.015
Variability in GDD - Season	0.023 ***	(0.009)	0.045 ***	(0.013)	0.016	0.016
Variability in KDD - Summer	0.015	(0.011)	0.001	(0.018)	0.014	0.017
Input intensity	-0.002	(0.018)	-0.070 ***	(0.025)	-0.152 ***	0.045
Specialisation	0.086 ***	(0.016)	0.067 ***	(0.025)	-0.013	0.036
AES payments	0.006	(0.017)	-0.019	(0.024)	-0.007	0.029
Input intensity x Variability in CWB - Winter	0.035 ***	(0.013)	0.021	(0.022)	0.013	0.026
Input intensity x Variability in CWB - Summer	0.015 *	(0.008)	0.027 **	(0.011)	0.006	0.011
Input intensity x Variability in GDD	0.012	(0.010)	0.017	(0.015)	-0.006	0.017
Input intensity x Variability in KDD	0.006	(0.013)	-0.055 *	(0.029)	-0.026	0.018
Specialisation x Variability in CWB - Winter	-0.013	(0.014)	0.006	(0.017)	-0.047 *	0.025
Specialisation x Variability in CWB - Summer	-0.015 *	(0.008)	-0.018 *	(0.010)	0.025 *	0.014
Specialisation x Variability in GDD	0.002	(0.008)	0.006	(0.013)	0.019	0.017
Specialisation x Variability in KDD	-0.009	(0.008)	0.034 **	(0.016)	0.016	0.019
AES payments x Variability in CWB - Winter	-0.008	(0.012)	0.000	(0.018)	-0.010	0.023
AES payments x Variability in CWB - Summer	0.002	(0.009)	-0.011	(0.016)	-0.002	0.015
AES payments x Variability in GDD	0.003	(0.009)	-0.016	(0.014)	0.002	0.016
AES payments x Variability in KDD	0.007	(0.009)	0.003	(0.014)	-0.010	0.019
Observations (n)	2357		1047		1128	
County (n)	56		38		57	
Farm (n)	512		262		318	
AIC	1636		911		1549	
BIC	1791		1044		1684	
logLik	-791		-429		-747	

Chapter 6 - General discussion

In this discussion chapter I begin by summarising the state of knowledge at the start of the project and the knowledge gaps that I have sought to address. I then discuss the key findings and form recommendations for farmers and policymakers. Following this I consider my research in a wider context and discuss farm vs regional scale stability. In the final section I discuss the limitations of this thesis research and opportunities for expanding this research in the future, before providing my concluding remarks.

1 State of knowledge before project and summary of knowledge gaps

The literature review in chapter 1 highlighted several gaps in the literature that I have sought to address. Firstly, analysis on the effect of adverse weather or climate variability on UK agriculture was often performed at a large scale, as part of a global or regional assessment and often using only a small number of sites from the UK (e.g. for wheat, Semenov *et al.* 2014; Trnka *et al.* 2014). I highlighted that within UK, at a local scale, daily weather conditions are likely to be wide ranging. Previous studies, focusing on the effect of adverse weather on wheat at a smaller spatial scale, identified spatial variability in drought and heat stress across areas of the UK for wheat production (Semenov, 2009). However, further research was needed to examine the effect of a wide range of adverse weather conditions, including heavy rainfall during sowing and harvest, waterlogging and lodging, at a small spatial scale across the UK.

The literature examined in chapter 1 also highlighted that agricultural production and incomes can be affected by a range of factors, including climate variability, farm management and characteristics, and policy, however these impacts were often examined separately, at different spatial scales, and across different disciplines. In particular, quantitative assessments examining the factors affecting agricultural stability were rare, especially at the farm level (Dardonville et al., 2020). Previous literature identified some important factors which may support the stability of agriculture which have been summarised in chapters 4 and 5, alongside the research gaps identified.

The extensive information collected in the Farm Business Survey as well as the spatial extent and large numbers of farms included, combined with climatic data, provided an opportunity to examine how a wide range of factors explain the stability of agriculture. I specifically focused on farm level adaptation, which had been less investigated, to provide recommendations for farmers and policy makers to improve the stability and therefore ultimately the sustainability of farm businesses and food production for consumers.

2 Summary and synthesis of findings

The main findings of the thesis are summarised in Table 1, in response to the research questions formulated in Chapter 1. There are several main findings and recommendations that can be drawn from this thesis, which are discussed further in this section. In combination the research undertaken in this thesis provides knowledge and understanding of the impact of adverse weather on the stability of agriculture, now and in the future, and important adaptation options to improve the stability of food production and farm income, in the context of a changing climate and more variable conditions.

Table 1 – Summary of the main results from each data chapter, in response to the research questions described in Chapter 1.

Key research question(s)	**Main findings**	**Chapter**
Focusing on wheat production, how does the frequency, magnitude and spatial patterns of a range of adverse weather conditions change throughout the UK during 21st century?	a) Generally, the UK climate is expected to remain favourable for UK wheat production. b) However, wetter winter and springs could cause issues with waterlogging (changing rainfall patterns appear more influential than temperature). c) Localised differences suggest it is important to examine climate conditions at a small spatial scale.	3
1) What affect do farming practices and subsidies have on the stability of farm income across England and Wales? 2) Do different measures affect the interpretation of stability and the relationships identified in the models?	a) Engaging in environmentally sustainable farming practices including agri-environment schemes, increasing agricultural diversity, and reducing the intensity of inputs, increases the stability of income for certain farm types. b) The alternative measures of stability used are correlated and provide similar results (but the choice of stability measure should depend upon the research question, and interpretation of stability).	4
What is the relative effect of climate variability, subsidies and farming practices on the temporal stability of food production and farm income, in England and Wales?	a) While variability in climate can be largely outside of the farmers control, my findings indicate that, under current conditions, farm management can have a comparatively large effect on stability. b) Greater agricultural diversity can increase the stability of both food production and farm income, and more precise use of agri-chemicals may improve income stability, whilst maintaining outputs. c) Practices to improve stability vary between farm types, therefore future agricultural policy should be adaptable to benefit different types of production.	5

2.1 Wetter winters and springs threaten agricultural production in the UK

Results from chapter 3 indicate that under a changing climate, changing rainfall patterns appear more influential than temperature for UK wheat production; the risk of waterlogging increases throughout the UK, with winter and spring predicted to be wetter, coupled with an increase in heavy precipitation events.

Beyond wheat, and considering risks to UK agricultural production more generally, heavy rainfall and waterlogging during the early season has, in previous literature, been found to reduce yields in other cereal crops, for example barley (de San Celedonio et al., 2014; Hakala et al., 2012). Wetter weather in the early season is also likely to threaten productivity in other crops grown in the UK through root anoxia, nutrient leaching and the ability to access fields. Wet weather in the early part of the season also favours a range of pathogens and fungal diseases which can affect crops in the UK, for example ‘eyespot’ (*Pseudocercosporella herpotrichoides)* which affects wheat, barley, oats, rye and triticale, (AHDB, 2019).

Adaptation options to manage or cope with waterlogging in the UK are important for farmers and policy makers to consider. There is some evidence that specific varieties of wheat and barley may be more tolerant to waterlogging (e.g. Setter and Waters, 2003). Diversity in crop rotations is often advocated as a method, and improve soil structure and drainage which could improve the ability to cope with wetter weather (Ball et al., 2005). As well as improving soil resilience, including the ability to tolerate both wet and dry conditions, including within the same season. Diverse crop rotations have previously been found to reduce the incidence of weeds, including blackgrass, as well as, improve soil properties and structure (Ball et al., 2005; Degani et al., 2019), which could improve the ability to cope with wetter weather in the early season, but also the ability to withstand drought during the summer. Diversification may therefore be an increasingly important practice for farmers to adapt to climate change. The benefits and challenges of increasing agricultural diversity are discussed further in section 2.2.1.

Further research into the effects of waterlogging would provide important knowledge for farmers and policy makers, for example by expanding process-based crop models and considering the effects of compound weather events during the season (e.g., water logging followed by drought). Further research is also required to better understand the effects of changing rainfall patterns on the wider agricultural system, by also incorporating the effects on pests and disease and soil management.

In the next section I discuss some of the farm management practices and policy strategies which could help farmers to improve the stability of food production and farm income in the face of more variable climatic conditions.

2.2 Farm management can have a large effect on the stability of food production and farm income

In this section I discuss the results in response to the main aim of this thesis; to identify farming practices and adaptation options for agriculture to improve the stability of food production and farm income in the context of a changing climate and more variable conditions. I discuss the key farming practices identified in chapters 4 and 5 that may provide opportunities for farmers to improve the stability and ultimately sustainability of agriculture. I also discuss the potential barriers to adopting some of these farming practices.

2.2.1 Increasing agricultural diversity is the best way to increase the stability of agricultural systems

The empirical analyses in this thesis find that increasing diversity in crop and livestock activities is associated with greater stability of farm income, across a range of stability measures (Chapter 4), and with greater stability of food production (Chapter 5). There are a variety of mechanisms by which agricultural diversity has been found to increase stability in previous research, for instance by improving the farmed environment and harnessing ecological functions to increase the resilience of landscapes and agricultural production, as well as reducing vulnerability to production and market or price risks, benefitting farm income (Pretty, 2008; Pretty and Bharucha, 2014; Rockström et al., 2017).

Recent literature has identified a range of specific benefits that can arise from crop diversification, of various types, to moderate the effect of production risks in a changing climate. Examples of crop diversification in agricultural systems and the potential benefits for agricultural production under climate change are summarised in table 2. Alongside benefits of agricultural diversity for soil, greater agricultural diversity has also been found to supress pests and disease, and may therefore reduce the need for agrochemical inputs and the associated negative effects on the environment (Davis et al., 2012; Liebman et al., 2004). Greater diversity in agricultural activities could therefore play an important role in increasing the stability of farm income and food production and at the same time preserving environmental health.

Many studies have been conducted on the effects of agricultural diversity on agricultural production. A small number of studies have found little or no benefit from specific types of agricultural diversity (e.g. species richness, Barkaoui et al. (2016) and root functional diversity, Carter and Blair (2012)); Schmid and Pfisterer (2002) found crop biodiversity increased yields under unperturbed conditions, however, species-rich cropping systems were less resistant to drought, in addition, plots containing legumes seemed to suffer larger reductions in yield due to drought. This contrasts with other studies which identify benefits of using legumes in cover or catch crops (table 2). Further research to understand the effect of specific species (e.g., legumes) within a rotation to improve yield stability and resistance to adverse weather could be an important area for future research.

As shown in Table 2 there are various types of agricultural diversification, including using crop rotations and growing a mixture of varieties in a monoculture. Due to lack of data on specific varieties or crop rotations I could not examine these types of diversity, however, there is a large collection of research which supports the finding of this thesis that greater diversity can increase the stability of agricultural outputs.

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Table 2 - Examples of crop diversification in agricultural systems and the potential benefits for agricultural production under climate change. Source: adapted and expanded from Lin (2011).

Type of crop diversification	Nature of diversification	Benefit	Mechanism for benefit	Reference(s)
Diverse crop rotations	Temporal diversity through crop rotations (and the use of cover crops)	Maintain yields under abiotic stress and lower risk of crop failure	Higher yield resilience through improved soil properties and water retention leading to better ability to withstand drought stress	(Degani et al., 2019; Gaudin et al., 2015)
		Disease suppression	Alternating cereal crops with broadleaf crops disrupts the disease cycle	(Krupinsky et al., 2002)
		Increased yield	Diverse rotations and cover crops can provide nutrients and biological regulation services	(Dardonville et al., 2020; Smith et al., 2008)
Genetic diversity in monoculture	Growing a number of different varieties of crop species in different fields across the farm	Increased mean income and income stability	Thought that greater genetic diversity in cereals makes a system more resilient to temperature and rainfall fluctuations	(DiFalco and Perrings, 2003)
		Increased yield stability	Increased temporal yield stability in grassland (under drought and non-drought conditions)	(Prieto et al., 2015)
Mixed plantings (polycultures)/intercropping/species (taxonomic) diversity	Growing two or more crop species within the field; spatial and temporal diversity of crops	Increased biomass production	Increased biomass production in grasslands, notably when subjected to a drought event	(Picasso et al., 2008; Prieto et al., 2015)
		Increased yield stability	Stabilizes ecosystem productivity in grasslands, by increasing resistance to climate events.	(Isbell et al., 2015; Tilman et al., 2006)
		Disease suppression	Grassland fields planted with multiple species decreased disease transmission	(Mitchell et al., 2002)
		Climate change buffering	More ecologically complex systems with wild varieties and temporal and spatial diversity of crops were able to grow under climate stress	(Tengö and Belfrage, 2004)
Functional diversity or composition effect	The diversity of species' niches or functions or the presence of species with certain traits	Increase yield stability	Legumes as catch or cover crops increased yield stability by improving soil structure and increasing nitrogen	(Gaudin et al., 2015; Urruty et al., 2017)

Over the past few decades modern farming has become more specialised and intensive. Specialisation has also been considered an advantageous strategy for farmers; enabling benefits from economies of scale, as well as more efficient technical production (de Roest et al., 2018). Despite these benefits, specialised farms are considered more economically vulnerable, being highly dependent on the commodity markets in which they operate (de Roest et al., 2018). My research in this thesis has demonstrated that it is important to consider this economic and production vulnerability (i.e., instability) when assessing farm performance, and the importance of agricultural diversity to increase stability.

This thesis does not examine total levels of income or food production, instead focuses on the stability of agriculture, by examining variations in food production and income around the mean, which is also a significant challenge for farmers. Large variation in income over several years can make farm decisions, for example investment choices, more difficult even if the farm has high income, which may also affect the variability of production with potential consequences on food security. However, as discussed in Chapter 4, previous research has indicated that practices associated with sustainable production systems, including crop rotations and reducing chemical inputs to preserve ecosystem services, can improve productivity and incomes (Pretty, 2008; Pretty and Bharucha, 2014; Rockström et al., 2017).

There can, however, be barriers and perceived limitations to increasing agricultural diversity; including implications for achieving economies of scale, large initial start-up costs for producing a new product (e.g., on machinery), as well as learning how best to produce and market it (Bradshaw et al., 2004). Policy instruments which could be used to ease some of these challenges and encourage an increase in agricultural diversity, are discussed further in section 3 below.

2.2.2 Increasing the efficiency of input use could increase the stability of income whilst maintaining agricultural production

The level of intensity, and use of agrochemicals, has previously been recognised as an important factor influencing agricultural system dynamics (Dardonville et al., 2020). Spending more on chemical inputs was previously associated with less stable farm incomes (Enjolras et al., 2014). However, the effects of fertiliser and pesticides on the stability of yields were less clear (Dardonville et al., 2020).

In chapters 4 and 5 of this thesis I find that increasing the amount spent on agrochemicals per hectare is associated with less stable income. In contrast, increasing input intensity was associated with more stable food production. As discussed in chapter 5 (section

4.2) this finding suggests a potential trade-off in the use of chemical inputs between the stability of food production and farm incomes. Improving the stability of food production and farm income is important for both food security and maintaining a sustainable farm business. Despite the benefits to production, the results of this thesis indicate that greater input intensity is not economically sustainable for farm businesses, with higher input costs reducing the stability of income.

Some research suggests farmers may use chemicals in excess, which has limited economic benefit, through declining nutrient efficiency and resistance (Roberts, 2008; Varah et al., 2020). Results from a Farm Business Survey report found only around a fifth of farms carried out precision farming techniques i.e., soil mapping and use of satellite technology to guide fertiliser application (21% in 2015/16) (Defra, 2017). Farmer behaviour and risk attitudes may also influence the use of chemicals; In a study of wheat farmers in France those in the ‘high-input’ group were driven by a ‘safety’ crop management plan to maximise yields, however they were the least profitable and least efficient group compared to low-input and medium-input farms (Nave et al., 2013). Incurring larger input costs can therefore reduce total profitability, as well as increasing the temporal variability of income with research indicating chemicals are often used in excess and therefore with limited economic benefit. The agronomist-farmer exchange may also influence the intensity and amount of money spent on chemicals. Supplier affiliated agronomists have been found to be less likely to recommend lower doses of pesticides than their independent counterparts (Pedersen et al., 2019). Engagement with or access to precision technology, farmer behaviours and farm advisors may therefore influence the use of agrochemicals and subsequently the ability to reduce chemical use.

Researchers, farmers and policy makers need to consider how to reduce input-use to increase the stability of economically sustainable farm businesses, but whilst also maintaining food production. It is likely there will be some optima of agrochemical use; agrochemicals at some level can improve productivity and stability of food production. Whilst I do not quantify an optimal level of agrochemicals, increasing the efficiency of input use is highly important to maintain production but supress costs (Duru et al., 2015). In parallel, currently the yield benefits of pesticides are also threatened by over-use, leading to widespread resistance and reduced effectiveness, therefore strategies to increase yields through food-production systems rather than pesticides are necessary (Varah et al., 2020).

Policy makers need to create the conditions which enable farmers to transition to different crop protection and soil management practices and increase the efficiency of input use in the long term. The policy implications and relevance of these findings are further discussed in section 3 below.

2.2.3 Agri-Environmental management also associated with greater stability

Agri-environment schemes compensate farmers for implementing measures to benefit the environment or biodiversity, or to support the wider rural economy (European Commission, 2005). The effect of agri-environment scheme payments on the stability of agricultural production or income, at the farm level, had not been examined previously. The results from this thesis generally indicate a positive association between agri-environment payments and the stability of both farm income and food production, however, this does vary between farm types.

Prior research has indicated options included in agri-environment schemes may help increase pest regulation (Menalled et al., 2003; Ottoy et al., 2018; Tschumi et al., 2016), pollination and climate regulation; reducing the effects of extreme weather events (Bishop et al., 2016; Degani et al., 2019). Improving these specific ecosystem services could increase stability of the agricultural system and therefore provide the related mechanism behind my findings. However, the effectiveness of agri-environment scheme options at actually delivering ecosystem service benefits has only just started to be scientifically tested and their overall effectiveness remains poorly understood (Batáry et al., 2015; Ottoy et al., 2018). However, the contrast between the effect of agri-environment scheme payments and 'direct payments' based on land area, which are generally found in chapters 4 and 5 to increase the variability of income and food production, suggest the environmental practices undertaken by the farmer are associated with greater stability.

Details of specific agri-environment scheme options farmers participated in were not available each year of the Farm Business Survey, therefore it was not possible to provide more specific recommendations as to which options are associated with greater stability. This would be an important area for future research; to look at the effect of enrolment in different agri-environment schemes and the options undertaken by the farmer.

3 How can government policy support stability?

Government policy should seek to combat production risks, including those from climate variability, and move towards greater agricultural sustainability to ensure we can continue to feed a growing population. The results of this thesis recommend three aspects of farm management to improve the stability of food production and farm income; increasing agricultural diversity, increasing the efficiency of chemical input use and the use of environmentally friendly farming options which are relevant to the farm type. I discuss below the policy implications of these findings and how policy instruments could be used to encourage these farming practices.

Previous research suggests farmers need more information and training about the options for, and implications of, agricultural diversification (de Roest et al., 2018). Firstly, farmers must have access to effective advisory services to provide technical support and advice as required. This could be through government funded services (e.g., Farming Advice Service), or charitable organisations (e.g., LEAF) to promote understanding, provide ecological expertise and access to different markets. Knowledge sharing could also be between farmers, and policies should encourage collaborative networks to share expertise on diversification (de Roest et al., 2018). Economic support could also be provided to subsidise the additional start-up costs required to diversify production systems.

Agricultural intensification over the last 50 years has led to higher yields, but at the same time has increased vulnerability in the agricultural system, reducing resilience and sustainability (FAO and OECD, 2012). Recent literature has recognised the challenges for policy makers to stimulate a reduction in chemical use among farmers; a review by Lee et al. (2019) considered of a range of policy instruments (e.g., bans, subsidies and taxes) and found no definitive policy instrument can achieve a pesticide use reduction. Policy makers could encourage the use of precision farming techniques, for example, by providing grants or subsidies for machinery and technology which allow for better targeted fertiliser and agrochemical applications. The use of robotics and other smart technologies in precision farming is also an emerging technology, which can provide benefits for the efficiency and productivity of production, and funding research and development in this area is important. However, it is also important policy makers engage with the farming community about future technological development and allow a dialogue between all those affected by the innovation including consumers, who may have concerns about emerging technologies (Rose and Chilvers, 2018). Indeed, it could also be seen as controversial for policy makers to fund precision farming technologies, which may be seen to legitimise chemical-based agriculture (Wolf and Wood, 1997).

Another approach is to promote the substitution of chemical inputs with less environmentally harmful ones, including integrated pest management (Barzman et al., 2015). Lefebvre et al. (2015) argues that there is a clear requirement for public intervention to promote the adoption of IPM. A combined suite of incentives, including regulation, incentive-based instruments and information dissemination are most likely to increase IPM uptake (Lefebvre et al., 2015). Governments must also take an active role in promoting the use of IPM, not only to farmers but also increasing knowledge and awareness more widely, so that retailers and consumers are aware of the environmental and health consequences of their food choices.

The results from this thesis indicate that for future ELM schemes to reduce the variability of food production and farm income, alongside achieving environmental benefits, it is important that payments are linked to farmers enhancing or maintaining the environment, and are not area based, to ensure payments do not act as a moral hazard. Whilst it is difficult to comment on specific options which should be targeted in future schemes, greater emphasis could be given to support agricultural diversification, as well as more precise chemical application, which offer the most important solutions to improve stability and also have environmental benefits. For example, it is important aspects of diversification which are not paid for directly through the market or production outputs, (e.g., cover crops or diverse lays) but which provide public goods through ecosystem services, are incentivised.

It is also important that future agricultural schemes are flexible, and options can be tailored to farms, with climate impacts and adaptation options found in this thesis to vary between farm types. Results from Chapter 4 of this thesis indicate LFA farms may not be able to receive the same stabilising benefits that other farm types gain from agri-environment schemes and agricultural diversification. LFA farms are highly reliant on dedicated support from the government (described further in Chapter 4 supplementary material), but also have the lowest farm income per hectare, on average, compared to other farm types, with subsidy payments constituting a large proportion of farm business income (Chapter 4, Table 3). Historically, support has been considered necessary to maintain the economic viability of farms in the uplands, whilst also preserving the environment and cultural landscape in Europe's rural areas (Bonn et al., 2008; DEFRA, 2006). However it has been argued farming marginal Less Favoured Areas may not always result in the best outcome for the environment (Merckx and Pereira, 2015). Recent research indicates subsidies to support 'rewilding' in some marginal land areas may deliver the most valuable outcome for biodiversity and ecosystem services (Merckx and Pereira, 2015). This strategy must however be balanced with the need to meet increasing food demands.

4 Moving from farm- to regional-scale stability of food production and farm income

The ability of agriculture to provide a sustainable source of food for a growing population is one of the major challenges of the 21st Century. This thesis considers the effects of climate variability and adaptation towards stability at the farm level. While adaptation strategies (e.g., changes in crop management practices) are mostly adopted at the farm level, previous research has also assessed the vulnerability and resilience of agriculture at the regional level; Abson et al. (2013) found that diversity of land use in the UK increased the resilience of agricultural returns in the face of uncertain environmental and market conditions. The results of this thesis suggest that larger farms are associated with more stable food production and farm income, at the farm level. However, at the regional level, previous research found greater diversity in farm size and the value of outputs per hectare reduced the vulnerability of crop production to climate variability across Europe (Reidsma and Ewert, 2008). Heterogeneity of farm characteristics, and yield responses, across larger land areas can therefore also help improve the stability and sustainability of UK agriculture in a changing climate. In addition to farm level adaptation, it is also important for policy makers to consider the diversity of farm characteristics and consider planned adaptation at a coarser scale e.g., region or country.

5 Limitations of the thesis research

Challenges associated with the statistical analysis have been discussed in chapter 2, including multicollinearity, confounding and endogeneity. Chapter 2 also highlights the spatial limitations of the farm data; the precise or gridded location of the farms are not known for confidentiality purposes. Therefore, the impact of small-scale characteristics particularly soil conditions, including the available water capacity, could not be examined. The average climate conditions across the counties were instead used as an estimate of the climate at the farm. A more precise location of the farms within each of the counties may have strengthened the analysis.

Farmers attitudes may also influence farming practices and how farmers adapt currently to variable conditions. There is no regular data collection in the Farm Business Survey on farmer attitudes and decision-making processes, which may also influence the stability of income and yields. Therefore, this would need to be assessed using large scale and detailed farmer surveys to allow analyses that could capture any differences in farmers attitudes between farms (including spatial characteristics and farm management) and farm types.

Farmers may also change management in response to unstable conditions, and endogeneity is discussed further in chapter 2.

Sociodemographic characteristics, e.g., age, gender, and education, may influence how farms are managed and therefore indirectly affect the stability of income and food production. In this thesis I focused on the direct effects of farm management, and therefore how farm management can help to adapt to more variable conditions. The Farm Business Survey does capture the age of the farmer and gender, however data on education status is limited (includes the level of education from school only, up to post graduate qualification). To examine which structural factors influence farm management and therefore farm performance, it would be better to consider what training or technical experience farmers have and other behavioural information, for instance whether they are part of cooperatives or groups and what their attitude to risk is. This could provide insight and knowledge on how to engage and encourage farmers to adopt certain practices (e.g., increasing agricultural diversification) which could improve stability. However, this could comprise a new research topic and further project in itself.

Despite the limitations, the analysis in this thesis clearly improves knowledge and provides insights into the farming practices and adaptation options that improve the stability of food production and farm income. Although aspects remain to be studied, the analyses revealed some important factors that need to be considered when examining stability of agriculture in the context of a changing climate and more variable conditions.

6 Opportunities for future work

There are several opportunities for work that arise from the model results and the discussion of results in this thesis. For example, chapter 3 of this thesis used agroclimatic indicators to examine the probability of occurrence of waterlogging and other adverse weather conditions excluded from process-based crop models, however, I could not quantify the yield impacts. Process based crop models could therefore be expanded to examine the full range of effects of waterlogging, and other abiotic stresses, identified as risks to wheat production, to gain further understanding of these effects.

In chapter 4 it is recognised that further analysis to identify which options (or environmental practices) in agri-environment schemes lead to greater stability could be of interest to farmers and policy makers, particularly given the current transition from direct payments to a new agricultural policy in the UK focusing on environmental land management and productivity measures. The effects of other types of agricultural diversification on stability could also be considered in future research; in particular examining functional diversity and specifically the ‘composition effect’ of legumes within a rotation, to improve yield stability and resistance to adverse weather, could be an important area for future research.

Chapter 5 considers the effect of current climate conditions, including climate variability, on the stability of food production and farm income. I did not explicitly model the effects of climate change on stability; interannual climate variability is driven by a range of different factors and modelling future climate variability is complex. In addition, I would have needed to account for additional factors such as changes in crop phenology in the future (i.e., advancing maturity due to rising temperatures). To make informative predictions about future conditions, assumptions would also likely need to be made on future subsidies, costs and farm adaptation, which could increase the level of uncertainty in the models. Whilst climate change was out of scope for chapter 5, this could be an opportunity for future work beyond this thesis.

7 Concluding remarks

The next few years presents a time of extreme challenges for agriculture. Climatic changes are expected to have multiple direct and indirect effects on agricultural production and farmers’ incomes. Improving the stability of yields is important for future food security and improving the stability of farm income could improve the economic viability and sustainability of farm businesses and in turn help provide a continuity of food supply, under more variable conditions. Therefore, the combined assessment in this thesis examining how farm management and policy affect stability of both food production and farm income was important to ensure the sustainability of farm businesses that can continue to produce food into the future. This thesis indicates that management practices, including increasing agricultural diversity and increasing the efficiency of agrochemical use, can have a relatively large effect on stability in comparison to the unpredictable effects of climate, and therefore farmers may have opportunities to improve stability in the face of more variable conditions. However, policy makers also need to support farmers to increase stability and reduce vulnerability to shocks, whilst also considering the multidimensional and sometimes competing challenges facing agriculture.

Agriculture provides or is linked to many ecosystem services, including food production, adapting to and mitigating climate change, preserving the natural environment and maintaining biodiversity. Managing these ecosystem services and considering any trade-offs is an important consideration of policy makers. In the UK this is currently a pivotal moment for agricultural policy; with agricultural land comprising more than 70% of the UK land cover it has been recognised that farmers are important stewards of our environment, with the new agricultural policy focused on supporting the rural economy and achieving ‘A Green Future’ for the UK environment. The stability of farming is important for future food security, however it is important that changes in farming practices and policy are not at the detriment of the natural environment.

References

Abson, D.J., Fraser, E.D.G., Benton, T.G., 2013. Landscape diversity and the resilience of agricultural returns: A portfolio analysis of land-use patterns and economic returns from lowland agriculture. Agric. Food Secur. 2. https://doi.org/10.1186/2048-7010-2-2

Acheampong, E.N., Ozor, N., Owusu, E.S., 2014. Vulnerability assessment of Northern Ghana to climate variability. Clim. Change 126, 31–44. https://doi.org/10.1007/s10584-014-1195-z

AHDB, 2019. Wheat and barley disease management guide.

Antle, J.M., 1987. Econometric Estimation of Producers' Risk Attitudes. Am. J. Agric. Econ. 69, 509–522. https://doi.org/10.2307/1241687

Ball, B.C., Bingham, I., Rees, R.M., Watson, C.A., Litterick, A., 2005. The role of crop rotations in determining soil structure and crop growth conditions. Can. J. Soil Sci. 85, 557–577. https://doi.org/10.4141/S04-078

Barkaoui, K., Roumet, C., Volaire, F., 2016. Mean root trait more than root trait diversity determines drought resilience in native and cultivated Mediterranean grass mixtures. Agric. Ecosyst. Environ. 231, 122–132. https://doi.org/10.1016/j.agee.2016.06.035

Bartholomeus, R.P., Witte, J.P.M., van Bodegom, P.M., van Dam, J.C., Aerts, R., 2008. Critical soil conditions for oxygen stress to plant roots: Substituting the Feddes-function by a process-based model. J. Hydrol. 360, 147–165. https://doi.org/10.1016/j.jhydrol.2008.07.029

Barzman, M., Bàrberi, P., Birch, A.N.E., Boonekamp, P., Dachbrodt-Saaydeh, S., Graf, B., Hommel, B., Jensen, J.E., Kiss, J., Kudsk, P., Lamichhane, J.R., Messéan, A., Moonen, A.C., Ratnadass, A., Ricci, P., Sarah, J.L., Sattin, M., 2015. Eight principles of integrated pest management. Agron. Sustain. Dev. 35, 1199–1215. https://doi.org/10.1007/s13593-015-0327-9

Batáry, P., Dicks, L. V., Kleijn, D., Sutherland, W.J., 2015. The role of agri-environment schemes in conservation and environmental management. Conserv. Biol. 29, 1006–1016. https://doi.org/10.1111/cobi.12536

Bishop, J., Jones, H.E., Lukac, M., Potts, S.G., 2016. Insect pollination reduces yield loss following heat stress in faba bean (Vicia faba L.). Agric. Ecosyst. Environ. 220, 89–96. https://doi.org/10.1016/j.agee.2015.12.007

Blaauw, B.R., Isaacs, R., 2014. Flower plantings increase wild bee abundance and the pollination services provided to a pollination-dependent crop. J. Appl. Ecol. 51, 890–898. https://doi.org/10.1111/1365-2664.12257

Bonn, A., Allott, T., Hubacek, K., Stewart, J., 2008. Drivers of environmental change in uplands, Drivers of Environmental Change in Uplands. https://doi.org/10.4324/9780203886724

Boody, G., Vondracek, B., Andow, D.A., Krinke, M., Westra, J., Zimmerman, J., Welle, P., 2005. Multifunctional agriculture in the United States. Bioscience 55, 27–38. https://doi.org/10.1641/0006-3568(2005)055[0027:MAITUS]2.0.CO;2

Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: Crop diversification in the Canadian prairies. Clim. Change 67, 119–141.

https://doi.org/10.1007/s10584-004-0710-z

Carter, D.L., Blair, J.M., 2012. High richness and dense seeding enhance grassland restoration establishment but have little effect on drought response. Ecol. Appl. 22, 1308–1319. https://doi.org/10.1890/11-1970.1

Challinor, A.J., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009. Crops and climate change: Progress, trends, and challenges in simulating impacts and informing adaptation. J. Exp. Bot. 60, 2775–2789. https://doi.org/10.1093/jxb/erp062

Chavas, J.P., 2019. Adverse Shocks in Agriculture: The Assessment and Management of Downside Risk. J. Agric. Econ. 70, 731–748. https://doi.org/10.1111/1477-9552.12312

Chavas, J.P., Cooper, J., Wallander, S., 2019. The impact of input and output decisions on agricultural production risk. J. Agric. Resour. Econ. 44, 513–535. https://doi.org/10.22004/ag.econ.292329

Corbeels, M., Berre, D., Rusinamhodzi, L., Lopez-Ridaura, S., 2018. Can we use crop modelling for identifying climate change adaptation options? Agric. For. Meteorol. 256–257, 46–52. https://doi.org/10.1016/j.agrformet.2018.02.026

Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184. https://doi.org/10.1016/j.agsy.2020.102913

Davis, A.S., Hill, J.D., Chase, C.A., Johanns, A.M., Liebman, M., 2012. Increasing Cropping System Diversity Balances Productivity, Profitability and Environmental Health. PLoS One 7, 1–8. https://doi.org/10.1371/journal.pone.0047149

de Roest, K., Ferrari, P., Knickel, K., 2018. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. J. Rural Stud. 59, 222–231. https://doi.org/10.1016/j.jrurstud.2017.04.013

de San Celedonio, R.P., Abeledo, L.G., Miralles, D.J., 2014. Identifying the critical period for waterlogging on yield and its components in wheat and barley. Plant Soil 378, 265–277. https://doi.org/10.1007/s11104-014-2028-6

Defra, 2020. Farming Statistics – provisional arable crop areas at 1 June 2020.

Defra, 2018. Farming Statistics Provisional Crop Areas, Yields and Livestock Populations At June 2018 - United Kingdom.

Defra, 2017. Fertiliser usage on farms: Results from the Farm Business Survey England 2015/16.

DEFRA, 2006. Hill Farm Allowance Explanatory booklet 2006.

Degani, E., Leigh, S.G., Barber, H.M., Jones, H.E., Lukac, M., Sutton, P., Potts, S.G., 2019. Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought. Agric. Ecosyst. Environ. 285, 106625. https://doi.org/10.1016/j.agee.2019.106625

DiFalco, S., Perrings, C., 2003. Crop Genetic Diversity , Productivity and Stability of Agroecosystems. A Theoretical and Empirical Investigation. Scott. J. Polit. Econ. 50, 207–216.

Duru, M., Therond, O., Martin, G., Martin-Clouaire, R., Magne, M.A., Justes, E., Journet, E.P., Aubertot, J.N., Savary, S., Bergez, J.E., Sarthou, J.P., 2015. How to implement biodiversity-based agriculture to enhance ecosystem services: a review. Agron. Sustain. Dev. 35, 1259–1281. https://doi.org/10.1007/s13593-015-0306-1

El Benni, N., Finger, R., Mann, S., 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. Agric. Financ. Rev. 72, 301–324. https://doi.org/10.1108/00021461211277204

Enjolras, G., Capitanio, F., Aubert, M., Adinolfi, F., 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. New Medit 13, 31–40.

European Commission, 2005. Agri-environment Measures Overview on General Principles, Types of Measures, and Application.

FAO, OECD, 2012. Building resilience for adaptation to climate change in the agriculture sector. Rome.

FAOSTAT, 2018. FAOSTAT Crops [WWW Document]. URL http://www.fao.org/faostat/en/#data/QC (accessed 11.22.18).

Fischer, E.M., Rajczak, J., Schär, C., 2012. Changes in European summer temperature variability revisited. Geophys. Res. Lett. 39, 1–8. https://doi.org/10.1029/2012GL052730

Fischer, E.M., Schär, C., 2009. Future changes in daily summer temperature variability: Driving processes and role for temperature extremes. Clim. Dyn. 33, 917–935. https://doi.org/10.1007/s00382-008-0473-8

Fones, H., Gurr, S., 2015. The impact of Septoria tritici Blotch disease on wheat: An EU perspective. Fungal Genet. Biol. 79, 3–7. https://doi.org/10.1016/j.fgb.2015.04.004

Gaudin, A.C.M., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C., Deen, W., 2015. Increasing crop diversity mitigates weather variations and improves yield stability. PLoS One 10, 1–20. https://doi.org/10.1371/journal.pone.0113261

Gebbers, R., Adamchuk, V.I., 2010. Precision Agriculture and Food Security. Science (80-.). 327, 828–831. https://doi.org/10.1126/science.1183899

Hakala, K., Jauhiainen, L., Himanen, S.J., Rötter, R., Salo, T., Kahiluoto, H., 2012. Sensitivity of barley varieties to weather in Finland. J. Agric. Sci. 150, 145–160. https://doi.org/10.1017/S0021859611000694

Harkness, C., Areal, F.J., Semenov, M.A., Senapati, N., Shield, I.F., Bishop, J., 2021. Stability of farm income: The role of agricultural diversity and agri-environment scheme payments. Agric. Syst. 187, 103009. https://doi.org/10.1016/j.agsy.2020.103009

He, C., Li, T., 2019. Does global warming amplify interannual climate variability? Clim. Dyn. 52, 2667–2684. https://doi.org/10.1007/s00382-018-4286-0

Hodgkinson, L., Dodd, I.C., Binley, A., Ashton, R.W., White, R.P., Watts, C.W., Whalley, W.R., 2017. Root growth in field-grown winter wheat: Some effects of soil conditions, season and genotype. Eur. J. Agron. 91, 74–83. https://doi.org/10.1016/j.eja.2017.09.014

Ingram, J., 2008. Agronomist–farmer knowledge encounters: an analysis of knowledge exchange in the context of best management practices in England. Agric. Human Values

25, 405–418. https://doi.org/10.1007/s10460-008-9134-0

Isbell, F., Craven, D., Connolly, J., Loreau, M., Schmid, B., Beierkuhnlein, C., Bezemer, T.M., Bonin, C., Bruelheide, H., De Luca, E., Ebeling, A., Griffin, J.N., Guo, Q., Hautier, Y., Hector, A., Jentsch, A., Kreyling, J., Lanta, V., Manning, P., Meyer, S.T., Mori, A.S., Naeem, S., Niklaus, P.A., Polley, H.W., Reich, P.B., Roscher, C., Seabloom, E.W., Smith, M.D., Thakur, M.P., Tilman, D., Tracy, B.F., Van Der Putten, W.H., Van Ruijven, J., Weigelt, A., Weisser, W.W., Wilsey, B., Eisenhauer, N., 2015. Biodiversity increases the resistance of ecosystem productivity to climate extremes. Nature 526, 574–577. https://doi.org/10.1038/nature15374

Jones, A.D., Shrinivas, A., Bezner-Kerr, R., 2014. Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. Food Policy 46, 1–12. https://doi.org/10.1016/j.foodpol.2014.02.001

Krupinsky, J.M., Bailey, K.L., McMullen, M.P., Gossen, B.D., Turkington, T.K., 2002. Managing Plant Disease Risk in Diversified Cropping Systems. Agron. J. 94, 198. https://doi.org/10.2134/agronj2002.0198

Lechenet, M., Dessaint, F., Py, G., Makowski, D., Munier-Jolain, N., 2017. Reducing pesticide use while preserving crop productivity and profitability on arable farms. Nat. Plants 3. https://doi.org/10.1038/nplants.2017.8

Lee, R., den Uyl, R., Runhaar, H., 2019. Assessment of policy instruments for pesticide use reduction in Europe; Learning from a systematic literature review. Crop Prot. 126, 104929. https://doi.org/10.1016/j.cropro.2019.104929

Lefebvre, M., Langrell, S.R.H., Gomez-y-Paloma, S., 2015. Incentives and policies for integrated pest management in Europe: a review. Agron. Sustain. Dev. 35, 27–45. https://doi.org/10.1007/s13593-014-0237-2

Liebman, M., Mohler, C.L., Staver, C.P., 2004. Ecological management of agricultural weeds. Cambridge University Press, Cambridge, UK.

Lin, B.B., 2011. Resilience in agriculture through crop diversification: Adaptive management for environmental change. Bioscience 61, 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Lobell, D.B., Asseng, S., 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environ. Res. Lett. 12. https://doi.org/10.1088/1748-9326/aa518a

Lobell, D.B., Sibley, A., Ivan Ortiz-Monasterio, J., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2, 186–189. https://doi.org/10.1038/nclimate1356

Lowe, J.A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard, T., Kaye, N., Kendon, E., Krijnen, J., Maisey, P., McDonald, R., McInnes, R., McSweeney, C., Mitchell, J.F., Murphy, J., Palmer, M., Roberts, C., Rostron, J., Sexton, D., Thornton, H., Tinker, J., Tucker, S., Yamazaki, K., Belcher, S., 2018. UKCP18 Science Overview report.

Magurran, A., 2004. Measuring Biologcial Diversity, Blackwell Publishing. Blackwell Science Ltd, Oxford, UK.

Malik, A.I., Colmer, T.D., Lambers, H., Setter, T.L., Schortemeyer, M., 2002. Short-term waterlogging has long-term effects on the growth and physiology of wheat. New Phytol. 153, 225–236. https://doi.org/10.1046/j.0028-646X.2001.00318.x

Manik, S.M.N., Pengilley, G., Dean, G., Field, B., Shabala, S., Zhou, M., 2019. Soil and crop management practices to minimize the impact of waterlogging on crop productivity. Front. Plant Sci. 10, 1–23. https://doi.org/10.3389/fpls.2019.00140

Menalled, F.D., Costamagna, A.C., Marino, P.C., Landis, D.A., 2003. Temporal variation in the response of parasitoids to agricultural landscape structure. Agric. Ecosyst. Environ. 96, 29–35. https://doi.org/10.1016/S0167-8809(03)00018-5

Merckx, T., Pereira, H.M., 2015. Reshaping agri-environmental subsidies: From marginal farming to large-scale rewilding. Basic Appl. Ecol. 16, 95–103. https://doi.org/10.1016/j.baae.2014.12.003

Mitchell, C.E., Tilman, D., Groth, J. V., 2002. Effects of grassland plant species diversity, abundance, and composition on foliar fungal disease. Ecology 83, 1713–1726. https://doi.org/10.1890/0012-9658(2002)083[1713:EOGPSD]2.0.CO;2

Nave, S., Jacquet, F., Jeuffroy, M.-H., 2013. Why wheat farmers could reduce chemical inputs: evidence from social, economic, and agronomic analysis. Agron. Sustain. Dev. 33, 795–807. https://doi.org/10.1007/s13593-013-0144-y

Ottoy, S., Angileri, V., Gibert, C., Paracchini, M.L., Pointereau, P., Terres, J.M., Van Orshoven, J., Vranken, L., Dicks, L. V., 2018. Impacts of selected Ecological Focus Area options in European farmed landscapes on climate regulation and pollination services: A systematic map protocol. Environ. Evid. 7, 1–10. https://doi.org/10.1186/s13750-018-0122-6

Pedersen, A.B., Nielsen, H.Ø., Christensen, T., Ørum, J.E., Martinsen, L., 2019. Are independent agricultural advisors more oriented towards recommending reduced pesticide use than supplier-affiliated advisors? J. Environ. Manage. 242, 507–514. https://doi.org/10.1016/j.jenvman.2019.04.091

Picasso, V.D., Brummer, E.C., Liebman, M., Dixon, P.M., Wilsey, B.J., 2008. Crop species diversity affects productivity and weed suppression in perennial polycultures under two management strategies. Crop Sci. 48, 331–342. https://doi.org/10.2135/cropsci2007.04.0225

Poon, K., Weersink, A., 2011. Factors affecting variability in farm and off-farm income. Agric. Financ. Rev. 71, 379–397. https://doi.org/10.1108/00021461111177639

Porter, J.R., Xie, L., Challinor, A.J., Cochrane, K., Howden, S.M., Iqbal, M.M., Lobell, D.B., Travasso, M.I., 2014. Food Security and Food Production Systems, in: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D. (Eds.), Climate Change 2014 Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 485–534. https://doi.org/10.1017/CBO9781107415379.012

Pretty, J., 2008. Agricultural sustainability: Concepts, principles and evidence. Philos. Trans. R. Soc. B Biol. Sci. 363, 447–465. https://doi.org/10.1098/rstb.2007.2163

Pretty, J., Bharucha, Z.P., 2014. Sustainable intensification in agricultural systems. Ann. Bot. 114, 1571–1596. https://doi.org/10.1093/aob/mcu205

Prieto, I., Violle, C., Barre, P., Durand, J.L., Ghesquiere, M., Litrico, I., 2015. Complementary effects of species and genetic diversity on productivity and stability of sown grasslands. Nat. Plants 1. https://doi.org/10.1038/nplants.2015.33

Reed, M.S., Moxey, A., Prager, K., Hanley, N., Skates, J., Bonn, A., Evans, C.D., Glenk, K., Thomson, K., 2014. Improving the link between payments and the provision of ecosystem services in agri-environment schemes. Ecosyst. Serv. 9, 44–53. https://doi.org/10.1016/j.ecoser.2014.06.008

Reidsma, P., Ewert, F., 2008. Regional Farm Diversity Can Reduce Vulnerability of Food Production to Climate Change. Ecol. Soc. 13, 38. https://doi.org/Artn 38

Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: A multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/s10113-008-0059-3

Rigby, D., Woodhouse, P., Young, T., Burton, M., 2001. Constructing a farm level indicator of sustainable agricultural practice. Ecol. Econ. 39, 463–478. https://doi.org/10.1016/S0921-8009(01)00245-2

Roberts, T.L., 2008. Improving nutrient use efficiency. Turkish J. Agric. For. 32, 177–182. https://doi.org/10.3906/tar-0801-9

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., Smith, J., 2017. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio 46, 4–17. https://doi.org/10.1007/s13280-016-0793-6

Rose, D.C., Chilvers, J., 2018. Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming. Front. Sustain. Food Syst. 2, 1–7. https://doi.org/10.3389/fsufs.2018.00087

Schmid, B., Pfisterer, A.B., 2002. Diversity-dependent production can decrease the stability of ecosystem functioning. Nature 416, 84–86.

Semenov, M.A., 2009. Impacts of climate change on wheat in England and Wales. J. R. Soc. Interface 6, 343–350. https://doi.org/10.1098/rsif.2008.0285

Semenov, M.A., Stratonovitch, P., Alghabari, F., Gooding, M.J., 2014. Adapting wheat in Europe for climate change. J. Cereal Sci. 59, 245–256. https://doi.org/10.1016/j.jcs.2014.01.006

Setter, T.L., Waters, I., 2003. Review of prospects for germplasm improvement for waterlogging tolerance in wheat, barley and oats. Plant Soil 253, 1–34. https://doi.org/10.1023/A:1024573305997

Severini, S., Tantari, A., Di Tommaso, G., 2016. Do CAP direct payments stabilise farm income? Empirical evidences from a constant sample of Italian farms. Agric. Food Econ. 4. https://doi.org/10.1186/s40100-016-0050-0

Sibhatu, K.T., Krishna, V. V., Qaim, M., 2015. Production diversity and dietary diversity in smallholder farm households. Proc. Natl. Acad. Sci. U. S. A. 112, 10657–10662.

https://doi.org/10.1073/pnas.1510982112

Smith, R.G., Gross, K.L., Robertson, G.P., 2008. Effects of crop diversity on agroecosystem function: Crop yield response. Ecosystems 11, 355–366. https://doi.org/10.1007/s10021-008-9124-5

Tengö, M., Belfrage, K., 2004. Local Management Practices for Dealing with Change and Uncertainty: A Cross-scale Comparison of Cases in Sweden and Tanzania. Ecol. Soc. 9. https://doi.org/10.5751/es-00672-090304

Tilman, D., Reich, P.B., Knops, J.M.H., 2006. Biodiversity and ecosystem stability in a decade-long grassland experiment. Nature 441, 629–632. https://doi.org/10.1038/nature04742

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4, 637–643. https://doi.org/10.1038/nclimate2242

Tschumi, M., Albrecht, M., Bärtschi, C., Collatz, J., Entling, M.H., Jacot, K., 2016. Perennial, species-rich wildflower strips enhance pest control and crop yield. Agric. Ecosyst. Environ. 220, 97–103. https://doi.org/10.1016/j.agee.2016.01.001

Urruty, N., Guyomard, H., Tailliez-Lefebvre, D., Huyghe, C., 2017. Factors of winter wheat yield robustness in France under unfavourable weather conditions. Eur. J. Agron. 90, 174–183. https://doi.org/10.1016/j.eja.2017.08.002

Urruty, N., Tailliez-Lefebvre, D., Huyghe, C., 2016. Stability, robustness, vulnerability and resilience of agricultural systems. A review. Agron. Sustain. Dev. 36, 1–15. https://doi.org/10.1007/s13593-015-0347-5

Varah, A., Ahodo, K., Coutts, S.R., Hicks, H.L., Comont, D., Crook, L., Hull, R., Neve, P., Childs, D.Z., Freckleton, R.P., Norris, K., 2020. The costs of human-induced evolution in an agricultural system. Nat. Sustain. 3, 63–71. https://doi.org/10.1038/s41893-019-0450-8

Wolf, S.A., Wood, S.D., 1997. Precision farming: Environmental legitimation, commodification of information, and industrial coordination. Rural Sociol. 62, 180–206. https://doi.org/10.1111/j.1549-0831.1997.tb00650.x

Zani, C.F., Gowing, J., Abbott, G.D., Taylor, J.A., Lopez-Capel, E., Cooper, J., 2020. Grazed temporary grass-clover leys in crop rotations can have a positive impact on soil quality under both conventional and organic agricultural systems. Eur. J. Soil Sci. 1–17. https://doi.org/10.1111/ejss.13002

Thesis appendix - Agroclimatic indices

1. Crops

1.1. Wheat

Climate shock	Indicator	Impact/Response	References (Location)
Temperature			
Frost with no snow	T_{min} ≤ -20°C for at least 1 day with <1cm snow cover[†]	Leaf chlorosis; burning leaf tips	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
Late Frost	T_{min} ≤ -2°C after the start of the following window, determined as the period when the mean air temperature is continuously 10°C (for at least five days) and does not drop below 10°C for more than two days in a row	Medium to severe yield loss	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
Frost during anthesis	Temperatures of -4 to -5°C canopy temperature around anthesis (Note: canopy minimum temperature is assumed a standard 2◦C cooler than air temperature)	0% yield loss at −5◦C to 100% yield loss at −6◦C (canopy temperatures)	(Barlow et al., 2015) (simulation)
Frost during stem elongation	Temperatures <−5 °C (air temperature)	Extensive damage to ears	(Fuller et al., 2007) (UK)
Anthesis heat stress	T_{max} > +31°C for at least 2 days during ±5 days around anthesis	Sterility and severe effect on yield	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
	Impact on Harvest Index (HI)[1]; a function of grain filling duration (GF) and daily increase of HI, for -5 days and +12 days around anthesis: $HI = dHI / dt \times GF$ Grain-set declines at 31°C and is 0% at 40°C	Decrease in grain-set and final harvest index (yield)	Moriondo et al. (2011) (Mediterranean)
	Temperature of ≥ +27°C mid-way through anthesis	Sterility and considerable yield loss	Mitchell et al. (1993) (UK)

[1] Using the model proposed by Challinor et al., (2005)

	T_{max}/T_{min} of 36/31°C for at least 2 days in 2/3 days prior to anthesis	Sterility and small shrunk kernels with notching and chalking (parthenocarpy)	Luo (2011)
	Cardinal temperatures for wheat during anthesis: • T_{base} 9.5°C • T_{opt} 21.0°C • T_{max} 31.0°C (in 5 days prior to anthesis)	Sterility and reduction in grain numbers	Porter and Gawith, (1999) (Global)
	Daily T_{max} >31.0°C occurs any days close to anthesis (when anthesis between days 135-166)	Reduction in wheat yield	Perry et al., (2002) (England & Wales)
	Critical temperatures for anthesis: - At field capacity: 31.7 ± 0.47 °C - At drought: 29.9 ± 0.47 °C	Critical temp arbitrarily chosen as 5% reduction in grain set	Alghabari et al., (2014) (UK)
	Heat (>30 - 33°C)	Reduced grain number and size	Barlow et al., (2015) (Simulation)
Heat stress during reproduction phase	T_{crit} is 27°C (critical temperature) T_{lim} is 40°C (limit temperature) T_{day} is daytime temperature Daily heat stress intensity (F_{HSd}) $FHsd = \begin{cases} 0.0 \; for \; Tday < Tcrit \\ \frac{Tday - Tcrit}{Tlim - Tcrit} for \; Tcrit \le Tday < Tlim \\ 1.0 \; for \; Tday \ge Tlim \end{cases}$	Mitchell et al., (1993) temperature of 27°C or higher midway through anthesis could result in a high number of sterile grains and considerable yield losses.	(Teixeira et al., 2013) (Global modelling)
Grain filling extreme heat exposure	T_{max} >35°C for at least 3 days from 5 days after anthesis to maturity	Speeds up development and substantial yield reduction	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
	Heat (>30-40°C)	Yield loss	Porter and Gawith (1999) (Global)
	T_{max} 28/15 °C (day/night), between anthesis and maturity (33 days for this temperature treatment)	Greatly reduced total yield and thousand grain weight (smaller grains)	(Savill et al., 2018) (UK)

	T_{max} 34/20 °C (day/night) for at least 7 days from 7 days after anthesis (DAA) (days after 50% anthesis), with greatest temporal sensitivity 7-14 and 14-21 DAA.	Shorter filling and lower seed weight. Bread making quality - Protein and S concentrations improved but SDS volumes damaged by brief high temperature.	(Nasehzadeh and Ellis, 2017) (UK)
	Tmax > 25°C on more than 14 days **or** More than 15mm rain in a day **and** wind speed of more than 10ms-1 or maximum temp exceeding 28C on 3 successive days	regional yield is likely to be reduced by more than 10%	(Russell and Wilson, 1994) (Europe) For winter and spring common wheat north of latitude 45 °N
	Daily T_{max} > 28°C on 3 successive days, or Daily T_{max} > 25°C on > 14 successive days	≥10% wheat yield losses	Perry et al., (2002) (England & Wales)
	Steady decline kernel development for in temperatures above this. 18/13°C (day/night)	Reduction in duration of growth, reducing the kernel size.	Chowdury and Wardlaw (1987) (Australia)
Booting	Critical temperatures: 5% reduction in grain set (t5) - At field capacity: 33.9 °C ± 0.50 - At drought: 26.5 °C ± 0.56 50% reduction in grain set (t50) - Irrigated = 36.9 ± 0.65 - Water withheld, = 31.3 ± 0.65;	Critical temperatures relate to a percentage reduction in grain set.	Alghabari et al., (2014) (UK)
	Successive single day transfers of pot-grown wheat to high temperature: 35/30◦C day/night	Dependent on genotype, growth stage: grain set dropped below 80% (20/15◦C) for Savannah.	Barber et al., (2017) (UK)
Precipitation			
Lodging event	At least 2 days with daily precipitation >40mm or >20mm and soil moisture on the previous day is at or above field capacity; the period from anthesis to five days before maturity is considered	Reduction in yield and quality	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
	> 15mm rain in 1 day during grainfill	Wheat yield losses ≥10%	(Russell and Wilson, 1994)(Europe) Perry et al., (2002) (England & Wales)

	Wind gusts of > 5 $m.s^{-1}$ and rain > 7 mm from flag leaf to maturity	10–90% yield loss ~ 0.5% of potential yield is lost for each percentage area of crop lodged (LT)	(Berry et al., 2003) and (Gobin, 2018)
Waterlogging stem elongation to anthesis	Waterlogging between stem elongation and anthesis	Yield reduced linearly with the duration of waterlogging 2% wlday−1	Marti et al. (2015) (Spain)
	Waterlogging between stem elongation and anthesis	34% to 92% yield losses	de San Celedonio et al. (2014) (Argentina)
Evapotranspiration			
Severe drought event sowing – anthesis	ET_a[§]/ET_r[ǀ] is less than 0.15 for at least 10 consecutive days between sowing and anthesis*	Reduction in growth/crop die back	Trnka et al. (2014) (Europe) Trnka et al., (2015)(Trnka et al., 2015) (Europe)
Severe drought event anthesis-maturity	ET_a[§]/ET_r less than 0.15 for at least 10 consecutive days between anthesis and maturity	Reduction in growth/crop die back	Trnka et al. (2014) (Europe) Trnka et al., (2015)(Trnka et al., 2015) (Europe)
Severely dry (sowing-maturity)	ET less than 0.15 for at least 21 days during period sowing to maturity*	Reduction in growth/crop die back	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
Soil moisture			
Extremely wet early season	Soil moisture at or above capacity for >60 days from sowing to anthesis*	Restricts growth and reduces yield	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
Adverse conditions at sowing	No more than 3 days during sowing window (sowing date ±15 days) with soil moisture in top layer <90% but >5% and rain on the day <5mm with ≤10mm on preceding day.	Restricts sowing window	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)

Adverse conditions at harvest	Fewer than 3 days during harvest window (maturity date +5 days up to maturity + 25 days) with soil moisture in top layer <85% and rain on given day <0.5mm and ≤5mm on preceding day	Restricts ability to harvest	Trnka et al. (2014) (Europe) Trnka et al., (2015) (Europe)
Drought suffered during stem elongation and grain-filling	Drought suffered during the stem elongation and grain-filling stages, calculated as the difference between the cumulative rainfall and the potential evapotranspiration.	Yield decrease	(Brisson et al., 2010)

Notes: * Excluding days with a mean temperature < 3°C
[†] The snow cover was estimated using a model validated by Trnka et al.
[§]The ET_a refers to the actual evapotranspiration calculated for winter wheat assuming a soil water-holding capacity of 0.27 m and a maximum rooting depth of 1.3 m (more details in the text).
[ǁ]The ET_r refers to the same crop surface as (§) but for reference evapotranspiration; the crop parameters were set according to (Allen et al., 1998)

1.2. Barley

Climate shock	Indicator	Impact/Response	References (Location)
Cold/frost tolerance	Minimal lethal temperature (LT50 – 50% of samples killed) between: -17.3°C and -12.9°C	LT50 – 50% of samples killed	Prášil et al., (2007) (Czech Republic)
High temperature during vernalisation	Mean temperature during vernalisation must not be > 11°C, where vernalisation between Dec and May (winter barley)	Not noted	Perry et al., (2002) (England & Wales)
Heat stress during heading to anthesis	Mean temperature during spring barley heading to anthesis must not be > 30°C (where period in last 10 days in June).	Not noted	Perry et al., (2002) (England & Wales)
Heat stress during anthesis to maturity	Mean temperature during spring barley anthesis to maturity must not be > 30°C	Not noted	Perry et al., (2002) (England & Wales)
Heat stress during warm season	Warm season classified as March-July (French study), heat stress conditions as follows: Winter barley: T_{max} >33°C Spring barley T_{max} >32°C	Statistically significant negative impact on yield (relative to freezing temp)	(Gammans et al., 2017) (France)
Waterlogging between stem elongation and anthesis	Waterlogging between stem elongation and anthesis	40% to 79% yield loss in winter barley	(de San Celedonio et al., 2014) (Argentina)
(Hakala et al., 2012) **- Agro-meteorological variables expected to have a marked influence on growth and yield formation in barley.**			
Rain before sowing	1. Rain during 1 month before sowing was classified according to monthly rainfall at: up to 23, 23–41 and 41–113mm of rain/month.	High rainfall before sowing and delayed sowing reduced barley yields.	(Hakala et al., 2012) (Finland)
Delayed sowing	2. Delayed sowing (sowing date).	See variable 1.	(Hakala et al., 2012) (Finland)
Drought/waterlogging after sowing	3. Early season drought and waterlogging (rain 0–3 weeks after sowing). Rainfall was divided into three classes: low (0–18·2 mm), moderate (18·3–33·6 mm) and high (33·7–122·4 mm).	Moderate rainfall resulted in high yields, while both high rainfall and low rainfall reduced yields considerably.	(Hakala et al., 2012) (Finland)

Drought after sowing	4. Drought at yield potential determination (rain 3–7 weeks after sowing).	Increase in rainfall increased yield. Drought at yield potential formation may reduce grain number and yield (Rajala et al. 2009, 2011).	(Hakala et al., 2012) (Finland)
Frost damage	5. Frost damage during early growth (lowest temperature during 0–4 weeks after sowing).	Significantly reduced yield of e.g. turnip rape, but has not been tested previously with barley	(Hakala et al., 2012) (Finland)
Heat stress at heading	7. High temperature stress (number of days with maximum temperature of 25 °C or higher 1 week before to 2 weeks after heading).	Reduce grain number and yield	(Hakala et al., 2012) (Finland)
Heat stress at heading	8. Very high temperature stress (number of days with maximum temperature of 28 °C or higher 1 week before to 2 weeks after heading).	See variable 7.	(Hakala et al., 2012) (Finland)
High temperature accumulation before heading	9. Rate of temperature sum (Tsum) accumulation before heading (Tsum accumulation rate from 14 days before heading to heading).	Increased rate of development at yield potential formation has been shown to reduce grain number and yield	(Hakala et al., 2012) (Finland)
High temperature accumulation at grain filling	10. Rate of Tsum accumulation at grain filling (Tsum accumulation rate from heading to yellow ripeness).	Shorten the duration of grain filling and may thus reduce grain yield.	(Hakala et al., 2012) (Finland)
High temperature accumulation at grain filling	11. Mean daily temperature sum accumulation rate at grain filling (Tsum accumulation rate (per (per day) from heading to yellow ripeness).	See variable 10.	(Hakala et al., 2012) (Finland)

1.3. Oil seed rape

Climate shock	**Indicator**	**Impact/Response**	**References (Location)**

Heat stress during anthesis	T_{max} > 35°C (Daytime temperatures increasing from 23°C to 35°C and night-time temperatures of 18°C) for 7 days during anthesis	Fruit and seed development, as well as seed weight, were significantly reduced.	(Young et al., 2004) (Canada)
	Heat stress of 35/15°C in the early flowering stage	Reduced harvest index relates to a reduction in seed weight and seeds per pod	(Angadi et al., 2000) (Canada)
Drought stress during anthesis	Drought stress is present when the actual soil water content, was < 40% of the plant available water content of the effective rooting depth after winter. DI (between 0 and 1) increased linearly with decreasing relative plant available water content of the effective rooting depth: DI = 1 – (1 / 0.4) × rel. plant available water content	Reduction in seed and oil yield.	(Weymann et al., 2015) (Germany)

1.4. Peas/beans

Climate shock	Indicator	Impact/Response	References (Location)
Peas			
Heat stress on pollen germination	Heat stress condition of 36/18°C (day/night) over 4 days	Reduced pollen germination by 30 and 55% in CDC Sage and CDC Golden cultivars, respectively.	(Lahlali et al., 2014) (Canada)
Heat stress during flowering	30/25°C (day/night) for 7 days	Caused atrophy and flowers to abort. Reduced plant height, dry matter, seed yield, seed number and weight, harvest index. Water deficiency also decreased use of 32% at 30/25°C	(Mcdonald and Paulsen, 1997)
Heat stress following germination on root growth	• Temperatures between 25°C and 32°C • Heat stress of 32°C (for 1 or 3 days)	Decrease in primary root growth	(Gladish and Rost, 1993)

	• However, the changes usually included a 1-2 day time lag and were reversible.	Inhibited the initiation of lateral roots	
Faba bean			
Heat stress during anthesis	Heat stress for 5 days during anthesis 32°C (t_{50} lethal temperature) Mass per bean was highest at 25°C	50% pollen germination estimated to be lost.	(Bishop et al., 2016) (UK)

1.5. Maize

Climate shock	**Indicator**	**Impact/Response**	**References (Location)**
Heat stress during/ around anthesis	High temperatures ~33-40°C 15 day period at pre-silking and from silking onwards.	4–6 Mg·ha−1 grain loss	(Rattalino Edreira and Otegui, 2012) (Argentina) and (Gobin, 2018)
	Critical temperature of 34°C However when using the air temperature for better performance increase the air temperature threshold to 39°C	Reduction in yield	(Gabaldón-Leal et al., 2016) (Grain Maize; Argentina and Spain)
Heat stress during reproduction phase	T_{crit} is 35°C (critical temperature) T_{lim} is 40°C (limit temperature) T_{day} is daytime temperature Daily heat stress intensity (F_{HSd}) $FHsd = \begin{cases} 0.0 \; for\; Tday < Tcrit \\ \frac{Tday - Tcrit}{Tlim - Tcrit} for\; Tcrit \leq Tday < Tlim \\ 1.0 \; for\; Tday \geq Tlim \end{cases}$	Negative impact on yield (for T >30°C) which increases under drought conditions (Lobell et al., 2011)	(Teixeira et al., 2013) (Global modelling)
Heat stress – during pollination	High temperatures of 40°C during pollination	Immediately reduces the in vitro fertilization percentage, and after 6 h of stress, no fertilization occurs	(Dupuis and Dumas, 1990) (France)

	High temperature of 38/32°C (day/night) just after anther emergence	Viability of pollen adversely affected.	(Schoper et al., 1987) (Illinois US)
	High temperature of 38/32°C (day/night) during pollination	Marked reduction in germination for all types at 38°C compared with 27/21°C, 32/26°C and several types showed no germination after 48 h at 38°C	(Herrero and Johnson, 1980) (Illinois US)
Heat stress during emergence	Mean temperature must not be >30°C where silage maize emergence is day 138-163 and grain maize emergence is 162-170	Not provided	Perry et al., (2002) (England & Wales)
Heat stress	Any 20-day average mean temp >32°C	Reduced yields of grain and silage maize	Perry et al., (2002) (England & Wales)
Heat stress during biomass growth	Accumulation of temperatures >30°C Hourly temperatures estimated from daily minimum and maximum T using a sinusoidal function, and extreme degree days (EDD) were calculated as: $EDD = \sum_{t=1}^{N} DD_{30+,t}$ $DD_{30+,t} = \begin{cases} 0 & if\ T_t < 30°C \\ \frac{T_t - 30}{24} & if\ T_t \geq 30°C \end{cases}$ Where DD30+t is the EDD for hour t, and t spans from 1 June to 31 August for a total of 2,208 h.	During biomass growth temperatures above >30°C reduce yield as a result of increasing demand for water and reducing future water availability.	(Lobell et al., 2013) (US)
Frost during the season	<-2◦C for a few minutes and 0◦C for more than 4 hours	Lethal damage to stem leaf and ear	(Sánchez et al., 2014)
Drought	Precipitation Jun-Aug <150mm	Lower limit for corn production, irrigation for grain maize essential	(Shaw, 1988)(Global) and Perry et al., (2002) (England & Wales)

Drought	Precipitation Jun-Aug <250mm	Grain maize irrigation beneficial	(Shaw, 1988)(Global) and Perry et al., (2002) (England & Wales)

1.6. Oats

Climate shock	**Indicator**	**Impact/Response**	**References (Location)**
Heat stress during spring and summer months	Critical max temperatures: April 24°C May 26°C June/July/August 36°C	Crop growth is close to zero at the maximum temperatures.	(Robertson et al., 2013)(Canada)
Critical minimum temperatures	Critical min temperatures: April 12°C May 5°C	No growth occurs below these minimum temperatures.	(Robertson et al., 2013)(Canada)

2. Livestock

2.1. Cattle

Climate shock	**Measurement**	**Impact/Response**	**References**
Heat stress	**THI = temperature-humidity index,** • THI = (dry bulb temperature °C) + (0.36 x dew point temperature °C) + 41.2 **THI threshold** = THI threshold above which heat stress occurs in a given animal class **THI thresholds**: • Dairy cows: 70 • Beef cows: 75 • Growing finishing hogs: 72 • Broiler chickens: 78	Above thermoneutral zone animals may change respiration rates, heart rate, sweating, blood chemistry and hormones. Behaviour changes with an increase in water intake and a decrease in food intake and therefore can reduce livestock productivity.	(Key et al., 2014) (U.S. Department of Agriculture (USDA), 2008)

	THI can be calculated from the following equations, where dry-bulb temperature (T_{db}), wet-bulb temperature (T_{wb}), and dew-point temperature (T_{dp}) are °C and relative humidity (RH) is %: • THI = 0.72 (T_{db} + T_{wb}) + 40.6; • THI = T_{db}+ (0.36 T_{dp}) + 41.2; • THI = 0.8T_{db} + RH (T_{db} – 14.4) + 46.4. These THI represent the overall impact on livestock Further THI Indexes listed in (Dikmen and Hansen, 2009) which compares THI as a predictor of heat stress in a sub-topical environment • THI = (1.8 x T_{db} + 32) – [(0.55 – 0.0055 x RH) x (1.8 x T_{db} – 26.8)] • THI = (0.35 x T_{db} + 0.65 x T_{wb}) x 1.8 + 32 • THI = (0.55 x T_{db} + 0.2 x T_{dp}) x 1.8 + 32 + 17.5 (• THI = (0.15 x T_{db} + 0.85 x T_{wb}) x 1.8 + 32 • THI = [0.4 X (T_{db} + T_{wb})] x 1.8 + 32 + 15	THI has proven successful in managing cattle and captures much of the impact of warm to hot thermal environments (albeit does have limitations – lacking thermal radiation/airflow and cold conditions.) (Hahn et al., 2009). 1. Livestock weather severity index (LWSI) – tactical guide for mitigating heat stress: • Normal: ≤ 74 • Alert: 75-78 • Danger: 79-83 • Emergency: ≥84 2. Milk production decline (MDEC, kg/cow-day) MDEC = 1.075 – 1.736 M + 0.02474 M × THI where M = normal level of milk production in thermoneutral conditions, kg/cow-day	Also discussed in: (U.S. Department of Agriculture (USDA), 2008) (Hahn et al., 2009)
	<u>Temperature Humidity Index (THI)-hours</u> For *Bos Taurus* cattle in feedlots exposed to single heat wave events (3 days with THI >70) Daily THI-hrs = $\sum_{h-1}^{24}(THI - base)$ THI-hours are a measure of the magnitude of daytime heat load (intensity x duration).	Other climatic factors e.g., solar radiation, wind speed and biological factors (e.g., heat tolerance, diet, acclimation to heat) can modify impacts. **Severe to extreme** conditions can be lethal combined with high solar radiation levels and low wind speeds, particularly with a maximum THI of 86 or higher.	Also discussed in: (U.S. Department of Agriculture (USDA), 2008) (Hahn et al., 2009)
	<u>Heat load index (HLI)</u> Based on humidity, wind speed and predicted black globe temperature (BGT) developed as a guide for managing unshaded	The thresholds are used to calculate the accumulated heat load (AHL) based on the THI-hours concept. When an animal is exposed to a HLI above its threshold, the	Also discussed in: (U.S. Department of Agriculture (USDA), 2008)

	Bos taurus cattle during hot weather (>28.C), by reviewing respiration rate and panting score Predicted BGT = $1.33 \times T_{db} - 2.65 \times T_{db}^{0.5} + 3.21 \times \log_{10}(SR + 1) + 3.5$ The HLI consists of two parts based on a black-globe temperature threshold of 25°C: $HLI_{BGT>25} = 8.62 + 0.38\ RH + 1.55\ BGT - 0.5\ WS + e^{(2.4 - WS)}$ where e is the base of the natural logarithm, and: $HLI_{BGT<25} = 10.66 + 0.28\ RH + 1.3\ BGT - WS$	core body temperature increases and the longer the exposure the greater the stress. A base threshold was developed (HLI = 86) for unshaded Angus steers. Adjustments are subsequently made on the basis of : - genotype - coat colour - health status - access to shade - days on feed manure management - drinking water temperature.	(Hahn et al., 2009)

2.2. Sheep

Climate shock	Measurement	Impact/Response	References (Location)
Heat stress	**Temperature humidity Index** • THI = db°C – {(0.31-0.31 RH) (db°C – 14.4)} db°C is dry bulb temp (°C) and RH is relative humidity (RH%)/100. The values indicate the following: <22.2 = absence of heat stress; 22.2 to <23.3 = moderate heat stress; 23.3 to <25.6 = severe heat stress and 25.6 and more = extreme heat stress	Decrease in feed efficiency and utilization, disturbances in water, protein, energy and mineral balances, enzymatic reactions, hormonal secretions and blood metabolites. Which is reflected in the impairment of their reproduction and production traits.	(Marai et al., 2007, 2001) and (Sejian et al., 2017)
	Estimate of the level of heat stress in dairy sheep in the Mediterranean region: • $THI = \{T - [0.55 \times (1 - RH)] \times (T - 14.4)\}$	Valle del Belice sheep, although originating from a hot environment, are affected by heat stress starting at THI = 23	(Finocchiaro et al., 2005)

	T is the average dry bulb temperature in °C and RH is the relative humidity in percentage	which decreases production yields. (Finocchiaro et al., 2005)	
	THI index based on the ambient temperature (Ta) and RH as follows: • THI = 9/5 × [(T × 17.778) − (0.55 − (0.55 × RH/100) × (T − 14.444)];	THI < 72 indicates thermo-neutral conditions during winter and a THI value between 76 and 78.5 represents mild-to-moderate heat stress in summer season.	(Sejian et al., 2017)
	The heat stress in sheep can also be estimated through another THI using the following formula: • THI = (Dry Bulb Temperature °C) + (0.36 Dew Point Temperature °C) + 41.2).	In this case, a THI exceeding 72 indicates mild stress, 80 indicates medium stress, and above 90 indicates severe heat stress	(Sejian et al., 2017)

2.3. Pigs

Climate shock	**Measurement**	**Impact/Response**	**References**
Heat stress	**A wet-/dry-bulb temperature index (WD Index)** for growing-finishing swine (typically 30-90 kg bodyweight) in acute heat conditions Based on ambient dry-bulb (T_{db}) temperatures from 34° to 43°C and wet-bulb (T_{wb}) temperatures from 23°C to 31°C correlated four physiological parameters (skin temperature, rectal temperature, respiration rate, and heart rate) to these temperature conditions, using: • Swine WD Index = $0.75T_{db} + 0.25T_{wb}$	Impact on swine performance	(Hahn et al., 2009)
	Temperature humidity Index Each hour, the temperature humidity index (THI) was calculated using outside temperature (°C) and relative humidity (RH) as:	Days were classified into THI categories based on the maximum THI, THI categories included "Normal" (< 23.33 °C), "Alert" (23.33 °C ≤ × < 26.11 °C),	(Cross et al., 2018)

	• THI(°C) = T(°C)−[0.55−(0.0055 × RH)] × T(°C)−14.5	"Danger" (26.11 °C ≤ × < 28.88 °C), and "Emergency" (≥ 28.88 °C)	
	Temperature humidity Index • THI = (dry bulb temperature °C) + (0.36 x dew point temperature °C) + 41.2 **THI threshold** = THI threshold above which heat stress occurs in a given animal class **THI thresholds**: Growing finishing hogs: 72	Lower conception rates, smaller litters and lighter weights. Lower feed intake, weight gain and feed efficiency.	(Key et al., 2014) (U.S. Department of Agriculture (USDA), 2008)

2.4. Poultry

Climate shock	Measurement	Impact/Response	References (Location)
	Temperatures between 32°C and 38°C	Feed consumption reduces for 5% for every 1 C rise in temperature between 32°C and 38°C.	(Bhadauria et al., 2014) (India)
	Temperature humidity Index • $THI_{broilers}$ = 0.85 Tdb + 0.15 Twb (1, Tao and Xin, 2003) • THI_{layers} = 0.6 Tdb + 0.4 Twb (2, Zulovich and DeShazer, 1990) • THI_{hen} turkeys = 0.74 Tdb + 0.26 Twb (3, Xin et al., 1992) • $THI_{tom\ turkeys}$ = 0.42 Tdb + 0.58 Twb (4, Brown-Brandl et al., 1997) where: THI = temperature-humidity index, °C Tdb = dry-bulb temperature, °C Twb = wet-bulb temperature, °C	as THI exceeds approximately 21°C, bird performance significantly declined and body temperature increased up to 1.7°C above nominal body temperature for broilers (41°C)	(Purswell et al., 2012) (USA)
	THI = temperature-humidity index, • THI = (dry bulb temperature °C) + (0.36 x dew point temperature °C) + 41.2 **THI threshold** = THI threshold above which heat stress occurs in a given animal class **THI thresholds**: Broiler chickens: 78	Lower feed intake and weight gain. Lower laying performance, decrease in egg weight. Extreme heat also increases bird mortality rates.	(Key et al., 2014) (U.S. Department of Agriculture (USDA), 2008)

3. Agricultural drought indices

Measurement	Impact/Response	References
<u>The Standardized Precipitation Index (SPI)</u> Based on the probability of precipitation for a given time-scale A 20 to 30 year precipitation record is fitted to a probability distribution (e.g. gamma or Pearson type III) and then converted into z-scores so that the average SPI for a specified time-step is zero. Deviation from this value provides a classification of either a drought or wet period.	Soil moisture conditions respond to precipitation anomalies on relatively short timescales, for example 1-6 months, so may wish to look at 1-month to 6-month SPI for agricultural drought (World Meteorological Organization, 2012)	Developed by: Mckee et al., (1993) Complete calculation procedures are available in World Meteorological Organization, (2012).
<u>The Standardized Precipitation Evapotranspiration Index (SPEI)</u> Based on the SPI but includes reference evapotranspiration (ETo). A water surplus or deficit for each month is calculated by subtracting ETo from precipitation. A three-parameter log-logistic distribution is then used to adjust the calculated surplus or deficit. Values can be accumulated at different time scales (from 1 to 24 months) which are then converted to standard deviations from the average.	The SPEI adopts the same drought classification as SPI.	Developed by: Vicente-Serrano et al., (2010) R package SPEI (Beguería et al., 2014) allows users to define parameters that best fit their specific use.
<u>The Palmer Drought Severity Index (PDSI)</u> Based on precipitation, ETo and soil available water capacity (AWC) data for input into a water balance model to assess soil recharge, run off and surface soil moisture loss. The PDSI provides dimensionless values, classified into 11 categories.	Published comparisons between the PDSI and soil moisture suggest PDSI might also give some indication of agricultural drought (Burke and Brown, 2008)	Developed by (Palmer, 1965)
<u>Aridity Index (AI)</u> By combining rainfall and temperature anomalies, a simple aridity index (AI) can be developed. Anomalies have been standardised by the irrespective standard deviations and combined with twice the weight apportioned to the rainfall anomalies: Aridity index = $-(P_i - \bar{P})/\sigma + 0.5(T_i - \bar{T})/\sigma$	Used in (Marsh et al., 2007) to examine the major droughts in England and Wales, 1800–2006. Used in (Oliver et al., 2015) to examine the interacting impacts of land use and extreme drought on butterfly populations.	Developed by Marsh, (2004).

In (Harouna and Carlson, 1994) used with equal weighting for rainfall and temp: Aridity index for month (i) and year (j): $AI_{ij} = (T_{ij} - \bar{T}_i / S_{ti}) - (P_{ij} - \bar{P}_i / S_{pi})$	Positive values are associated with warm and dry conditions. Opposite for negative. Air temp and rainfall equally weighted	Equal weighting of rainfall and temp in Harouna and Carlson, (1994)
Consecutive dry days (CDD) Max number of dry days without rain (below a given threshold typically 1mm day-1) within a consecutive period. For seasonal time frames, can be considered bound to specific seasons.		(IPCC, 2012)
Precipitation Potential Evaporation Anomaly (PPEA) Cumulative difference, over a 12 month, period between precipitation and potential evapotranspiration The PPEA provides an alternate estimate of meteorological drought at time scales of 12 months. It is given by: PPEA = $(P - P_c) - (PE - PE_c)$ where P and PE are the average values of the precipitation and potential evaporation for the preceding 12 months, and Pc and PE are the 20-yr precipitation and potential evaporation climatologies, respectively.		Used in Burke and Brown, (2008):

References

Alghabari, F., Lukac, M., Jones, H.E., Gooding, M.J., 2014. Effect of Rht Alleles on the Tolerance of Wheat Grain Set to High Temperature and Drought Stress During Booting and Anthesis. J. Agron. Crop Sci. 200, 36–45. https://doi.org/10.1111/jac.12038

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration. Guidelines for Computing Crop Water Requirements, European Journal of Agronomy. Rome, Italy.

Angadi, S. V, Cutforth, H.W., Miller, P.R., Mcconkey, B.G., Entz, M.H., Brandt, S.A., 2000. Response of three Brassica species to high temperature stress during reproductive growth 693–702.

Barber, H.M., Lukac, M., Simmonds, J., Semenov, M.A., Gooding, M.J., 2017. Temporally and Genetically Discrete Periods of Wheat Sensitivity to High Temperature. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.00051

Barlow, K.M., Christy, B.P., O'Leary, G.J., Riffkin, P.A., Nuttall, J.G., 2015. Simulating the impact of extreme heat and frost events on wheat crop production: A review. F. Crop. Res. 171, 109–119. https://doi.org/10.1016/j.fcr.2014.11.010

Beguería, S., Vicente-Serrano, S.M., Reig, F., Latorre, B., 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: Parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int. J. Climatol. 34, 3001–3023. https://doi.org/10.1002/joc.3887

Berry, P.M., Sterling, M., Baker, C.J., Spink, J., Sparkes, D.L., 2003. A calibrated model of wheat lodging compared with field measurements. Agric. For. Meteorol. 119, 167–180. https://doi.org/10.1016/S0168-1923(03)00139-4

Bhadauria, P., Kataria, J.M., Majumdar, S., Bhanja, S.K., Kolluri, G., 2014. Impact of Hot Climate on Poultry Production System-A Review Thermoregulatory Mechanism of Poultry 2, 56–63.

Bishop, J., Potts, S.G., Jones, H.E., 2016. Susceptibility of Faba Bean (Vicia faba L.) to Heat Stress During Floral Development and Anthesis. J. Agron. Crop Sci. 202, 508–517. https://doi.org/10.1111/jac.12172

Brisson, N., Gate, P., Gouache, D., Charmet, G., Oury, F.X., Huard, F., 2010. Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. F. Crop. Res. 119, 201–212. https://doi.org/10.1016/j.fcr.2010.07.012

Burke, E.J., Brown, S.J., 2008. Evaluating Uncertainties in the Projection of Future Drought. J. Hydrometeorol. 9, 292–299. https://doi.org/10.1175/2007JHM929.1

Challinor, A.J., Wheeler, T.R., Craufurd, P.Q., Slingo, J.M., 2005. Simulation of the impact of high temperature stress on annual crop yields. Agric. For. Meteorol. 135, 180–189. https://doi.org/10.1016/j.agrformet.2005.11.015

Cross, A.J., Keel, B.N., Brown-Brandl, T.M., Cassady, J.P., Rohrer, G.A., 2018. Genome-wide association of changes in swine feeding behaviour due to heat stress. Genet. Sel. Evol. 50, 1–12. https://doi.org/10.1186/s12711-018-0382-1

de San Celedonio, R.P., Abeledo, L.G., Miralles, D.J., 2014. Identifying the critical period for waterlogging on yield and its components in wheat and barley. Plant Soil 378, 265–277. https://doi.org/10.1007/s11104-014-2028-6

Dikmen, S., Hansen, P.J., 2009. Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? J. Dairy Sci. 92, 109–116. https://doi.org/10.3168/jds.2008-1370

Dupuis, I., Dumas, C., 1990. Influence of temperature stress on in vitro fertilization and heat shock protein synthesis in maize (Zea mays L.) reproductive tissues. Plant Physiol. 94, 665–670. https://doi.org/10.1104/pp.94.2.665

Finocchiaro, R., van Kaam, J.B.C.H.M., Sardina, M.T., Misztal, I., 2005. Effect of heat stress on production in Mediterranean dairy sheep. Ital. J. Anim. Sci. 4, 70–72. https://doi.org/10.4081/ijas.2005.2s.70

Fuller, M.P., Fuller, A.M., Kaniouras, S., Christophers, J., Fredericks, T., 2007. The freezing characteristics of wheat at ear emergence. Eur. J. Agron. 26, 435–441. https://doi.org/10.1016/j.eja.2007.01.001

Gabaldón-Leal, C., Webber, H., Otegui, M.E., Slafer, G.A., Ordóñez, R.A., Gaiser, T., Lorite, I.J., Ruiz-Ramos, M., Ewert, F., 2016. Modelling the impact of heat stress on maize yield formation. F. Crop. Res. 198, 226–237. https://doi.org/10.1016/j.fcr.2016.08.013

Gammans, M., Mérel, P., Ortiz-Bobea, A., 2017. Negative impacts of climate change on cereal yields: statistical evidence from France. Environ. Res. Lett. 12, 054007. https://doi.org/10.1088/1748-9326/aa6b0c

Gladish, D.K., Rost, T.L., 1993. The effects of temperature on primary root growth dynamics and lateral root distribution in garden pea (Pisum sativum L., cv. “Alaska”). Environ. Exp. Bot. 33, 243–258. https://doi.org/10.1016/0098-8472(93)90070-V

Gobin, A., 2018. Weather related risks in Belgian arable agriculture. Agric. Syst. 159, 225–236. https://doi.org/10.1016/j.agsy.2017.06.009

Hahn, G.L., John, B.G., Terry, L.M., Roger, A.E., 2009. Chapter 5: Thermal Indices and Their Applications for Livestock Environments, in: Livestock Energetics and Thermal Environmental Management. ASABE, St. Joseph, Mich, pp. 113–130. https://doi.org/ASABE # 801M0309

Hakala, K., Jauhiainen, L., Himanen, S.J., Rötter, R., Salo, T., Kahiluoto, H., 2012. Sensitivity of barley varieties to weather in Finland. J. Agric. Sci. 150, 145–160. https://doi.org/10.1017/S0021859611000694

Harouna, S., Carlson, R.E., 1994. Analysis of an Iowa Aridity Index in Relationship to Climate and Crop Yield. J. Iowa Acad. Sci. JIAS 101, 14–18.

Herrero, M.P., Johnson, R.R., 1980. High temperature stress and pollen viability in maize. Crop Sci. 20, 796–800.

IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation Special Report of the Intergovernmental Panel on Climate Change. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, Cambridge. https://doi.org/10.1017/CBO9781139177245

Key, N., Sneeringer, S., Marquardt, D., 2014. Climate Change, Heat Stress, and U.S. Dairy Production. U.S. Department of Agriculture, Economic Research Service.

Lahlali, R., Jiang, Y., Kumar, S., Karunakaran, C., Liu, X., Borondics, F., Hallin, E., Bueckert, R., 2014. ATRâ€“FTIR spectroscopy reveals involvement of lipids and proteins of intact pea pollen grains to heat stress tolerance. Front. Plant Sci. 5, 1–10. https://doi.org/10.3389/fpls.2014.00747

Lobell, D.B., Bänziger, M., Magorokosho, C., Vivek, B., 2011. Nonlinear heat effects on African maize as evidenced by historical yield trials. Nat. Clim. Chang. 1, 42–45. https://doi.org/10.1038/nclimate1043

Lobell, D.B., Hammer, G.L., McLean, G., Messina, C., Roberts, M.J., Schlenker, W., 2013. The critical role of extreme heat for maize production in the United States. Nat. Clim. Chang. 3, 497–501. https://doi.org/10.1038/nclimate1832

Luo, Q., 2011. Temperature thresholds and crop production: A review. Clim. Change 109, 583–598. https://doi.org/10.1007/s10584-011-0028-6

Marai, I.F.M., Ayyat, M.S., Abd El-Monem, U.M., 2001. Growth performance and reproductive traits at first parity of New Zealand White female rabbits as affected by heat stress and its alleviation under Egyptian conditions. Trop. Anim. Health Prod. 33, 451–462. https://doi.org/10.1023/A:1012772311177

Marai, I.F.M., El-Darawany, A.A., Fadiel, A., Abdel-Hafez, M.A.M., 2007. Physiological traits as affected by heat stress in sheep-A review. Small Rumin. Res. 71, 1–12. https://doi.org/10.1016/j.smallrumres.2006.10.003

Marsh, T., Cole, G., Wilby, R., 2007. Major droughts in England and Wales, 1800-2006. Weather 62, 87–93. https://doi.org/10.1002/wea.67

Marti, J., Savin, R., Slafer, G.A., 2015. Wheat Yield as Affected by Length of Exposure to Waterlogging During Stem Elongation. J. Agron. Crop Sci. 201, 473–486. https://doi.org/10.1111/jac.12118

Mcdonald, G.K., Paulsen, G.M., 1997. High temperature effects on photosynthesis and water relations of grain legumes 47–58.

Mckee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales. AMS 8th Conf. Appl. Climatol. 179–184. https://doi.org/citeulike-article-id:10490403

Mitchell, R.A.C., Mitchell, V.J., Driscoll, S.P., Franklin, J., Lawlor, D.W., 1993. Effects of increased CO2 concentration and temperature on growth and yield of winter wheat at two levels of nitrogen application. Plant, Cell Environ. 16, 521–529. https://doi.org/10.1111/j.1365-3040.1993.tb00899.x

Moriondo, M., Giannakopoulos, C., Bindi, M., 2011. Climate change impact assessment: The role of climate extremes in crop yield simulation. Clim. Change 104, 679–701. https://doi.org/10.1007/s10584-010-9871-0

Nasehzadeh, M., Ellis, R.H., 2017. Wheat seed weight and quality differ temporally in sensitivity to warm or cool conditions during seed development and maturation. Ann. Bot. 120, 479–493. https://doi.org/10.1093/aob/mcx074

National Research Council, 1971. A guide to environmental research on animals. National Academy of Science, Washington, DC.

Oliver, T.H., Marshall, H.H., Morecroft, M.D., Brereton, T., Prudhomme, C., Huntingford, C., 2015. Interacting effects of climate change and habitat fragmentation on drought-sensitive butterflies. Nat. Clim. Chang. 5, 941–946. https://doi.org/10.1038/nclimate2746

Palmer, W.C., 1965. Meteorological Drought, U.S. Research Paper No.45. Washington, DC.

Perry, M., Park, S., Dockerty, T., Harrison, P., Jones, P., Harrington, R., Osborne, T., Rounsevell, M., Shoo, J., Viner, D., Wheeler, T., Arnell, N., Butterfield, R., Park, J., Rehman, T., 2002. Investigation of thresholds of impact of climate change on agriculture in England and Wales (No. Research report number 4).

Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat a review. Eur. J. Agron. 10, 23–36.

Prášil, I.T., Prášilová, P., Mařík, P., 2007. Comparative study of direct and indirect evaluations of frost tolerance in barley. F. Crop. Res. 102, 1–8. https://doi.org/10.1016/j.fcr.2006.12.012

Purswell, J.L., Dozier III, W.A., Olanrewaju, H.A., Davis, J.D., Xin, H., Gates, R.S., 2012. Effect of Temperature-Humidity Index on Live Performance in Broiler Chickens Grown From 49 To 63 Days of Age, in: 2012 IX International Livestock Environment Symposium (ILES IX). American Society of Agricultural and Biological Engineers, St. Joseph, MI, pp. 1–9. https://doi.org/10.13031/2013.41619

Rattalino Edreira, J.I., Otegui, M.E., 2012. Heat stress in temperate and tropical maize hybrids: Differences in crop growth, biomass partitioning and reserves use. F. Crop. Res. 130, 87–98. https://doi.org/10.1016/j.fcr.2012.02.009

Robertson, S.M., Jeffrey, S.R., Unterschultz, J.R., Boxall, P.C., 2013. Estimating yield response to temperature and identifying critical temperatures for annual crops in the Canadian prairie region. Can. J. Plant Sci. 93, 1237–1247. https://doi.org/10.4141/cjps2013-125

Russell, G., Wilson, G.W., 1994. An Agro-Pedo-Climatological Knowledge-Base of Wheat in Europe, Joint Research Centre, European Commission, Luxembourg. Luxembourg.

Sánchez, B., Rasmussen, A., Porter, J.R., 2014. Temperatures and the growth and development of maize and rice: A review. Glob. Chang. Biol. 20, 408–417. https://doi.org/10.1111/gcb.12389

Savill, G.P., Michalski, A., Powers, S.J., Wan, Y., Tosi, P., Buchner, P., Hawkesford, M.J., 2018. Temperature and nitrogen supply interact to determine protein distribution gradients in the wheat grain endosperm. J. Exp. Bot. 69, 3117–3126. https://doi.org/10.1093/jxb/ery127

Schoper, J.B., Lambert, R.J., Vasilas, B.L., Westgate, M.. ., 1987. Plant factors controlling seed set in maize. Plant Physiol. 81, 121–125. https://doi.org/10.1104/pp.83.1.121

Shaw, R.H., 1988. Climate requirement, in: Sprague, G.F., Dudley, J.W. (Eds.), Corn and Corn Improvement. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, pp. 609–638.

Teixeira, E.I., Fischer, G., Van Velthuizen, H., Walter, C., Ewert, F., 2013. Global hot-spots of heat stress on agricultural crops due to climate change. Agric. For. Meteorol. 170, 206–215. https://doi.org/10.1016/j.agrformet.2011.09.002

Trnka, M., Hlavinka, P., Semenov, M.A., 2015. Adaptation options for wheat in Europe will be limited by increased adverse weather events under climate change. J. R. Soc. Interface 12, 20150721. https://doi.org/10.1098/rsif.2015.0721

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4, 637–643. https://doi.org/10.1038/nclimate2242

U.S. Department of Agriculture (USDA), 2008. The Effects of Climate Change on Agriculture , Land Resources , Water Resources , and Biodiversity in the United States, Synthesis and Assessment Product 4.3 Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research.

Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. J. Clim. 23, 1696–1718. https://doi.org/10.1175/2009JCLI2909.1

Weymann, W., Böttcher, U., Sieling, K., Kage, H., 2015. Effects of weather conditions during different growth phases on yield formation of winter oilseed rape. F. Crop. Res. 173, 41–48. https://doi.org/10.1016/j.fcr.2015.01.002

World Meteorological Organization, 2012. Standardized Precipitation Index User Guide, (M. Svoboda, M. Hayes and D. Wood). Geneva. https://doi.org/10.1175/2007JCLI1348.1

Young, L.W., Wilen, R.W., Bonham-Smith, P.C., 2004. High temperature stress of Brassica napus during flowering reduces micro- and megagametophyte fertility, induces fruit abortion, and disrupts seed production. J. Exp. Bot. 55, 485–495. https://doi.org/10.1093/jxb/erh038