CRANFIELD UNIVERSITY

David Clarke

Assessing the impacts of drought on UK wheat production

Cranfield Water Science Institute (CWSI)
MSc by Research in Water Science

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Academic Year: 2016 - 2017

Supervisor: Professor Jerry Knox, Dr Tim Hess
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ABSTRACT

Water limitations typically reduce UK wheat yields on average by 1-2 t ha^{-1}, although this can be considerably more in extreme drought years. With the frequency and intensity of droughts expected to increase under a changing climate, an improved understanding of the impacts of drought and better systems for agricultural drought monitoring are required. Previous studies, however, have found no significant relationship between UK wheat yields and commonly employed drought severity indices (DSI). Using historical (1911-2015) daily weather data for Cambridge the Standardized Precipitation Index (SPI), the Standardized Precipitation and Evapotranspiration Index (SPEI), the Palmer Drought Severity Index (PDSI) and the Potential Soil Moisture Deficit (PSMD) were calculated on various time steps (e.g. 1-12 months for SPI and SPEI) to provide a drought record for the site. A wheat crop growth simulation model (Sirius) was then used to simulate the effects of the identified historic droughts on wheat yields. The use of the Sirius crop model removed the non-drought related yield losses (e.g. disease, pests, and lodging) present in national yield records. Using the Spearman's Rho correlation coefficient (r) the simulated yield record was then correlated against the different DSIs. The droughts of 1921, 1976 and 2010 were found to be the most extreme in term of yield reduction. In addition, there were also two noticeable periods of successive yield loss in the early 1940s and between 2009 and 2013. All DSIs showed significant ($p = 0.05$) correlations on monthly time steps between April and August. The SPI, SPEI and PSMD showed a strong correlation to wheat yields (r = 0.64 to 0.66) on time steps incorporating the end of the 'construction' and the entirety of the 'production' phases for wheat growth. The PDSI showed the weakest correlation (r = 0.55), although it may be helpful in identifying yield-limiting droughts earlier in the year. The research has contributed new scientific insights and understanding of the impacts of historic droughts on wheat productivity, and demonstrated the application of DSIs in monitoring potentially yield-limiting droughts. The research also provides new evidence to support developments in UK food security and drought management for agriculture.

Keywords: Drought severity indices, Sirius crop model, simulation, cereals, agricultural drought

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AWC	Available Water Capacity (mm/m)
BSF	Boxworth: Samson Field met station
CBG	Cambridge Botanic Garden met station
CN	Cambridge NIAB met station
CSM	Crop Simulation Model
cv.	Cultivar
DSI	Drought Severity Indices
DSSAT	Decision Support System for Agrotechnology Transfer
EDII	European Drought Impact report Inventory
EDO	European Drought Observatory
ET	Evapotranspiration (mm day^{-1})
ETo	Reference crop evapotranspiration (mm day^{-1})
EU	European Union
M&EW	Monitoring and Early Warning
MA	Moving Average
MAE	Mean Absolute Error (t ha^{-1})
MBE	Mean Bias Error (t ha^{-1})
MRD	Maximum Rooting Depth (m)
PDSI	Palmer Drought Severity Indices
PM	Penman-Monteith method
PO	Potential yield (t ha^{-1})
$PSMD_{Max}$	Maximum Potential Soil Moisture Deficit for the growing season (mm)
$PSMD_{Month}$	Maximum Potential Soil Moisture Deficit for a signal month (mm)
RH	Relative Humidity (%)
RLT	Recommended List Trials
RMSE	Root Mean Square Error (t ha^{-1})
RRMSE	Relative Root Mean Square Error (%)
RUE	Radiation Use Efficiency (%)
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
VP	Vapour Pressure (mbar)
WL	Water Limited yield (t ha^{-1})
≈	Approximately

1 Introduction

Wheat is the most widely cultivated cereal globally, contributing 20% of total dietary calories consumed (Shiferaw et al., 2013). A 40% increase in cereal production is needed by 2050 to feed a larger, wealthier population (FAO, 2009). However, Hall and Richards, (2013) report of the ‘hard truth’ that the vast majority of data indicates that currently the potential yield increase rates fall well below that needed to meet future food demands.

The UK produces a small, but not insignificant proportion of global wheat. Recent short intense periods of drought (Kendon et al., 2013; Parry et al., 2013) have highlighted the risks to UK wheat production. It is reported that approximately 30% of the UK wheat crop is grown on soils prone to drought, resulting, on average, to a 10% to 20% (£72m) loss in total production (Foulkes, et al., 2007; Ober et al., 2011). However, this can be considerably more in severe drought years. It is unsurprising then, that stakeholders from across the UK wheat sector rank ‘unpredictable weather’ highly among perceived risks to wheat production (Ilbery et al., 2013).

Despite the risks from drought to agriculture in the UK, metrics such as Drought Severity indices (DSI) are an underutilized resource (Barker et al., 2016). DSI can help describe the magnitude, duration, severity and spatial extent of droughts. They often form the primary tool for disseminating drought warnings and forecasts (Zargar et al., 2011), and constitute an integral part of drought monitoring and early warning systems (M&EW) in many countries. Before a DSI is implemented in drought M&EW it is advantageous to determine which is the most appropriate for measuring sector specific risks (Quiring and Papakryiakou, 2003). However the lack of reliable information on drought impacts make this task problematic (Bachmair et al., 2016). There is no regional or local database documenting drought impacts and trends to the UK wheat sector. Such information would allow a comparison between DSI and wheat yield allowing for a more sector targeted drought M&EW system.

1.1 Background

This section provides an overview of the importance of UK wheat production internationally, the history of wheat production in the UK, and finally an outline of the current UK wheat production system.

1.1.1 UK position within global and EU wheat market

Table 1 shows the leading countries for wheat production, harvested area and yield average globally. Wheat is considered a temperate species, making conditions particularly favourable in Western Europe (Braun et al., 2010). Western Europe produces seven of the ten highest wheat-yielding countries, including the UK. The UK's 8.6 t ha^{-1} average yield allows its relatively small wheat cropped area of 2 million ha to produce approximately 2% of global output (305 million t) (FAOSTAT, 2016). Although this remains small compared to countries with vast agricultural areas such as China, India, the United States of America (USA) and Russia, it remains an important contributor to the European market. The European Union (EU) produces more wheat than any nation or political-economic union in the world and maintains a large export market

Table 1 Countries by wheat production (million t), area harvested (million ha) and yield (t ha^{-1}) in 2014 (FAOSTAT, 2016)

Rank	Country	Production (million t)	Rank	Country	Area harvested (million ha)	Rank	Country	Average Yield (t ha^{-1})
1	China	2246	1	India	31	1	Ireland	10.0
2	India	1538	2	China	25	2	Belgium	9.4
3	USA	1254	3	Russia	24	3	Netherlands	9.2
4	Russia	910	4	USA	19	4	Germany	8.6
5	France	751	5	Australia	13	5	New Zealand	8.6
6	Canada	531	6	Kazakhstan	12	**6**	**UK**	**8.6**
7	Germany	451	7	Canada	9	7	U.A.E	7.5
8	Australia	431	8	Pakistan	9	8	Denmark	7.5
9	Pakistan	423	9	Turkey	8	9	France	7.4
10	Turkey	413	10	Ukraine	6	10	Zambia	7.2
11	Ukraine	356	11	Iran	6	11	Sweden	6.8
12	**UK**	**305**	12	France	5	12	Namibia	6.7
13	Argentina	274	13	Argentina	5	13	Egypt	6.5
14	Kazakhstan	243	14	Germany	3	14	Czech Republic	6.5
15	Iran	238	**22**	**UK**	**2**	15	Switzerland	6.2

(Barassi & Ghoshray 2007). The UK provided 10.5% of EU wheat in 2014 (FAOSTAT, 2016) making it a key producer in what is collectively the most important wheat growing area (Pohankova et al. 2013).

1.1.2 UK wheat production

1.1.2.1 Wheat cropped area, yield and management

Figure 1 shows UK wheat area, wheat yields and agricultural nitrogen application, between 1885 and 2015. Over 1.8 million hectares (40% of the UK arable area) was dedicated to wheat production in 2015. With outputs valued at £2.03 billion (DEFRA, 2016). Contributing significantly to the UK rural economy. Wheat area experienced rapid expansion from the mid-1970s, due to wheat's increased productivity compared to barley (Marks & Britton, 1988 cited in Bolton et al. 2015). Stabilising during the mid-1980s, with the 5 year moving average (MA) remaining just below 2 million ha ever since, with significant annual fluctuations. These fluctuations are a result of farmer's ability to respond to market pressures (Spink et al., 2009) and/or seasonal weather variations. For example, 2008 resulted in a 14% increase in wheat area as a result of favourable autumn sowing conditions, strong market prices and changing attitudes and policy (DEFRA, 2008).

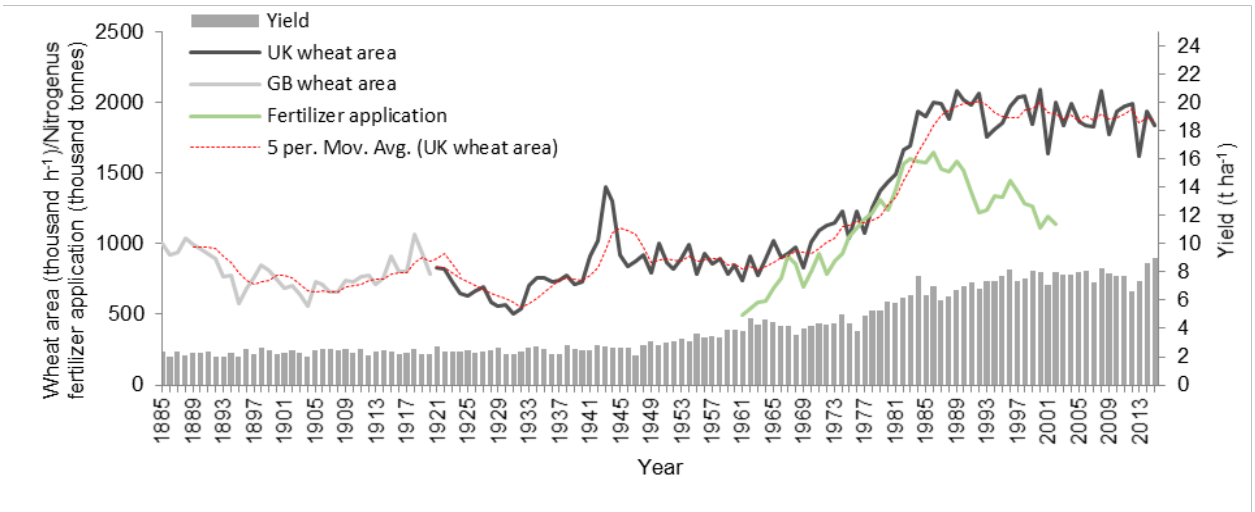


Figure 1 UK time series of wheat area 1885-2015 (thousand ha^{-1})(DEFRA, 2015a)**, nitrogenous fertiliser application 1961-2002 (thousand t)** (FAOSTAT, 2016) **and wheat yield 1885-2015 (t ha^{-1})** (DEFRA, 2015c)

The UK's average yield increased just 0.5 t ha^{-1} between the late 19th century and the middle of the 20th century, with 1953 witnessing the first yield above 3 t ha^{-1}. During the second half of the twentieth century yields increased dramatically (Bonjean et al., 2011), slowing in the 1990s when the rate of improvement declined (Spink et al., 2009). Mackay et al., (2011), citing the work of Silvey (1978; 1981 and 1986), reported that roughly 50% of yield increase between 1947 and 1983 could be accredited to advances in plant breeding and selection. The remainder was likely to be a consequence of mechanisation, improved soil management, fertiliser application and an increase in herbicide and pesticides use. Mackay et al. (2011) building on the work of Silvey (1978; 1981 and 1986) reported that since 1982 at least 88% of the improvement in cereal yield could be attributed to genetic improvements with little evidence that agronomic practices have improved yields.

There is evidence to suggest that yield increases seen in Europe over the last 60 years are unlikely to be maintained. Spink et al.(2009) report that since 2002 genetic gains in yield appear to have halted, with some studies suggesting stagnation started as early as 1992-1995 (Peltonen-Sainio et al., 2009; Finger, 2010). Spink et al. (2009) attribute the recent decline in yield increase to a combination of possible factors, including reduced on farm investment and management attention, declining market size and profitability of agricultural input supplies, reduced investment and innovation, poor profitability of commercial plant breeding, constraints on applying new technologies, agricultural polices limiting production through restriction on chemical use and the need for farmers to invest in environmental schemes. Not all studies attribute the stagnation of yield increases to a reduction in genetic and agronomic advances or investment. In contrast, Brisson et al. (2010) reported that genetic progress in France has not declined, and that depressed yields are more likely a result of climate change (high temperatures during grain filling and drought during stem elongation) but do not rule out the effect of negative agronomic practices (in particular the decline of legumes in cereal production).

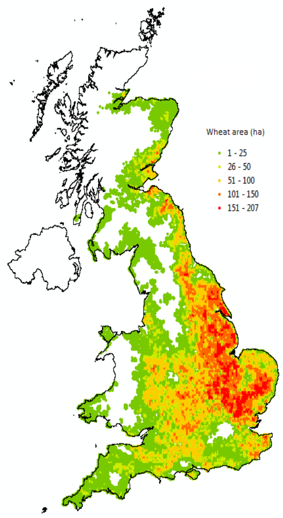
The required increase in production is constrained more than ever by limited resources (Conway, 1998). Therefore, it is likely that more food will need to be produced from the same amount, if not less, agricultural land (Godfray et al., 2010) leading to increased attention on minimizing yield losses from water limitations . Recent studies have investigated the potential for irrigation (El Chami et al., 2015) the use of film antitranspirants (Kettlewell et al., 2010), cultivar improvement (Semenov and Stratonovitch, 2013), varietal performance (Henley, 2012) and improved soil and agricultural practices (Ghaffari et al., 2002a; Spink et al., 2009). Despite many of these adaptation/mitigation options relying on accurate measurements of drought risk few studies have managed to correlate DSI across different time steps using UK wheat yield data.

1.1.2.2 Contemporary UK wheat production system

The majority (≈95%) of wheat grown in the UK is winter wheat, which is typically sown between September and November. The mild humid climate allows the plant to develop through the winter, producing higher yields than spring sown varieties (AHDB, 2015a; El Chami et al., 2015). The favorable climate also makes UK cereal production among the most water efficient in the world with just 0.3% receiving irrigation (Watts et al., 2016). England contains 93% of UK wheat area, with a quarter (26%) located in Eastern England (Table 2). Winter wheat requires between 180-250 growing days to mature (FAO, 2016). With a growing season length of 290 to 310+ days (Met Office using definition Perry and Hollis, 2005) and with relatively large fields, fertile soils and flat topography, Eastern England is considered ideal for wheat production.

A full description of UK winter wheat growth is produced by the AHDB (AHDB, 2015a)., The growing season is split into three phases; the foundation phase (sowing to stem elongation), the construction phase (first node to flowering (anthesis), and the production phase (anthesis to ripening) (Figure 2) (Tottman and Broad, 1987).

Table 2 Regional UK wheat averages 2010-2015, and UK plotted wheat cropped area (2010) ha per 2 km² grid square, data from (EDINA, 2016) **(no data for NI)**

Region	Area (000 ha)	Production (000 t)	Yield (t ha^{-1})	UK wheat cropped area 2010 (ha per 2 km^2)
England	1,743	13,634	7.8	
North East	65	501	7.7	
North West & Merseyside	34	202	5.9	
Yorkshire & The Humber	240	1,922	8.0	
East Midlands	353	2,803	7.9	
West Midlands	165	1,227	7.4	
Eastern	487	3,904	8.0	
South East and London	231	1,855	8.0	
South West	167	1,221	7.3	
Wales	22	159	7.1	
Scotland	105	864	8.2	
N. Ireland	9	70	7.5	
United Kingdom	1,880	14,728	7.8	

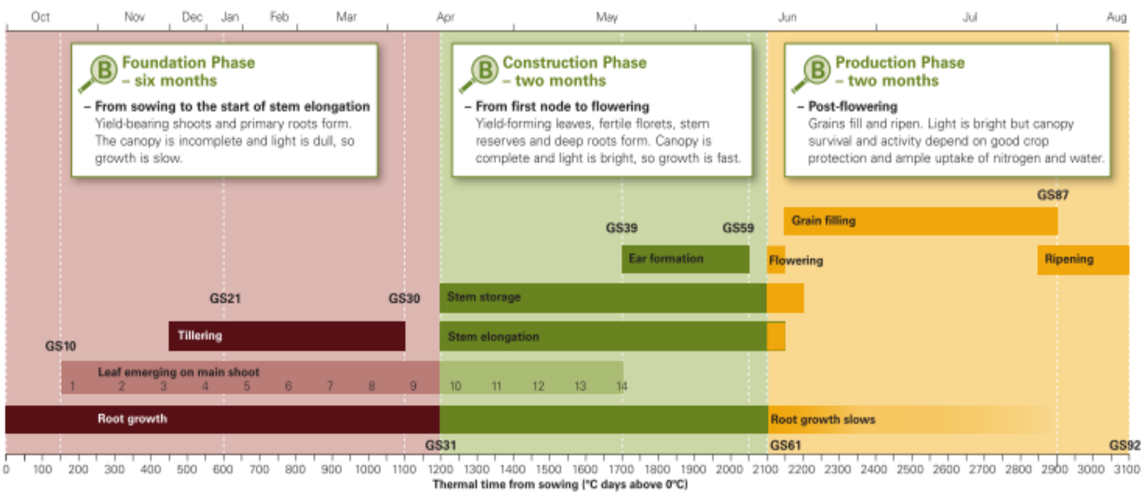


Figure 2 Winter wheat crop development in the UK based on the Tottman and Broad, (1987) **decimal code for wheat growth** (AHDB, 2015a)

1.2 Literature review

This review addresses the following key questions:

1. What is the relationship between droughts, wheat yield and climate change in the UK?

2. How are drought severity indices (DSI) defined and used in agricultural drought monitoring and what potential is there for integration with crop simulation modelling?;

3. Which crop simulation model (CSM) is the most suitable for evaluating the impacts of historic climate variability on UK wheat.

1.2.1 Relationship between drought and wheat yields

1.2.1.1 Wheats response to water stress

The UK produces some of the world's highest yielding wheat (Table 1). However average yields are significantly lower than the potential of modern varieties (Spink et al., 2009). In 2015 a Lincolnshire farmer achieved the wheat yield world record of 16.52 t ha^{-1} (Jones, 2015). Over double the 2010-2015 average for that region (Table 2). Reduced yields result from a number of external pressures including pests and disease (2-6% average loss) (Hardwick et al., 2001; Spink et al., 2009), lodging (widespread once every 4 years, losses recorded up to 16%) (Berry et al., 1998; Sterling et al., 2003), and field accessibility (reduced autumn planting/increased spring drilling resulted in a 19% reduction in area in 2013) (DEFRA, 2013). However, one of the most detrimental yield impacts is through water limitations. It is reported that approximately 30% of the UK wheat crop is grown on soils prone to drought causing losses of c1-2 t ha^{-1} on average, equivalent to 10%-20% of total production (Foulkes, et al., 2007) and costing the economy c.£72 million a year (Ober et al., 2011). However, this can be considerably more in severe drought years. A recent study which interviewed 34 actors from across the UK wheat sector, including 16 growers ranked ‘unpredictable weather’ highly among perceived risks to wheat production (Ilbery et al., 2013). The extent of yield loss depends significantly on the timing and magnitude of water limitations in relation to sensitive stages of crop development (Dodd et al., 2011).

Wheat is particularly vulnerable to drought stress over a number of key phenological stages. During the foundation stage drought can reduce germination and increase tiller death (Baker, 1989). In the UK, however, drought threat is thought to be negligible during the foundation phase (El Chami et al., 2015) as there is typically sufficient rainfall and minimal water loss through evapotranspiration (ET). However, as ET rates increase over the construction phase, the drought risks increase. Stem extension and early booting stage (pollen development) is reported to be particularly sensitive to drought. Water stress over this period reduces pollen sterility resulting in fewer grains at maturity (Dodd et al., 2011a; Ober et al., 2011; Dolferus et al., 2011; Fischer, 1973; Kettlewell et al., 2010). During the production phase drought accelerates senescence (Baker, 1989). Water stress during anthesis (flowering) results in low grain numbers reducing yield. Grain filling (up to one month after anthesis) is when the grain accumulates more water than dry matter allowing cells to first divide then expand. During this period as dry matter growth accelerates, drought stress can cause the grain to inadequately fill and heat stress then affects floret fertility, leading to a reduction in yield (AHDB, 2015; Trnka et al., 2014).

It is likely that climate change will cause a decrease in summer precipitation and an increase in evaporation rates, resulting in increased soil moisture deficits, particularly in the east of England (Gornall et al., 2010; Knox et al., 2010) and thus increasing drought risk to crops (Richter and Semenov, 2005). Many studies however, predict that under future climates wheat yields are likely to benefit from increased radiation use efficiency (RUE) from elevated atmospheric CO_2 concentrations and through earlier maturation, thus avoiding severe summer drought effects (Richter and Semenov, 2005). Semenov and Shewry (2011) using the Sirius wheat crop model, projected that across Europe relative yield loss from drought will be smaller in future. Semenov (2009) reported that modern cultivars would mature almost three weeks earlier under a high emissions scenario in the 2050s, increasing yields in East Anglia by 12.5 to 17.5%. However, there is evidence to suggest these increases may not materialise. El Chami and Daccache (2015) reported that the increase in drought periods in future will result in a yield reduction of between 5.4% and 32-9% in East Anglia. This supports Semenov (2009) findings that increased heat stress around anthesis could potentially cause substantial yield loss.

Despite the projected increases in yield in response to climate change, it is also recognised that there is potential for extreme losses and crop failures from adverse weather conditions to increase in Europe (Trnka et al., 2014). In order to assess the possible impacts of a current or future drought quantitative information on both the severity of past events and their related impacts is required (Naumann et al., 2015).

1.2.1.2 Historic droughts and winter wheat

Droughts are often non-structural and difficult to quantify, and spread over a large spatial area (Wilhite 2000). However negative socio-economic impacts are often reported, particularly for agricultural production (Naumann et al., 2015). Table 3 shows the major reported UK droughts and their documented agricultural impacts. The iconic, nationwide 1976 drought had quantifiable impacts including a 10-15% reduction in cereal yields and £500m in agricultural losses. However not all droughts affect the entirety of the country. Droughts often exhibit substantial regional variations in intensity such as those of 2004-2006 and 2010-2012 (Marsh et al., 2007), making it harder to identify impacts. As a result the variability in production on a single farm is often larger than that of a aggregated figure from a larger area as the variability tends to be averaged out (Heady et al. 1954 cited in Marra & Schurle 1994). In addition, some of the extreme UK drought episodes occur outside living memory, where documented impacts are rare (e.g. 1912, 1933-34) (Table 3).

Table 3 Characteristics of the major 20th and 21st century droughts and their documented impact. Other notable 20th Century droughts reported by Cole & Marsh (2006a) **also feature**

Drought episode	Details
2010-2012	Among the ten most significant one to two year droughts in lowland England in the last 100 years (Kendon et al., 2013). By spring, 2012 severe drought conditions affected much of southern central and eastern regions. The Drought was terminated with wettest April to July, 2012 in almost 250 years (Kendon et al., 2013). Farmers struggled to grow and harvest crops (Kendon et al. (2013). In 2010 crops were affected by the dry spell in April and May followed by continued dry weather during grain filling (June and July) causing stress to crops on all soil types (DEFRA, 2010). In 2011 wheat crop yields varied widely with the drought in spring and early summer having the greatest effect on lighter soils in the south and east (DEFRA, 2011)
2004-2006	Drought developed from late autumn 2004 and lasted until early winter 2006 across much of the English lowlands. There drought episode had a very strong regional focus. With the English low lands particularly South East experience particular strong summer droughts in 2005 and 2006 (Marsh 2007, Marsh et al. 2007). There is little documented evidence of the effect of the 2004 to 2006 drought on agriculture.
2003	The driest UK February-October since 1921, episodic across much of the UK, with a damp late spring and early summer (Marsh, 2004) The soil moisture deficit developed quickly in April but more erratically thereafter, but remaining well above average throughout the summer-causing problems for the agricultural community(Marsh, 2004).
1995-1997	Third lowest England and Wales 18 month rainfall total. Resulting in a major drought with intense period effecting eastern Britain in the summer of 1995 (Marsh et al., 2007). August (1995) rainfall totals were 15% of average for most of England (Marsh, 1995). Caused £180m agricultural losses (mainly to root crops, vegetables and livestock) (Palutikof et al. 1997, cited in Cole & Marsh 2006)
1990-1992	Widespread and protracted rainfall deficiencies. Intense during the summer of 1990 in southern and eastern England (Marsh et al., 2007). Agriculture impacts felt more in continental Europe than the UK (Marsh et al., 1994).
1983-1984	June 1983 to October 1984, borderline Class 1 drought,with no core months (Phillips and McGregor, 1998) Drought impacts less serve with minor impact on agriculture

1976	May 1975 to August 1976 was the lowest 16 month rainfall in England and Wales. Drought was at its most extreme during the summer of 1976 (Marsh et al., 2007). Although affected the UK as a whole, Intensity most extreme across central and southern England (Hamlin & Wright 1978, cited in Marsh et al. 2007). Substantial affects on agriculture, with more than £500 million in failed crops. Cereal yields 10-15 % below the 1970-1974 average (Cole and Marsh, 2006b)
1959	A major drought, most intense in eastern, Central and North Eastern regions, although there was significant spatial variation in intensity (Marsh et al., 2007)
1933-1934	Major drought episode autumn 1932 to autumn 1934, most intense across southern Britain (Marsh et al., 2007). Low reservoir levels and inflows and many woodland fires, it was the first time there was no water in the well at Kew since 1914 (Cole and Marsh, 2006b)
1921-1922	Autumn 1920 to early 1922 a major drought with second and third lowest 6 and 12 month rainfall totals respectively (England and Wales), sever across much of England and Wales, including east Anglia and the south east (Marsh et al., 2007). Relatively few reports of impacts (Cole and Marsh, 2006b)
Other notable 20th century droughts reported by Cole & Marsh (2006a)	
1911; 1913; 1914-1915; 1919; 1929; 1937-38; 1941; 1943-44; 1947-1949; 1955-56; 1962-65; 1972-73; 1988-89	

Few studies have attempted to identify the complexity of drought impacts at both local and regional scales, with databases documenting impacts and trends for individual sectors virtually non-existent (Wilhite et al., 2007). To be able to assess the likely impact of an ongoing or potential future drought event sufficient information on historic drought severity and impacts is required (Naumann et al., 2015). However, It is difficult to assess and compare the economic, social, environmental and agricultural losses from droughts due to lack of reliable historical estimates of impacts (Wilhite 2000 and Quijano et al. 2015). Records for UK average wheat yields date back to 1885 with some nationwide drought events causing noticeable depression in yields (e.g. 1976 and 1992) (Wreford and Adger, 2011). However, some droughts that display a strong regional focus appear not to have affected national yields (e.g. 2004-2006). It is hard to provide a regional perspective of yield-drought relationships due to the limited temporal span of regional records (1999-2015) (DEFRA, 2015a). In addition, the rapid increase in yields (1.2% yr^{-1}) (Shearman et al., 2005) over the 20th century (Figure 1) means the effects of drought can be masked, although de trending can remove some of this uncertainty (Vicente-Serrano et al., 2012). Losses due to drought can also be misinterpreted or hidden by yield reductions brought about through other pressures such as lodging (Sterling et al., 2003), disease (Fones and Gurr, 2015) and pest outbreaks (Millet and Miner, 2009). These limitations are likely contributing factors to why few studies have compared the effect of historic droughts on UK wheat yields. Wreford and Adger (2011) compared the effects of recent (1976-2006) droughts on national average wheat yields and reported a lessening of drought impacts. However, they do recognize the imprecision of using national wheat yields, ignoring the regional influences of drought.

It has become common practice to use crop simulation models (CSM) to study the impacts of historic climate variability on yields (Garcia Y Garcia et al., 2006). A CSM is 'the dynamic simulation of crop growth by numerical integration of constituent processes with the aid of computers'' (Sinclair and Seligman, 1996). Matthews and Stephens, (2002) expand on this describing a CSM as a computer program describing the dynamics of crop growth in response to the environment, on a time step below a growing season. Meinke and Hammer, (1995) used a CSM to reconstruct historic peanut yields in Northern Australia, demonstrating how a period of less variable, wet summers encouraged industry expansion. Also for peanuts Garcia Y Garcia et al. (2006) analysed the impacts of climate variability on long-term historic simulated yields in Georgia, USA. Song et al., (2006) used long-term (1961-2000) weather data from across China with the wheat CSM World Food Studies (WOFOST) to demonstrate yield changes because of observed climate change. Few studies however, have used historic climate data and a CSM to assess the effects of historic droughts on UK agriculture. Environmental growth models have been used to reconstruct the effect of historic climate on other biotic processes. Yu and Berry (2016) simulated historic drought induced tree mortality in the Thames basin between 1960-2006, identifying two peak mortality episodes (1981-87 and 1995-2001).

Therefore, by using a CSM with long-term climate data, external influences on yield can be removed and just the impact of climate variability on production considered, thus allowing for an assessment of potential yield loss from historic UK droughts on a modern wheat production system.

1.2.2 Agricultural applications of drought severity indices (DSI)

The onset, termination and spatial extent of droughts are difficult to determine. These difficulties are compounded by the absence of precise measures of severity that other hazards possess (e.g. Richter scale, earthquakes). Because of this considerable scientific effort has been dedicated to developing tools that provide an objective and quantitative evaluation of drought severity (Vicente-Serrano et al. 2012). These tools are often referred to as Drought Severity Indices (DSI). DSI describe the magnitude, duration, severity and spatial extent of droughts and are typically derived from meteorological or hydrological variables, such as precipitation, evapotranspiration, streamflow, soil moisture or groundwater levels. Converting such data into an index is easier to interpret than considering the raw data (Zargar et al., 2011; Wilhite, 2005). It is estimated that between 80-150 DSI have been developed (Niemeyer, 2008).

DSI often form a primary tool for disseminating drought warnings and forecasts among entities. Usually through publicly accessible gridded drought situation maps (Zargar et al., 2011). There are numerous examples of drought monitoring and early warning systems (M&EW) (Table 4); for example, the North American Drought Monitor (NADM) provides monthly updates of the PDSI and SPI across the North American continent. The European Drought Observatory (EDO) provides blended and interpolated monthly SPI from SYNOP station across Europe. The SPEI Global Drought Monitor delivers monthly 0.5 degree gridded global SPEI. National drought M&EW are also in place, focusing on two European Examples; the German Drought Monitor provides daily Soil Moisture Index values for across Germany; and the Portuguese Institute of the Sea and Atmosphere (IPMA) disseminates monthly SPI, PDSI and soil water (%) throughout Portugal.

Table 4 Drought Monitoring systems employing DSI

Drought Monitor	Source
The North American Drought Monitor	https://www.ncdc.noaa.gov/temp-andprecip/dro ught/nadm/indices)
The European Drought Observatory	http://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1111)
The SPEI Global Drought Monitor	http://sac.csic.es/spei/map /maps.html
The German Drought Monitor	http://www.ufz.de/index.php?en=37937
The IPMA (Portugal)	https://www.ipma.pt/pt/oclima/observatorio.secas/

In the UK, DSI as part of a drought M & EW system are not widely used (Barker et al., 2016). Monthly water situation reports for England and its regions are produced by the Environment Agency. These reports feature precipitation totals for the current month and the last 3, 6 and 12 months, classified based on their occurrence percentage. Maps for soil moisture deficits, river flow, and groundwater and reservoir storage are also produced. These metrics however have little context in terms of quantifying expected impacts nor provide warning to specific sectors, leading some to conclude that more easily interpreted DSI are an underutilized resource in drought monitoring and management in the UK (Lennard et al., 2014). Because of this, few studies in the UK and internationally have performed statistically evaluated DSI recommending preferential use of one over another, particularly on their relative performance at identifying impacts on a particular system (Vicente-Serrano et al., 2012; Bachmair et al., 2016b)

In a UK context Bachmair et al., (2016) tested four DSI including the SPI and SPEI for correlations with regional text-based agricultural impacts from the European Drought Impact report Inventory (EDII). It was reported that there was significant regional variation in the strength of correlation, with little difference in performance of the SPI and SPEI. Although a useful exercise, Bachmair et al., (2016b) generalization of impacts to agriculture provides little insight into crop specific responses to DSI classification. Vicente-Serrano et al. (2012) correlated (Pearson correlation coefficients) six DSI (including the SPI, SPEI and PDSI) with de-trended UK national wheat yields between 1960 and 2009. Reporting the SPEI showed the strongest correlation (<0.3). More recently Naumann et al.

(2015) found no significant (*p-0.05*) correlation to UK de-trended cereal yields and the SPI and SPEI at 3 and 12 month time steps.

The main obstacle in evaluating DSI performance for identifying impacts on a specific sector is the lack of reliable information on drought impacts (Bachmair et al., 2016). The use of national yield records (e.g. Vicente-Serrano et al., 2014; Naumann et al., 2015) has two major limitations. Firstly, the regional variation in yield caused by the spatial variability in intensity and duration of droughts in the UK (Marsh, 2007) is excluded. And secondly, although de-trending goes some way to remove the effects of advances in technological and management practices on yield (Vicente-Serrano et al., 2012) it fails to remove other causes of yield loss including lodging (Sterling et al., 2003), disease (Fones and Gurr, 2015) and pest (Millet and Miner, 2009) outbreaks. Therefore the use of a CSM to simulate the impacts of climate variability to a sector (Garcia Y Garcia et al., 2006) could provide a localised, long-term data set of simulated drought impacts that can provide a more robust analysis between DSI and yield impacts.

This study focuses on four of the most widely used DSI; the Standardized Precipitation Index (SPI) (Mckee et al., 1993); Standardized Precipitation Evapotranspiration Index (SPEI) (Vincente-Serrano et al., 2010); Palmer Drought Severity Indices (PDSI) (Palmer, 1965); and the Potential Soil Moisture Deficit (PSMD) (Knox et al., 1997). The following sections will review each of these focusing on their computational differences, strengths, weaknesses and any demonstrated relationship to agriculture (in particular wheat).

1.2.2.1 SPI

The SPI is based on the probability of precipitation for a given time scale. A 20 to 30 year (50+ optimal) precipitation record (Mckee et al., 1993; Guttman, 1998) is fitted to a probability distribution (e.g. gamma or person iii). This is then converted to a normal distribution so that the average SPI for a specified time step is zero. Deviation from this provides a classification of drought or wet period (Table 5) (Wilhite, 2005; World Meteorological Organization, 2012; Vicente-Serrano et al., 2012). Complete calculation procedures can be consulted in Mckee et al., (1993) and World Meteorological Organization (2012). The SPI is standardized, meaning regardless of location the values (classifications) have the same probabilities of occurrence. It's reported that a moderate drought will be classified 9.2 % of the time, a severe drought 4.4% of the time and an extreme drought 2.3% of the time (Mckee et al., 1993).

Table 5 SPI and SPEI classification (Mckee et al. 1993 and World Meteorological Organization 2012)

SPI/SPEI	Classification
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

The SPI simplicity, requiring just a single parameter (precipitation) and its ability to be computed on different time steps (1-24 months) are its main strengths (World Meteorological Organization, 2012). Its weakness lies in its inability to account for other drought influencing variables such as reference evapotranspiration (ETo). It also assumes that precipitation data has no temporal trend, i.e. the climate is becoming wetter or drier (Vicente-Serrano et al., 2012).

The SPI has been demonstrated to identify impacts on agriculture. Including major crop yields in Southeast Anatolia, Turkey (Ozelkan et al., 2016) and for rice and wheat in the Indo-Gangetic Region of India (Subash and Mohan, 2011). The SPI has been employed in the UK including the aforementioned Vicente-Serrano et al., (2012) and Naumann et al., (2015) studies. As well as studies involving drought categorization (Folland et al., 2015), resource management (Lennard et al., 2016; Lennard et al., 2014) and hydrological and meteorological drought identification (Barker et al., 2016).

1.2.2.2 SPEI

The SPEI is based on the calculation procedure of the SPI, with the difference that reference evapotranspiration (ETo) is included. A water surplus or deficit for each month is calculated by subtracting evapotranspiration from precipitation (Vicente-Serrano et al., 2010). A three parameter log-logistic distribution is then used to adjust the calculated surplus or deficit. Values can be accumulated at different time scales (1-24 months), which are then converted to standard deviations from the average (Vicente-Serrano et al., 2012). Comprehensive calculation procedures can be referred to in Vicente-Serrano et al., (2010) and Beguería et al., (2014). The SPEI adopts the same classification system as the SPI (Table 5). With Potopová et al., (2015) reporting a 2% frequency of extreme drought a 5% frequency of severe drought and 10% frequency of moderate drought.

The SPEI maintains the simplicity of the SPI computation but provides the capacity to account for the effects of ETo on drought formation (Vicente-Serrano et al., 2012). However, weather variables to calculate ETo are not always readily available (Vicente-Serrano & NCAR 2015). The SPEI has been applied to a number of agricultural impact studies (Beguería et al., 2014), including; the effects of drought on wheat, maize, sugar beet and sunflower in the Republic of Moldova (Potopová et al., 2015a), vegetable crops (Potop et al., 2012) and eleven agricultural crops, including wheat (Potopová et al., 2015b) in the Czech Republic. Potopová et al. (2015) correlated wheat yields with the SPEI on lags from 1-12 months in Czech Republic, highlighting specific periods of intensified drought risk that can be useful when investigating the potential consequence of droughts on agricultural production. The SPEI has had limited agricultural applications in the UK. It has, however, been used for drought identification and comparison (Spinoni et al., 2015) and in the impact assessments of Vicente-Serrano et al., (2012) and Naumann et al., (2015).

1.2.2.3 PDSI

The PDSI, developed in the 1960s (Palmer, 1965), requires precipitation, ETo and soil available water capacity (AWC). From these a water balance equation is used that features expressions of evapotranspiration, soil recharge, run off and surface soil moisture loss (Alley 1984; Jacobi et al., 2013). A full computational methodology is described in Alley, (1984). The PDSI provides dimensionless values, classified into 11 categories (Table 6). Wilhite, (2005) report that the cumulative frequency of the drought classification as Extreme drought 4%, severe drought 5-10% and mild to moderate drought 11-27%.

Table 6 PDSI classification (Lloyd-Hughes and Saunders, 2002)

PDSI	Classification
4.00 or more	Extremely wet
3.00 to 3.99	Very wet
2.00 to 2.99	Moderately wet
1.00 to 1.99	Slightly wet
0.50 to 0.99	Incipient wet spell
0.49 to-0.49	Near normal
-0.50 to -0.99	Incipient dry spell
-1.00 to -1.99	Mild drought
2.00 to -2.99	Moderate drought
-3.00 to -3.99	Severe drought
-4 or less	Extreme drought

The PDSI is one of the most widely used DSI, and forms the basis for a number of drought M&EW systems (e.g. NADM). Like the SPEI, the PDSI also factors the effects of ETo on drought formation. The PDSI has a number of documented limitations; it requires the largest number of parameters i.e. ETo, precipitation and AWC of the soil; It cannot be calculated on varying time steps like the SPI and

SPEI therefore its ability at identifying shorter drought episodes diminishes (Vicente-Serrano et al., 2012).

The PDSI has been applied to agricultural drought monitoring in a wide range of environments, including; Canada (Quiring and Papakryiakou, 2003), the Czech Republic (Kolár et al., 2014), Greece (Mavromatis, 2007) and China (Wang et al., 2016) its use for in studies on agriculture in the UK is limited. Todd et al., (2013) use the self-calibrated PDSI to analyses historic drought characteristic in southeast England.

1.2.2.4 PSMD ($\boldsymbol{PSMD_i = PSMD_{i-1} + ETo_i - P_i}$)

The PSMD (mm) can be estimated on a monthly, weekly or daily time step using a simple water balance model. At the start of the season the PSMD is assumed to be zero then for each time step (month, week or day) the ETo - precipitation is added to the PSMD (ETo – precipitation) for the previous time step. If after heavy rainfall the PSMD is less than zero any previous moisture deficit is assumed to have been filled and excess water is lost through percolation or runoff (PSMD is never below 0) (Rodriguez-Diaz et al., 2007). The seasonal maximum PSMD ($PSMD_{Max}$) can then be used as a drought indicator. The main strengths of the PSMD are its simple computation, it does not depend on any site characteristics such as AWC, it accounts for the effects of ETo and it does not rely on long term weather data that the other DSI require (Rodriguez-Diaz,. et al. 2007).

The $PSMD_{Max}$ has been shown to have a strong correlation with irrigation needs. Knox et al. (1997) use the $PSMD_{Max}$ in an assessment of irrigation requirements for main crops in the UK. Downing et al., (2003) used the change in $PSMD_{Max}$ under different climate scenarios to estimate changes in irrigation demand in the UK in the future; and Silva et al. (2007) estimate irrigation requirements on paddy fields in Sri Lanka. However, no study has directly correlated yield loss with the $PSMD_{Max}$ for rainfed crops.

1.2.3 Wheat crop simulation models (CSM)

The use of a CSM allows for a comparative analysis between historic climate variability and wheat yields. Moreover, the relationship between the long-term simulated yield record and four commonly used DSI can be explored. There are numerous CSM available. It is therefore necessary to critically evaluate models based on their intended use (Bennett et al., 2013). Models vary in complexity. The more complex capture a wider range of parameters accounting for genetic features and complex plant, water and nitrogen interactions. These however often require more parameters, which are not always obtainable (Sadras et al, 2015). Brooks & Tobias (1996) recommend using the simplest model that meet the needs of the objectives. The simpler the model the easier it is to parameterise, interpret and understand (Brooks et al., 2001). Ittersum et al. (2013) report that models used in yield gap analysis should use daily weather data, incorporate management practices, be crop specific and should have been validated through peer-reviewed publications. Hess and Stephens, (1996) identify constraints that have hindered the uptake of the PARCH model in Africa. Although not directly related to this study these provide and useful set of criteria desired by the selected CSM (Table 7).

A review based on the criteria set out in Table 7 was conducted for seven widely used wheat CSM; AquaCrop, CropSyst, DSSAT, Sirius2005, WOFOST and STICS (Table 8). These do not represent all the available wheat CSM. Asseng et al., (2013) reported on 27 used in the AgMIP wheat study. The seven reviewed in this study were selected through discussion regarding the aims of the research with experienced crop modellers.

There is no evidence of the use of STICS and DAISY for simulating wheat yields in the UK and the only mention of CropSyst is reported by Hunt (2008) who cite Hanley et al., (2006) as simulating wheat yields under different climate change scenarios across England and Scotland. WOFOST has been applied to studies investigating yield gaps (Boogaard et al., 2013) and historic trends in wheat yields (Supit et al., 2010) across Europe. However, there is no evidence of site-specific validation of WOFOST in the UK. In addition the accuracy of WOFOST, STICS

Table 7 Constrains hindering the uptake of the PARCH crop simulation model (Stephens and Hess, 1996) **and there application for model selection for simulating UK winter wheat**

Stephens and Hess (1996)		**Application to this study**
No relevant application	→	Has it been used for wheat simulation in the UK?
Not convinced of credibility	→	Has it been demonstrated to accurately simulate yields?
Lack of access	→	Is the model open access?
Couldn't understand the model	→	Is it of intermediate complexity?
Couldn't obtain meteorological data	→	Are the parameters (weather, cultivar, soil) obtainable?
Lack of technical/intellectual support	→	Is there suitable support available to aid in calibration?

and CropSyst at simulating grain yield is reported to be less than other available models (Palosuo et al., 2011). Therefore, CropSyst, DAISY, STICS and WOFOST were not considered appropriate models for this study. AquaCrop was validated to simulate wheat yields in the East Anglia, UK (El Chami and Daccache, 2015; El Chami et al., 2015). However, the 'reasonable' reported accuracy of validation (El Chami et al., 2015) is uninspiring compared to reported accuracy of other models e.g Sirius ('very well' Richter and Semenov, 2005). In addition (El Chami et al., 2015) is the only documented use of AquaCrop for winter wheat simulation in the UK.

Palosuo et al., (2011) provided a comparison on eight wheat CSM in variable European Climates (not including AquaCrop or Sirius) and reported that DSSAT was one of the most accurate models for yield simulation. DSSAT has been used in UK wheat studies. Falloon et al., (2012) used yields from the Broadbalk field experiment at Rothamsted from 1999-2009 to validate a generic cultivar, but reported an overestimation of yield. Ghaffari et al., (2002a) calibrated and validated the cultivar (*cv.*) Mercia on 5 soil types for the 1991-1994 period. It was reported grain yield simulations were ‘quite good’ (Root Mean Square Difference = 0.55 t ha^{-1}). Soltani and Sinclair (2015) reported however that DSSAT requires 211 parameters, over four times more than simpler models (CropSyst). This complexity and the documented difficulty in obtaining modelling parameters (Sadras et al., 2015) made DSSAT-Ceres an unsuitable choice for this study.

Sirius has been demonstrated to accurately simulate grain yield of modern wheat cultivars in a wide varitey of enviroments including the UK, Europe, New Zealand and USA (Semenov and Doblas-Reyes, 2007) (Figure 22, APPENDICES A) It has been extensively used in the UK to assess the impacts of climate change (Richter and Semenov, 2005; Semenov, 2009) cultivar adaptation in response to climate change (Semenov and Stratonovitch, 2015; Stratonovitch and Semenov, 2015) crop nitrogen uptake (Jamieson and Semenov, 2000; Semenov et al., 2007) and disease (Madgwick et al., 2011). It is recognised that Sirius does not provide the published operational manual or online support forum that other models offer (e.g DSSAT, AquaCrop and STICS). However its simplicity, along with technical advice obtained through personal comunication with Rothamsted Research overcomes this deficency.

Table 8 Characteristics of wheat crop simulation models

Details			Resources		Stresses modelled				Application		
Model	Open access	Complexity	Detailed user manual	Online Support/Forum	Water stress	Temperature	Waterlogging	Irrigation	Globally	Europe	UK
AquaCrop (Steduto et al., 2009)	✓	Simple (Steduto et al, 2009; Asseng et al., 2013)	✓	✓	✓	✓	✓	✓	Mkhabela and Bullock (2012) Canadian prairies	Soddu et al., (2013) in Southern Sadinia, Italy	El Chami et al., (2 015) and (El Chami and Daccache, 2015) East of England
CropSyst (Stockle et al., 2003)	✓	Simple (Donatelli et al, 1997; Asseng et al., 2013)	✓	×	✓	✓	✓	✓	Benli et al., (2007) in Turkey; Anwar et al., (2007) in Australia	Torriani et al., (2007) Switzerland; Palosuo et al., (2010) Europe wide	Hunt, (2008) cite Hanley et al., (2006) effects of climate change scenarios in Scotland and UK
DAISY (Abrahamsen and Hansen, 2000)	✓	Complex but flexible, recommended users have a good understanding of agronomic and physical processes (University of Copenhagen, 2016)	✓	×	✓	✓	✓	✓	Manevski et al., (2016) in China;	(Takac et al., 2011) in Slovakia; Palosuo et al., (2010) Europe wide; Svendsen et al., (1995) in Germany	No application found
DSSAT (CERES-Wheat) (Jones et al., 2003)	✓	Complex (Soltani and Sinclair, 2015)	✓	✓	✓	✓	✓	✓	Attia et al., (2016) in USA; He et al., (2014) in Canada; Singh and Kalra, (2016) in India.	Alexandrov and Hoogenboom, (2000) in Bulgaria; Palosuo et al., (2011) Europe; Mihailović et al., (2015) in Serbia.	Ghaffari et al., (2002a) South East England; Falloon et al., (2012) across all 13 UK administrative boundaries.
Sirius 2005 (Jamieson et al., 1998b; Lawless et al., 2005)	✓	Low to intermediate complexity	×	×	✓	✓	×	✓	Ewert et al., (2002) in Arizona, USA;	Ewert et al., (2002) at Braunschweig and Giessen in Germany; Vanuytrecht et al., (2015) in Belgium	Semenov, (2009) 18 sites across the UK; Brooks et al., (2001)at Rothamsted and Edinburgh; Crout et al., (2014) in England;
STICS (Brisson et al., 2009)	✓	STICS relies on the simplification of existing models (Brisson et al., 2003)	✓	✓	✓	✓	✓	✓	Hadria et al., (2007) on the Haouz plain, Morocco. Sansoulet et al., (2014) in Eastern Canada	Coucheney et al., (2015) France; Dumont et al., (2016) in Belgium; Palosuo et al., (2011) across Europe	No application found
WOFOST (van Diepen and de Wit, 2009)	✓	Fairly complex database structure	✓	×	✓	✓	×	✓	Song et al., (2006) in China; Confalonieri et al.,(2013) in Morocco	Boogard et al (2013) Throughout the EU.Palosuo et al., (2010) Europe; Eitzinger et al., (2001) in north-eastern Austria.	No application found

1.3 Aim and objectives

1.3.1 Aim

To assess the impacts of historical drought on UK wheat yields and evaluate the performance of DSI in quantifying drought risk.

1.3.2 Objectives

1) To parameterise and validate the Sirius crop simulation model for wheat using existing industry field trials and published scientific data;

2) To simulate the impacts of historic climate variability on UK wheat yield, and;

3) To assess the performance of selected drought indices for drought management for the UK wheat industry and agricultural sector.

2 Methodology

This study uses the Sirius wheat CSM (Jamieson et al., 1998b) to assess the impacts of drought on wheat yields in East Anglia together with a suitability assessment of DSI for agricultural drought management and early warning.

The methodology included six key stages;

1) Identify a site in East Anglia with long term historic climate record and observed yield data;

2) Calculate the SPI, SPEI, PDSI and PSMD from the long term weather record;

3) Parameterise and validate the Sirius wheat crop model for the defined location;

4) Generate simulated historic wheat yield record for at the defined location;

5) Conduct a sensitivity analysis to assess the impacts of contrasting soil types and rooting depths on yield, and;

6) Correlate modelled wheat yields with DSI

2.1 Site identification and data collection and processing

UK wheat cropped area was mapped in ArcGIS using the 2010, 2 km^2 gridded wheat area data set compiled from the June Agricultural Census (EDINA, 2016). This was then compared to the record of Met stations with long term daily climate variables (BADC, 2016) and observed yield records from the AHDB Recommended List Trials (RLT) (AHDB, 2015b). Figure 3 shows Cambridge, Cambridgeshire (52.20 °N, 0.12 °E) in relation to UK wheat area, met stations with historic long-term daily variables and observed yield records from the RLT and their underlying soil types. Cambridge was selected as the representative site for this study for a number of reasons. Firstly, Cambridge is situated in the intense wheat-producing region of East Anglia. Secondly, the close proximity of met stations to provide daily weather variables from which a long term daily weather record could be assembled. Thirdly, there was a large assembly of yield records (for use in model validation) from the UK AHDB RLT for the period 2001-2015. Finally, the dominant soil series (Evesham 3) for the RLT sites was considered representative of that typically used for wheat cultivation, a slowly permeable calcareous clayey or fine loamy over clayey soil (Cranfield University, 2016).

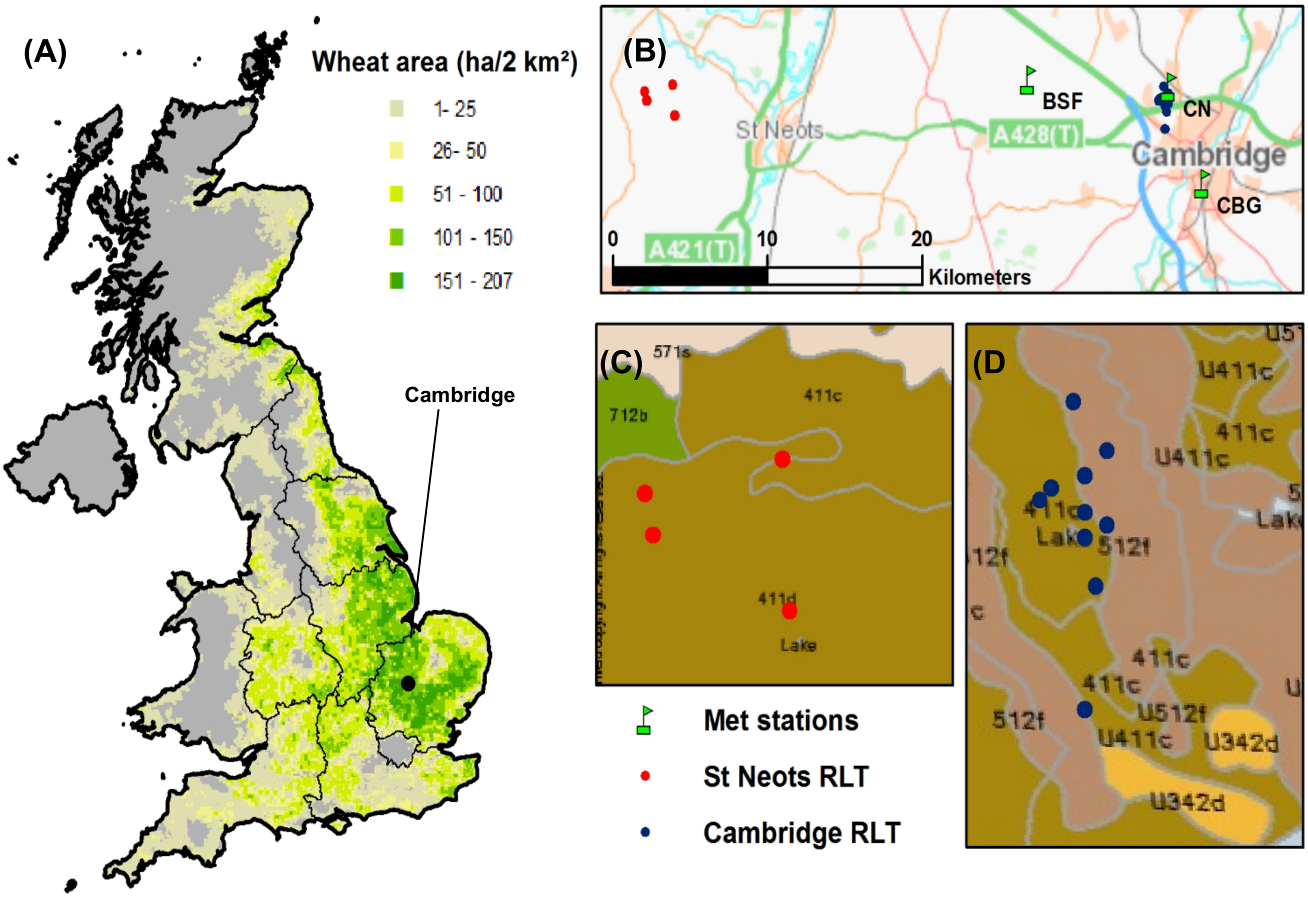


Figure 3 (A) Cambridge in relation to the UK (exc N.Ireland) 2010 wheat cropped area (ha/2 km^2) (EDINA, 2016), **(B) RLT yield records for two sites in Cambridge and near St Neots in relation to Met stations used to compile long term daily climate record. (C) St Neots RLT yields in relation to the locations Soil series, (D) Cambridge RLT yields in relation to the location Soil Series**

2.1.1 Meteorological summary

Cambridge provides a well suited location to investigate the effects of climate variability on UK wheat production due the surrounding high wheat productivity and vulnerability to water stress. The East of England accounted for around 26% of the UK wheat area and production in 2015 (DEFRA, 2015b), making it the largest wheat producing area in the UK. However, East Anglia is the driest region in the UK (Figure 4) with Cambridge receiving, on average less than 580 mm of rain a year (Met Office, 2016). ETo is also considerably higher than precipitation during the summer months (Figure 5). Almost all of the wheat in the UK is rain-fed due to the favourable humid climate and distribution of summer rainfall (El Chami et al., 2015). However yield loss is common place due to insufficient moisture availability (Foulkes, et al., 2007).

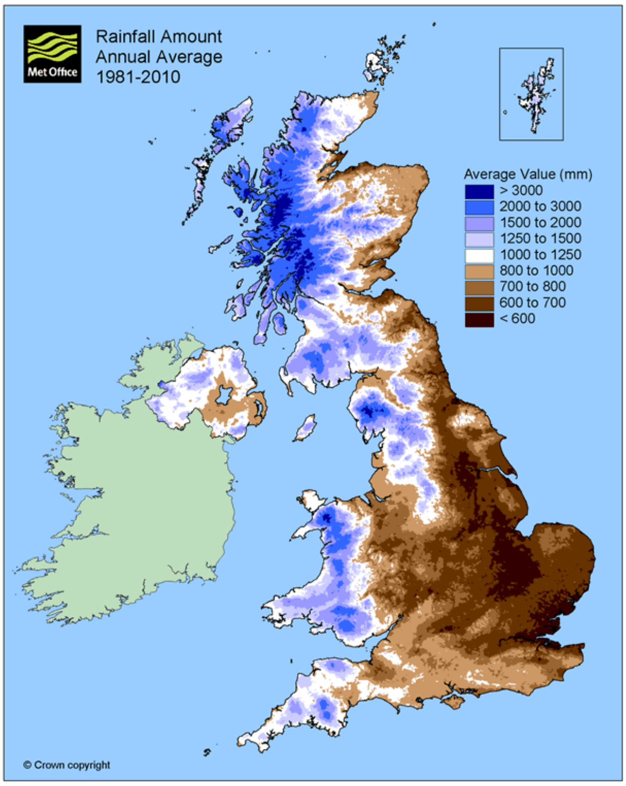


Figure 4 UK Annual averages rainfall (mm) for 1981-2010 (Met Office, 2016)

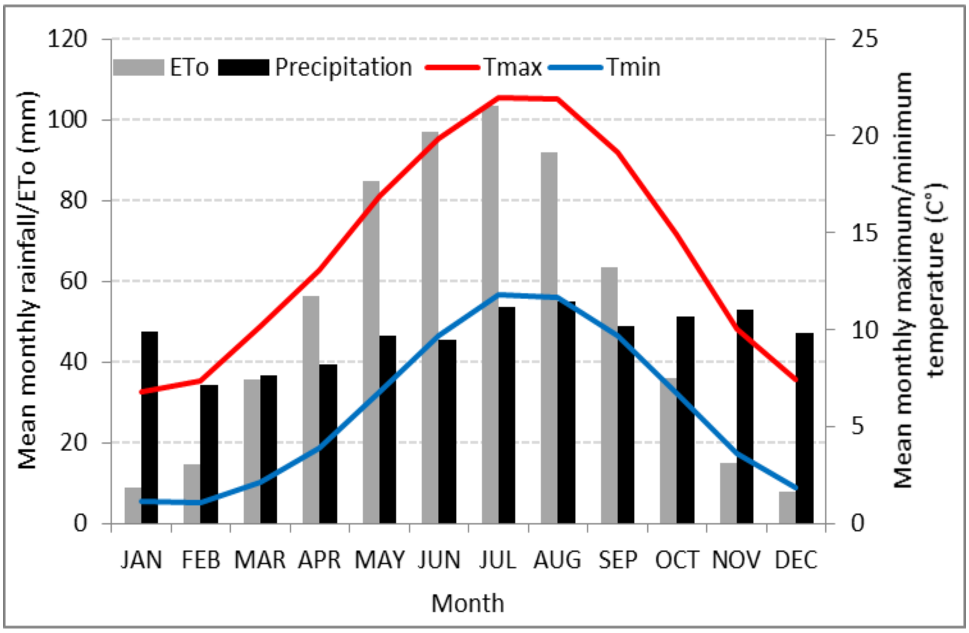


Figure 5 Monthly climate averages for Cambridge (1911-2015)

2.1.2 Long-term climate record

Assessments of historic drought on agriculture require a long period of climate data to provide stochastic stability and ensure sufficient dry years are included (El Chami et al., 2015). The central mechanism for models that attempt to simulate the effects of drought on yields is the calculation of ETo and the depletion of soil water. Sirius typically calculates ETo using the Penman-Monteith method (Richter and Semenov, 2005). The SPEI, PDSI and PSMD drought indices are based on a climatic water balance derived from precipitation and ETo (Vicente-Serrano et al., 2012). The FAO recommends the use of the FAO-56 Penman-Monteith equation for calculating ETo as it provides estimates that are more consistent with actual crop water use data worldwide (Allen et al., 1998). Both methods require measurements of air temperature vapour pressure (VP), solar radiation and wind speed.

A 105 year (1911-2015) daily time-step weather series for Cambridge was compiled from three Met stations from the Met Office Integrated Data Archive System (MIDAS) Land and Marine surface stations data (Met Office, 2012), extracted from the British Atmospheric Data Centre. Cambridge Botanic Garden

(CBG) (Lat: 52.1935, lon:0.13113), Cambridge NIAB (CN) (Lat:52.245, Lon:0.10196) and Boxworth: Samson field (BSF) (Lat:52.2515, Lon:0.03094) (Figure 3 (B) and Figure 6) In addition, a small period of radiation data was received from colleagues at Cambridge NIAB. CN started recording in the late 1950s. To increase the temporal length of the data set daily weather variables were obtained from CBG. To ensure that the data from the two stations can be used in conjunction with each other and do not differ considerably in daily climate measurements a comparison of daily maximum and minimum temperature and precipitation was carried out (Figure 23, Figure 24 and Figure 25 in APPENDICES B). There was no overlapping sun hours data for CN and CBG, however radiation is unlikely to vary considerably over such a small spatial scale (Hess et al., 2015). Data from BSF and Met Office Hadley Centre Central England Temperature data (HadCET) (Parker et al., 1992) was used to patch small periods of missing data. These records also showed a very close correlation with weather data from CN (Figure 26, Figure 27, Figure 28 and Figure 29 in APPENDICES B).

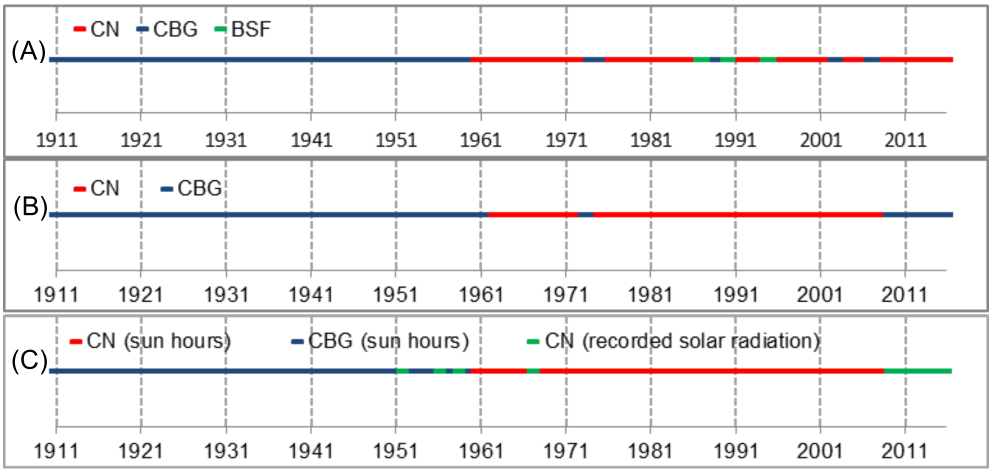


Figure 6 Temporal composite of daily weather records from Cambridge NIAB (CN) , Cambridge Botanic Garden (CBG) and Boxworth Samson Field (BSF) for temperature (A), precipitation (B) and radiation (C)

2.1.2.1 Temperature (°C)

Daily maximum and minimum temperature (C°) were patched from the CN, CBG and BSF met stations (Figure 6). For single days when data was not recorded at either of these stations, the average of day^{+1} and day^{-1} was used. If more than a single day of data was absent the HadCET (Parker et al., 1992) was used to fill in the gaps.

2.1.2.2 Precipitation (mm)

The daily precipitation record was comprised of recorded values from the CBG and CN met stations (Figure 6).

2.1.2.3 Solar radiation (MJ/m^2/day)

A short period (1957-1971) of recorded daily solar radiation (MJ/m^2/day) was available for CN. Sunshine hours however, recorded at CN and CBG spanned the majority of the 1911-2015 period. A record of solar radiation was compiled using the Angstrom formula which relates solar radiation to extra-terrestrial radiation and recorded sunshine hours (Allen et al., 1998) (Equation 1). Where records for sunshine hours were absent recorded, solar radiation (MJ/m^2/day) (1957-1971) was extracted from CN, or through personal communication with colleagues at NIAB, Cambridge (Figure 6).

$$R_S = \left(a_s + b_s \frac{n}{N}\right) R_a \qquad \text{Equation 1}$$

Where

R_s = Solar or shortwave radiation (MJ/m^2/day

n = actual duration of sunshine (hour)

N = maximum possible duration of sunshine/daylight (hour)

n/N = relative sunshine duration

R_a = extra-terrestrial radiation (MJ/m^2/day)

a_s = regression constant, expressing the fraction of extra-terrestrial radiation reaching the earth on overcast days (n=0)

a_s+b_s = fraction of extra-terrestrial radiation reaching the earth on clear days (n-N)

2.1.2.4 Wind (m/s at 2 m)

A record of daily wind speed was not available from the Met office stations around Cambridge for 1911-2015 period. As wind speed cannot be readily estimated from other variables it is recommended the global average of 2 ms^{-1} is used (Allen et al. (1998). However a daily record from 1972-2007 was available from the CN station, therefore daily averages for each month from 1972-2007 were extrapolated across the whole record (1911-2015).

2.1.2.5 Vapour pressure (VP)

With the absence of recorded variables, including relative humidity and dew point temperature, VP was estimated from the daily minimum temperature record (Allen et al., 1998) (Equation 2). To improve the accuracy of the estimated VP from minimum temperature the VP for CN derived from relative humidity (RH) was used to adjust the temperature derived VP. The RMSE was calculated for the years that estimated VP from minimum temperature and VP derived from RH (1972-2007). Using the Excel solver function the estimated VP from minimum temperature was adjusted so that the Relative Root Mean Square Error (RMSE) was minimized. The solver function added 0.103 to the estimated VP daily for the period. The remaining estimated VP (1911-1972 and 2007-2015) values were amended by +0.103.

$$e^{o}(Tmin) = 0.6108\exp\left(\frac{17.27 * (Tmin)}{Tmin + 237.3}\right) \qquad \text{Equation 2}$$

2.1.2.6 Reference evapotranspiration (ETo) (mm d^{-1})

The Sirius wheat model calculates ETo directly from the weather data provided using the Penman-Monteith (PM) method (Richter and Semenov, 2005).The tool used to compute PDSI (Jacobi et al., 2013) also calculates ETo directly using the Hargreaves method (Hargreaves and Samani, 1982). The SPEI and PSMD however require ETo to be externally calculated. For this daily ETo was calculated using the PM method from daily weather values for Cambridge (1911-2015) using the WaSimET program (Hess, 2000). The SPI does not require ETo to be computed.

2.1.3 Observed yield records

Variety trials, if carried out under optimal management and on sufficient plots size are acknowledged as a good source of yield and phenology data (Grassini et al., 2015), and have been previously used for the validation of Sirius (Madgwick et al., 2011). For this study 10,901 observed yield records from the AHDB Recommended List Trials (RLT) (2000-2015)(AHDB, 2016a) from across the UK were obtained. The RLT data provides annual records of sowing date, yield, soil type, trial location (i.e. latitude and longitude), and nitrogen, phosphorus and potassium applications for varieties on the RL at a specific trial site. Trials are often carried out in the same locality for a number of years, providing a series of yield records. A full description of the RLT protocol can be found on the AHDB website (AHDB, 2015b). Two sites, one to the north of Cambridge provided 195 yield records from 57 cultivars and second near St Neots provided 66 yield records from 23 cultivars, for 2000-2011 period. These trials were grown on soils representative of that used in UK wheat production (Table 9).

Table 9 Dominant soil series for the RLT field sites near Cambridge (National Soil Resource Institute, 2016b) **(Figure 3)**

Site	Soil series	Description / Land use	Drought vulnerability
Cambridge	Evesham 3 (411c)	Slowly permeable calcareous clayey, and fine loamy over clayey soils / Winter cereals and grassland	slightly or moderately droughty for cereals
St Neots	Hanslope (411d)	Slowly permeable calcareous clayey soils/ winter cereals with other arable crops, some grassland	slightly deficient for arable crops

2.2 Drought severity indices (DSI)

The SPI, SPEI, PDSI and PSMD were derived from the 1911-2015 daily weather record for Cambridge. The SPI required only monthly precipitation totals (mm), the SPEI; monthly precipitation and ETo totals (mm), the PDSI; monthly precipitation, temperature averages and soil available water capacity (AWC) and the PSMD requiring daily precipitation and ETo (mm). The SPI, SPEI and PDSI were computed using widely established computation programs, with all parameters set to the recommended defaults for each program to allow for an unbiased comparison between each DSI and to represent those typically used.

2.2.1 SPI

The SPI was calculated using an open source SPI program (SPI_SL_6.exe) recommended by the World Meteorological Organisation (WMO), who provide an operational manual (WMO, 2012). The program has been employed in a number of previous studies (Dabrowski et al. 2014; Vijaya Kumar et al. 2013; Kgosikoma & Batisani 2014; Pratoomchai et al. 2015) and can be downloaded from http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx. The SPI was calculated at time steps from 1-12 months from monthly precipitation totals.

2.2.2 SPEI

Using monthly precipitation and ETo values from the Cambridge (1911-2015) data set SPEI values at time steps from 1-12 months were calculated within the R package SPEI (Beguería and Vicente-Serrano, 2013). This is a widely employed method of computing SPEI (Levesque et al. 2013; Dorman et al. 2015; Marcos et al. 2015 and Potopová et al. 2015) designed by the developers of SPEI (Vincente-Serrano et al., 2010). The R Package allows users to define parameters that best fit their specific use. The choice of three probability distributions (Log-Logistic, Gamma and Pearsons III) is provided. The recommended Log-Logistic was selected for this study. Users are required to select from three distribution functions (unbiased probability weighted moment, plotting position and maximum likelihood); again, the recommended unbiased probability weighted moment was selected. Different kernel functions allow previous time steps to be allocated different weights (rectangular, triangular, circular and Gaussian) the default rectangular kernel function was selected, therefore the highest weight will be given to the observation of the current month.

2.2.3 PDSI

Most of the studies that use the PDSI do not provide methods of calculation, making it difficult to compute PDSI independently. Furthermore the various computer codes available for calculating PDSI lack transparency and ease of use (Jacobi et al., 2013). To overcome these concerns Jacobi et al. (2013) present an easy to use, well documented and transparent MATLAB tool for calculating monthly PDSI at any spatial scale and location. Since its publication Jacobi et al.(2013) this tool has been extensively applied in drought studies (Gunda et al. 2016; von Freyberg et al. 2015 and Hess et al. 2016). The tool uses the Thornthwaite (1948) method of calculating evapotranspiration requiring mean monthly temperature and precipitation averages in addition to the latitude of the weather station. The PDSI factors in the water content of the soil into its water balance equations, requiring AWC to be entered. The AWC for the Evesham 3 soils series at the Cambridge trial sites was used (150 mm/m) derived from the Soil Series Horizon Hydraulic Data set from NATMAP (Hollis et al. 2015). The full weather record was used to calculate the "Climatologically Appropriate for Existing conditions'' calibration. It is recognised that using different ETo calculation methods such as Thornthwaite (PDSI) and Penman-Monteith (SPEI and PSMD) is likely to cause variations in the ETo used to calculate the DSI. Although it is accepted that some methods provide better results than others in estimating ETo (Droogers and Allen, 2002) Vincente-Serrano et al., (2010) report that the use of ETo in DSI is to obtain a relative temporal estimation, and therefore the method used in calculation is not critical.

2.2.4 PSMD

Growing season ($PSMD_{Max}$) and monthly ($PSMD_{Month}$) maximum potential soil moisture deficit (PSMD) were calculated from the daily climate record (Equation 3).

$$PSMD_i = PSMD_{i-1} + ETo_i - P_i \qquad \text{Equation 3}$$

Where

$PSMD_i$ = potential soil moisture deficit at the end of month *i, mm*

$PSMD_{i-1}$ = potential soil moisture deficit at the end of the month *i*-1, mm

ETo_i = Potential evapotranspiration in month *i*, mm

P_i = Precipitation in month *i*, mm

At the start of each growing season (October) the PSMD is assumed to be zero. If the PSMD reaches a point less than zero, for example after heavy rains, any previous moisture deficit is assumed to be filled and excess precipitation is assumed lost as runoff or deep percolation (PSMD is reset to zero) (Rodriguez-

Diaz et al., 2007). In addition to calculating the seasonal maximum PSMD ($PSMD_{Max}$) the maximum soil moisture deficit for each month within the season was calculated ($PSMD_{OCT}$, $PSMD_{NOV}$, $PSMD_{DEC}$, $PSMD_{JAN}$, $PSMD_{FEB}$, $PSMD_{APR}$, $PSMD_{MAY}$, $PSMD_{JUN}$, $PSMD_{JUL}$ and $PSMD_{AUG}$). Figure 7 shows the evolution of the PSMD through a growing season with the $PSMD_{Max}$ and maximum PSMD for an example month (May) ($PSMD_{MAY}$) shown.

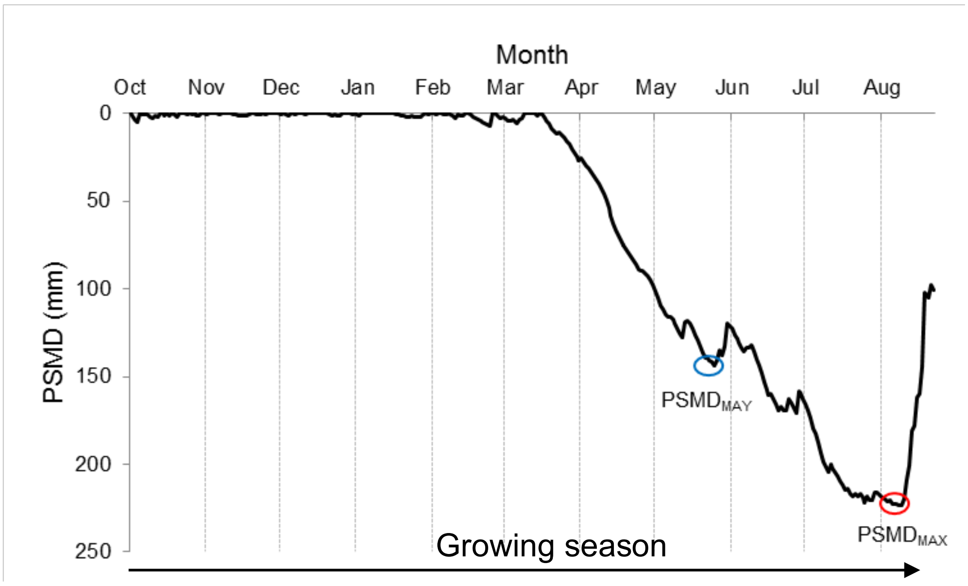


Figure 7 Evolution of the PSMD through a growing season with the $PSMD_{max}$ for the entire growing season and the maximum PSMD for May ($PSMD_{MAY}$) is highlighted.

2.2.5 DSI synthesis

The results from the various DSI analyses were synthesised to produce a complete drought indices record for Cambridge from 1912 to 2015. The use of all four DSI in drought identification allows for comparison of each DSI to be included. The SPI and SPEI are multi-scalar therefore can identify drought on different time scales, this temporal versatility makes it easier to identify the onset and cessation of droughts (Lloyd-Hughes and Saunders, 2002). Despite this, the PDSI offers the useful feature of taking into account the AWC of the soil at the defined location.

Table 10 shows the time steps of each DSI used in drought identification in relation to typical winter wheat development in the UK. The PDSI relates to a fixed temporal scale (between 9 and 12 months) (Vincente-Serrano et al., 2010). Guttman (1998) report the SPI best correlates with the PDSI on a 9 month scale. The SPI-9, SPEI-9 and the PDSI for August (harvest month) were used as an indicator of drought affecting the crop from December (early tillering) to August (harvest). This period includes half of the foundation, the entire construction and production phases of wheat growth in the UK. The SPI-6 and SPEI-6 for August provide an indicator of drought for the entire construction and production stages

Table 10 Crop development phases and growth stages using the Decimal Code System for measuring wheat growth (Tottman and Broad, 1987) **with timings and diagrams for a benchmark winter wheat crop in the UK** (AHDB, 2015a) **and the temporal span of each DSI at a given scale for the harvest month (August), PSMD$_{Max}$**

Growth Stage	GS0-12	GS13	GS20-29	GS30	GS31	GS39	GS59	GS61	GS71	GS87	GS93
Description	Sowing, emergence and 2 leaves unfolded	3 leaves unfolded	Tillering	Stem elongation	First node detectable	Flag leaf blade all visible	Ear completely emerged above flag leaf ligule	Start of flowering (anthesis)	Grain watery complete	Hard dough	Harvest
Timing	October to middle November	Late November	Late November to late March/ early April	Late March/ Early April	Early/ middle April	Middle/ late May	Early June	Early/ middle June	Middle/ late June	Late July	Early/ middle August
SPI/SPEI-9											
PDSI											
SPI/SPEI-6											
SPI/SPEI-3											
PSMD$_{MAX}$											

(March-August). The SPI-3 and SPEI-3 for August identifies of droughts that have occurred over the production phase (June-August) incorporating drought sensitive growth stages such as anthesis and grain filling (AHDB, 2015a).

The PDSI uses a different classification system to the SPI and SPEI (Section 1.2.2). However, the three upper most drought classifications use the same terminology, ‘extreme’, ‘severe’ and ‘moderate’ drought. The reported occurrence rates of each DSI do differ slightly (see section 1.2.2). In a study across Europe, however, it is reported that the mean number of extreme and moderate droughts for the SPI and PDSI (1901-1999) on a 0.5° grid is of near equivalence on a 9 to 12 month lag. The SPI-9 and PDSI were reported to experience 9 and 8 extreme droughts on average respectively and 30 and 26 moderate droughts respectively (Lloyd-Hughes and Saunders, 2002). Therefore, in this study it was assumed that the PDSI, SPI-9 and SPEI-9 will not differ substantially for the amount of droughts in each category. Allowing direct comparison to how years are classified by each DSI. The classification of ‘moderate’ drought has been used as the baseline classification in recognising drought for all DSI. The less severe categories of the PDSI (‘incipient’ and ‘mild’ drought) were not identified as drought years. It is recognised that the SPI, PDSI and SPEI have been calculated in independently unrelated programs therefore their distributions and frequencies of classification are likely to differ, but not to the point that a single DSI will be considerably over represented in the synthesis.

2.3 Sirius crop modelling

2.3.1 Description

The Sirius wheat simulation model (Jamieson et al., 1998) was selected to assess the impacts of drought on winter wheat. The model simulates biomass production from intercepted photosynthetically active radiation and radiation use efficiency. Leaf area index (LAI) is established from a thermal time sub model, with phenological development being calculated from mainstream leaf appearance rate and final leaf number. Water and nitrogen limitations are simulated through their effects on leaf area index (LAI) development and radiation use efficiency (Jamieson et al., 1998b). Sirius provides outputs for potential (PO) and water limited (WL) yield. PO yield is calculated by assuming the crop has sufficient water availability to maximise yield. Annual variations in PO yield are a product of temperature and radiation. The WL yield is defined as “the expected losses in simulated grain yield due to water stress’’ (Semenov et al., 2009). Sirius has been previously validated and demonstrated to accurately simulate grain yields in a wide range of countries and environments including Bulgaria (Ewert et al., 2002), New Zealand, USA (Jamieson and Semenov, 2000) and the UK (Semenov 2009, Jamieson & Semenov 2000). Sirius is of medium to intermediate complexity making it suitable for research, and is free to download: http://www.rothamsted.ac.uk/mas-models/sirius.

2.3.2 Model parameterisation

2.3.2.1 Cultivar parameters

Sirius requires a set of cultivar-specific parameters that determine which variety of wheat is simulated (Table 11). Although Sirius is of intermediate complexity, often there are difficulties in measuring many of the cultivar parameters (Brooks et al., 2001). This can be attributed to limited experimental data. Crop systems experimentation is time consuming and requires land, equipment and man power (Wallach et al., 2006). Due to time constraint of this study it was not possible to perform the necessary experiments to obtain the parameters required to calibrate Sirius with some of the most widely grown cultivars such as cv. JB Diego (10.2%), cv. Skyfall (8%) and cv. Revelation (6.3%) (*Pers. Comm 1*). The data required to parameterise a cultivar appears not to be readily available from the information gathered by breeders or the information provided in the AHDB RLT data.

The parameters for the *cv.* Claire were selected (Table 11). It is the only cultivar that is on the 2016/17 AHDB Recommended List that has been previously calibrated in Sirius. Claire is popular group 3 wheat grown on 2% of the UK wheat area (*pers. Comm 1*). It has been on the RL since 1999 making it the oldest

Table 11 Cultivar parameters required in Sirius and values used previously to calibrate cv. Claire, provided in the Sirius download (Rothamsted Research, 2016)

Cultivar Parameter	Values for cv. Claire
Thermal time from sowing to emergence	150
Thermal time from anthesis to beginning of grain fill	100
Thermal time begging of grain fill to end of grain fill	650
Thermal time end grain fill to harvest maturity	200
Potential maximum leaf size	0.007
Phyllochron in degree days	110
Minimum possible leaf number	8
Absolute maximum leaf number	18
Day length response in leaves per hour of day length	0.5
Response of vernalisation rate to temperature	0.0012
Vernalisation rate (1/days) at 0 C°	0.012
PAR extinction coefficient	0.7
Max protein concentration (% at 15% grain moisture)	15

variety on the RL and remains the benchmark for group 3 wheats (AHDB, 2016b). It is important to note that there are limitations in using Claire. Its popularity amongst growers is less than that of other cultivars such as the *cv.* Skyfall and *cv.* JB Diego. However, varieties have an increasingly short lifespan, with new varieties being registered each year. It is therefore impossible to identify cultivars that are likely to be extensively grown in subsequent years (Wallach et al., 2006). Although *cv.* Skyfall and cv. JB Diego are currently popular, there is no evidence to suggest they will remain leading cultivars. The yield average for *cv.* Claire in the RLT is also lower than for some more modern cultivars (Table 12). Despite this, the AHDB identifies several reasons why varieties are removed from the RL including non-competitive yields, increased susceptibility to disease, and no longer meeting the requirements of the end user or insufficient market share (AHDB, 2016c). Since *cv.* Claire remains on the RL it is still comparable to other, more modern wheat cultivars.

Table 12 Reported yields of *cv.* Claire compared to most popular cultivars taken from the most recent recommended lists, Control is calculated by selecting a number of established varieties from each years trials and the average UK yield of these varieties is set to 100% (AHDB, 2016a)

	% of control				
Recommended List	**Claire**	**Skyfall**	**JB Diego**	**Revelation**	**Control (t/ha)**
2014/2015	97	102	102	103	9.9
2015/2016	98	102	102	103	10
2016/2017	98	101	102	101	10.4

cv. Claire is the oldest cultivar on the RL meaning there is considerably more yield data (16 years) compared to more modern cultivars such as *cv*. Skyfall (3 years), *cv*. JB Diego (9 years) and *cv.* Revelation (4 years). The cultivar parameters for *cv.* Claire have been used in a number of studies simulating wheat yields in Sirius. Semenov & Stratonovitch (2013) optimised the parameters for *cv.* Claire for climate change scenario, in addition they compared these optimised ideotypes to that of the modern *cv.* Claire. Madgwick et al. (2011) did not use *cv*. Claire, however they refer to it being a cultivar that is on the UK RL and has been calibrated for Sirius. Jamieson et al. (2007) reported that correlations between observed and simulated duration from sowing to anthesis for the wheat *cv.* Claire at Lincoln, New Zealand in Sirius was very high (r=0.996). Semenov et al. (2014) compared the anthesis and maturity dates, and grain yields of cv. Claire at Edinburgh, UK, Wageningen, Netherlands and Mannheim Germany with future wheat ideotypes created using an evolutionary algorithm to optimize ideotypes for future climatic conditions. It is recommended that the parameters for Claire are used for European winter wheats in the Sirius download package.

Claire provides a suitable cultivar to examine the impacts of drought on UK wheat production for a number of reasons. Firstly, given the time constraints of this study and apparent lack of sufficient data from other experimental studies make it difficult to parameterise a modern cultivar. Secondly, there is no guarantee that a newly calibrated cultivar will provide an accurate representation of UK wheat in near future. Thirdly, the availability of extensive validation data for Claire improves the validation procedure. Finally, *cv.* Claire has been previously calibrated and validated in a number of locations and climates.

2.3.2.2 Climate and location parameters

Sirius requires location data and daily precipitation, maximum and minimum temperature, wind speed and vapour pressure. Location parameters were defined for the CN station (lat. 52.25; long. 0.10; Alt 26 m). Daily maximum and minimum temperature (C°), precipitation (mm), wind run and vapour pressure (m-bar) for 1999-2006 were extracted from the 1911-2015 Cambridge climate record. CO_2 concentration (ppm) was set according to the NOAA globally averaged marine surface annual mean (Dlugookencky and Tans, 2016) for the year of sowing (Table 15).

2.3.2.3 Evesham 3 soil parameters

Sirius requires soil parameters for; saturation water content (soil porosity), drained upper and lower limits at different depths, a percolation coefficient and a variety of parameters on the distribution and accumulation of nitrogen within the soil. With the exception of the percolation coefficient and nitrogen related parameters all the necessary parameters for UK soils were obtained from the National Soil Map (NATMAP) using the dominant soil series at the point of interest (as recommended by Semenov, 2009). The Evesham 3 soil series (Table 9 and Figure 3) was selected as the dominant soil type as it is that featured at the site of RLT yields at site to the north of Cambridge, close to the met stations used. The Handslope soil series featured at the additional site near St Neots is a very similar calcareous clayey soil type with similar drought classification (Table 9 and Figure 3). Therefore, it was decided to use the same soil parameters (Evesham 3) for all the selected observed yield records.

The soil profile depth intervals and corresponding values for saturation moisture content, drained lower limit and were taken directly from the Soil Series Horizon

Hydraulics Data (National Soil Resource Institute, 2016a) for the Evesham 3 soil series. Sirius requires field capacity to be expressed at 33 kPa. However, the Soil Series Horizon Hydraulics data (National Soil Resource Institute, 2016a) only provides volumetric water content at -1, 5, 10, 40, 200 and 1500 kPa. In addition, there is no corresponding pedotransfer function defined by Hollis et al. (2015) (the pedotransfer functions used to construct the Soil Series Horizon Hydraulics data set). Addiscott & Whitmore (1991) report however, there is likely to be only a small difference between the values at 0.33kPa and 0.40kPa, therefore the latter was used. The percolation coefficient was estimated using the nonlinear regression relationship for British soils from clay content (%) (Table 13) derived in Addiscott & Whitmore (1991) used by Semenov (2009);

If % Clay ≤9.5 percolation coefficient = 1.0

If % Clay 9.5-58.3 percolation coefficient = 1.0271-0.000302 $(\% \text{ Clay})^2$

If % Clay is ≥58.3 percolation coefficient =0.0

Clay (%) content for the Evesham 3 soil series was acquired from the Soil series Horizon Summary Data set (National Soil Resource Institute, 2016a). The average clay content for the horizons under 1m was used by Addiscott and Whitmore (1991), therefore the average of the 0-75cm depth horizons were used to calculate the average for clay content to derive percolation coefficient for Evesham 3.

Table 13 Calculation of percolation coefficient using nonlinear regression relationship for British soils (Addiscott and Whitmore, 1991)

Percolation coefficient		
Clay (%) Evesham 3 (average 0-75cm)	=	54.3
1.0271-0.000302*(54.3)^2	=	0.135
Percolation coefficient	=	0.14

The RL trial yields used in the validation follow the guidelines that "Nitrogen applications should be tailored to give maximum yield" (AHDB, 2015b). As this study is an investigation into the effects climate has on wheat production (not fertiliser application) and all yields used in validation are assumed not to suffer any nitrogen deficiency all simulations were carried out without nitrogen limitation, therefore all soil parameters relating to nitrogen did not require specification. Table 14 shows the soil parameters used in Sirius for the Evesham 3 soil series in validation.

Table 14 Soil parameters required in Sirius for the Evesham 3 soil series (National Soil Resource Institute, 2016a)

Soil parameter	Evesham 3 depth (m)			
	0.25	**0.50**	**0.75**	**1.50**
Saturation moisture content vol% (soil porosity)	55.9	53.6	49.9	48.8
Drained Upper limit vol% at 33 kPa tension	41.4	46.5	43.2	42
Lower limit vol% at 1500 kPa tension (wilting point)	26.8	34.8	32.5	31.7
Percolation coefficient	0.14			
Available water Capacity	169			
Maximum rooting depth (cm)	150			

2.3.2.4 Management parameters

Sirius allows users to define management practices regarding nitrogen application, irrigation and sowing date. Since only a tiny proportion of wheat is irrigated in the UK, the wheat crop simulated in Sirius model was assumed to be rainfed. All RL trials are designed not to induce nitrogen deficiency, therefore Sirius was set to assume the crop has sufficient nitrogen to maximise yield. Sowing date was defined according to the RLT data.

2.3.3 Model validation

2.3.3.1 Observed yield records

Ten yield records for the *cv*. Claire for a site north of Cambridge were available in the RLT data. Four of these were defined as being grown on a 'medium' soil type, one on 'deep silt' and five on 'deep clay' according to the Defra (2010) classification system (Table 24, In Appendix C). Using the Soil Site Reporter (National Soil Resource Institute, 2016b) the principal soil series for the area including the RL trials was Evesham 3. This constitutes a slowly permeable calcareous clayey and fine loamy over clayey soils, some slowly permeable seasonally waterlogged non-calcareous clayey soils. As the description of 'deep silt' and 'medium' soils (DEFRA, 2010b) do not match the description of the Evesham 3 soil series, they were discarded from the validation data set. To extend the validation procedure four additional 'deep clay' yield records <40km (near St Neots) east of Cambridge were added (Table 15). It is recognised that the spatial distance between the climate record and the St Neots yield records has the potential to affect the accuracy of simulated yields, as simulations may experience weather that was not experienced by the crop. Despite this Hess et al (2016) report that in the month of maximum ETo (July) mean absolute deviation from the median is generally low in Eastern, Central and Southern England (all lowland areas). In addition, monthly precipitation values (1930-1949) for St Neots met station did not differ substantially to that of CB (Figure 30, Figure 30 APPENDICES B).

2.3.3.2 Model validation

The Sirius model validation involved simulating WL yields for *cv.* Claire with Evesham 3 soil parameters at an altitude of 26m. For each simulated year sowing date was matched to the RLT and CO_2 levels adjusted (Table 15). Nine years (5 at Cambridge and 4 at St Neots) of simulated yields compared to the observed yields to assess model performance. There are a number of methods that can be used to compare simulated and observed data. As there is no single definitive method, it is good practice to use a number of methods (Wallach et al., 2006). Five methods of evaluation were used Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Relative Root Mean Square Error (RRMSE) and the square of the Pearson product moment correlation coefficient (R^2). The methods were selected to complement each other, seeking to provide a thorough evaluation of the Sirius model performance.

Table 15 Sowing date, yield, location (AHDB, 2016a) **and atmospheric CO_2** (Dlugookencky and Tans, 2016) **for the Cambridge and St Neots observed used in the validation procedure**

Site	Trial year	Sowing date	Observed Yield (t ha^{-1})	Lat/Long	Atmospheric CO_2 (ppm)
Cambridge	2000	12/10/1999	9.99	52.239/0.09304	368
Cambridge	2001	20/10/2000	10.13	52.23618/0.10023	369
Cambridge	2004	01/10/2003	10.68	52.23533/0.09726	375
Cambridge	2005	09/10/2004	10.44	52.24157/0.10048	377
Cambridge	2006	04/10/2005	9.04	52.23713/0.09734	379
St Neots	2003	11/12/2002	8.54	52.25024/-0.39433	372
St Neots	2004	17/10/2003	9.98	52.23727/-0.36697	375
St Neots	2005	05/11/2004	8.78	52.25347/-0.36784	377
St Neots	2006	19/10/2005	11.81	52.24573/-0.39303	379

Jacovides and Kontoyiannis (1995) recommend the use of the MBE (Equation 4) and the RMSE (Equation 5) for model evaluation. The MBE returns the average difference between the simulated and observed yields. Explaining how much a model is over-predicting (positive) or under-predicting (negative) yields. A MBE close to zero would imply that the model is estimating yields well; however it could equally be a result of large over and under predictions cancelling each other out (Wallach et al., 2006). The RMSE can be employed to eliminate the problem of compensation between over- and under- predictions. By squaring the error all numbers are returned positive. However because the RMSE uses the average of the squared differences, large differences are weighted more heavily. The Mean Absolute Error (MAE, Equation 6) which by definition averages the absolute errors (all errors are positive) can overcome the over-weighting of large differences (Wallach et al., 2006). The RRMSE (Equation 7 and Equation 8), is obtained by dividing the RMSE by the mean of the recorded yields, returning a percentage. This allows a comparison between different data sets and validation results (Wallach et al., 2006). As the RRMSE is a uniform scale, Jamieson (1991) provide boundaries that allows users to objectify the performance of a model: RRMSE <10% = excellent, 10-20% = good, 20-30% = fair and >30% = Poor. The R^2, (Equation 9) is the Square of the Pearson's product moment correlation of simulated and recorded yield. This can be interpreted as how well a model explains variation in yield.

$$MBE = \frac{1}{N}\sum_{i=1}^{n} D_i$$ Equation 4

$$RMSE = \sqrt{MSE}$$ Equation 5

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |Di|$$ Equation 6

$$RRMSE = \frac{RMSE}{\bar{y}}$$ Equation 7

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} \frac{\left|Y_i - \hat{Y}_i\right|}{|Y_i|}$$ Equation 8

$$R^2 = (\frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}})^2$$ Equation 9

2.3.4 Sirius yield simulation

Water limited (WL) and potential (PO) modelled yields for 104 years (1912-1915) for Cambridge using the validated Evesham 3 soil parameters were simulated using the Sirius model. Simulations used cultivar parameters for *cv.* Claire, location parameters for the CN met station, and a typical sowing date for England and Wales (10th October) (Semenov, 2009). Atmospheric CO_2 levels were set to the 2015 global average (399 ppm) (Dlugookencky and Tans, 2016). The use of the same cultivar, sowing date, soil series parameters and CO_2 ensures only modelled variations in climate affect annual yields, bias due to non-climatic factors such as fertilizer application, cultivar change, improved technology, tiller practices and weed control found in long term recorded yields (Potopová et al., 2015b) is removed.

2.3.5 Sensitivity analysis

A sensitivity analysis was performed to investigate the relative impacts of soil parameters on yield. This was done by reducing maximum soil profile depth at 10cm intervals from 1.5 m to 0.7m, and as a consequence reducing the root zone AWC. Simulations were run with a maximum (1) and minimum (0.0) Percolation coefficient. The results corresponded with other studies that reported fluctuations in AWC resulted in variations in simulated yields in England (Lawless et al. 2008). Therefore, using a GIS, gridded wheat area (ha per 2km^2) data for England and Wales was overlaid with a 2km gridded soil data set (average crop non specific available water capacity (AWC)) (NATMAP, 2016) to estimate the split between wheat area and AWC for England and Wales (Figure 8). Crop nonspecific AWC is defined as the water available to the soil between 5 and 1500 kPA to 1 m (Hall et al., 1977).

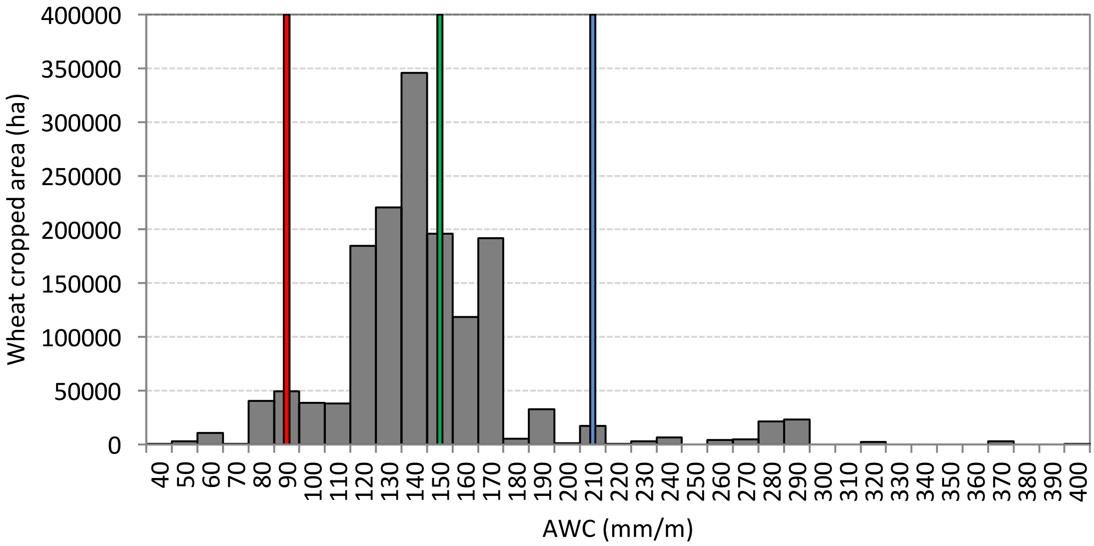


Figure 8 Total wheat cropped area (ha) (EDINA, 2016) **by available water capacity (mm /m)**(NATMAP, 2016)**. Red line represents low AWC soil series (Badsey), the green line represents the medium AWC soil series (Evesham 3) and the blue line represents a high AWC soil series (Hanworth)**

The majority (88%) of wheat grown in England and Wales is cultivated on soils with a crop nonspecific AWC between 95-215 mm/m (Figure 9). The validated Evesham 3 soil series placed in the middle of this range with an AWC of 150 mm/m making it a suitable soil series for yield simulations on a medium AWC. Two additional soil series, Badsey and Hanworth, were selected to represent soils with high and low AWC, respectively (Figure 8 and Figure 9). As well as the physical structure of the soil (texture and organic matter content) affecting AWC, a shallow rooting depth or impeding layer and stone content can reduce water availability to the crop (Lucas et al., 2000). Barraclough & Weir (1988) reported that typically the rooting depth in a compacted light sandy loam soil reached a maximum of 1m at anthesis, compared to 1.4m in an unimpeded soil. Therefore in addition to simulations assuming a representative low, medium and High AWC soil. A deep (1.5m) and shallow (1m) profile for each soil series was also included.

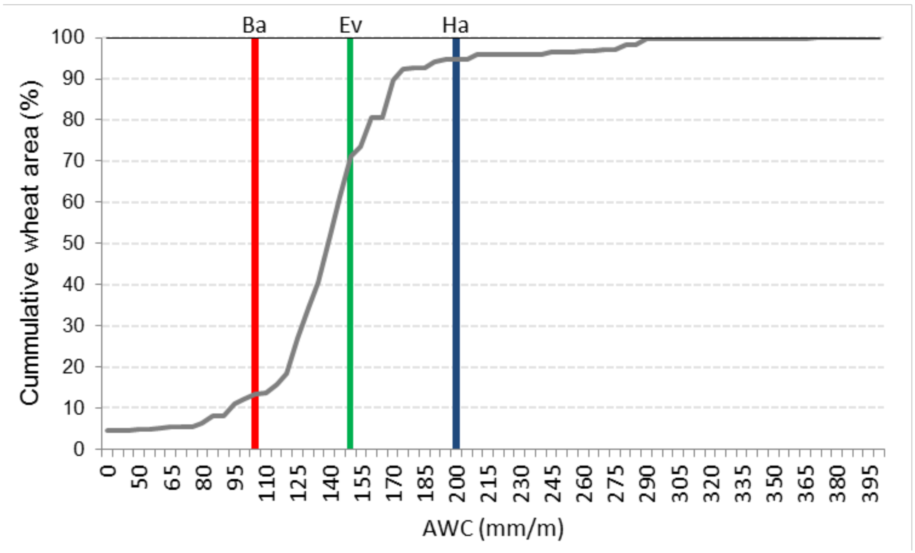


Figure 9 Cummulative wheat area (%) (EDINA, 2016) **correlated against soil AWC, with the three representative soil series highlighted, Badsey (Ba), Evesham 3 (Ev) and Hanworth (Ha)**

The soil parameters required in Sirius for each soil series were extracted from the National Soil Resource Institute (2016a) and NATMAP (2016). WL yields were then simulated for 3 different AWC soils (low, medium and high AWC) on 1m and 1.5m deep soils, (Table 16). It is important to note that the Badsey and Hanworth soil series have high percolation coefficents which is likely to increase their drought risk as water is lost through the soil profile at a quicker rate.

Table 16 Soil AWC, and percolation coefficients for the three representative soil series

Soil Parameter	Badsey	Evesham 3	Hanworth
Crop nonspecific AWC $_{(mm/m)}$	105	150	190
Percolation Coefficient	0.98	0.14	1

2.4 Correlating simulated yield with drought severity

The relationship between DSI and simulated yield was assessed using the non-parametric Spearman’s Rho coefficient with a significant threshold of *p<0.05*, a method similar to that employed for agricultural yields and SPEI in the Czech Republic by Potopová et al. (2015). The simulated WL yields (t ha^{-1}) were ranked in ascending order. This was repeated for the DSI values at the various time steps (e.g. SPI/SPEI 1-12 month lags) for each month of the growing season. For example the lowest value (indicating drought) for the SPI-1 for January was ranked, 1, the wettest, 104. This was repeated for each month for all monthly time steps (1-12 months). The Spearman's Rho coefficient was then applied to the ranked yield data and drought indices at various time steps for each month in the respective growing season.

3 Results

3.1 DSI analysis

Table 17 shows the Spearman's rho correlation coefficients (r) between the SPI-9, SPEI-9 and the PDSI for August and $PSMD_{Max}$ (1912-2015). The SPI and the SPEI (0.92) show the strongest correlation, the SPI and the $PSMD_{Max}$ show the weakest (0.70). The PDSI shows similar levels of correlation with the SPEI, SPI and $PSMD_{Max}$ (0.81, 0.78 and 0.77, respectively). Although the DSI show good agreement between each other the correlation coefficients suggest there may be variations in how individual DSI categorise the weather for a specific time period. Therefore, the drought analysis has been undertaken using the results from all four DSI.

Table 17 Spearman's Rho Correlation Coefficient between DSI index values for the SPI-9, SPEI-9 and PDSI for August and the $PSMD_{Max}$

	SPEI	SPI	PSMD	PDSI
SPEI		0.92	0.84	0.81
SPI	0.92		0.70	0.78
PSMD	0.84	0.70		0.77
PDSI	0.81	0.78	0.77	

Figure 10 shows the SPI 9, SPEI 9 and the PDSI for August (harvest) along with the $PSMD_{Max}$ values for the winter wheat growing seasons 1912-2015. Droughts are identified at varying magnitudes by all four DSI. The majority of the major droughts reported in the UK (Cole and Marsh, 2006a) are recognised by the DSI (i.e. 1921, 1934 and 1976). Droughts such as 1921 and 1934 whose impacts are less well understood are evident in all DSI, allowing this study to simulate the potential impact of these historic droughts on a modern wheat production system. Previously reported droughts that do not appear to manifest over the majority of a winter wheat growing season include 1959 and 1983-1984.

The extent of the UK seasonal variability in weather is clearly observed (Figure 10), an example being the significant drought during the 2011 season followed by a significantly wet season in 2012. In contrast, there are episodes where drought years are clustered, the most prominent during the early 1940s, where, using the SPEI and PDSI as an example 1940, 1942, 1943, 1944 and 1945 are all identified as drought years (Figure 10). The 1921 and 1976 droughts are the most prominent regarding the SPI-9, SPEI-9, PDSI for August and the $PSMD_{Max.}$

Table 18 provides a synthesis of the DSI results for the SPI 9, SPI 6, SPI 3, SPEI 9, SPEI 6, SPEI 3, and PDSI for August (harvest) and $PSMD_{Max}$ for Cambridge. For the years featured, one or more of the SPI-3/6/9, SPEI-3/6/9 or PDSI have identified a 'moderate' drought in August. The occurrence (%) of each drought classification for each DSI is also shown at the bottom of Table 18 and whether a drought for that year was reported in the literature.

Despite the humid climate, droughts frequently manifest themselves at different scales during the growing season. One or more of the SPI 9, 6, 3, SPEI 9, 6, 3 or the PDSI identified the occurrence of a 'moderate' drought episode in 30 of the 104-years (1911-2015) at Cambridge (Table 18). For a large proportion of years, the DSI can be described as being in agreement with each other. The 1921 season is identified as an 'extreme' drought by all the DSI on all time steps. This is also true for 1976 with the exception of the SPI 3. The 2011 drought is also categorised as 'severe' drought by all the DSI at a 9 and 6-month time step and no drought on the 3 month time step. Despite this documented agreement between DSI, there are seasons where the DSI classifications differ markedly. For example, for 1972 and 1990 on a 9 month time step the years can be categorized as either severe', 'moderate' or 'no' drought depending on the choice of DSI. The DSI analysis (Table 18) demonstrates variations in the temporal extent of droughts affecting wheat. The droughts of 1921 and 1976 are classified as 'extreme' regardless of the time step (with the exception of SPI 3, 1976). This is not the case for 1975, 1983 and 1994. The majority of the DSI at the 9 and 6-month time steps do not identify a drought event for these years. They do however; identify a 'severe', 'moderate' and 'severe/extreme' drought respectively for the SPI 3 and SPEI 3. A number of years demonstrate an opposing trend, for example, 1944/45, 1973 and 2011 are not identified as drought years by SPI 3 and SPEI 3, however, the weather for the majority of the growing season (SPI 9, SPEI 9 and PDSI) is classified as a drought year.

The DSI also identify a number of droughts that have not been previously identified in the literature. For example 1935, 1940, 1942, 1952, 1957, 1961 and 2000 are all identified as ‘moderate’ droughts by one or more of the DSI. The 1994 season is classified as an ‘extreme’ (SPI 3) and ‘severe’ (SPEI 3) drought over the production phase. The literature however often identifies the drought periods of 1995-1997 and 1990-1992 but no study identifies the significant drought experienced during the summer of 1994.

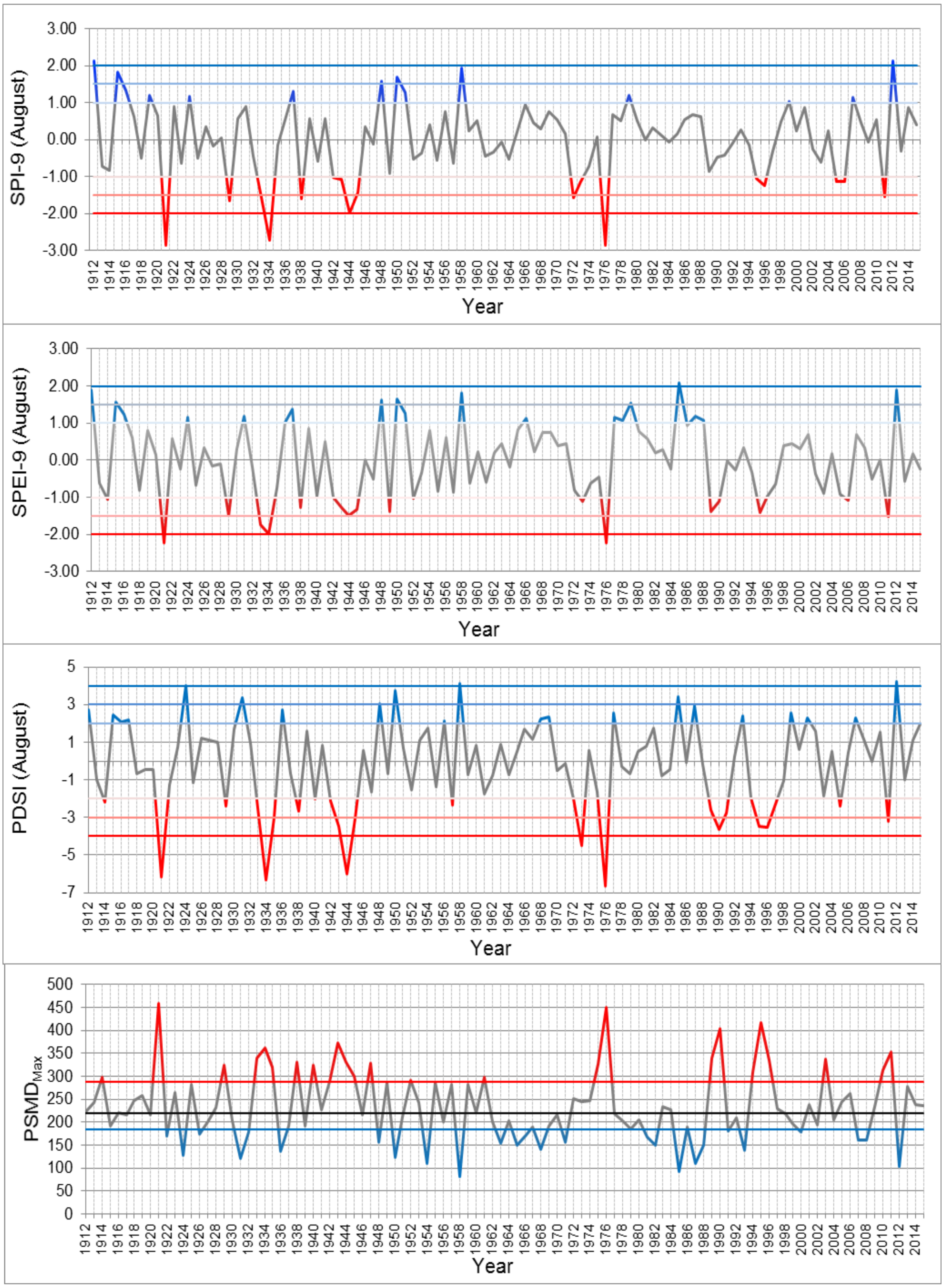


Figure 10 Annual time series plot of the SPI-9 (A), SPEI-9 (B) and PDSI (C) for August (harvest month) and the growing season $PSMD_{MAX}$ (D) (1912-2015). For the SPI and SPEI the coloured lines represent different drought/wetness classifications in Table 5, for the PDSI the lines indicate the classifications in (reference figure). The PSMD marked by the average (black line), 25^{th} percentile (blue line) and 75^{th} percentile (red line)

Table 18 Cambridge winter wheat growing season drought record. Complied using the SPI and SPEI at a 9, 6 and 3 month lags from August and the PDSI August. It is also reported whether the growing season occurs within a published drought. The occurrence (%) for each DSI classification is attached to the bottom of the table.

Harvest Year	SPEI 9	SPI 9	PDSI (9)	SPEI 6	SPI 6	SPEI 3	SPI 3	PSMDmax	Literature
1913	-0.6	-0.7	-1.0	-0.5	-0.9	-0.6	-1.2	244	(Cole and Marsh, 2006a)
1914	-1.1	-0.8	-2.2	-0.7	-0.2	-0.4	-0.3	297	(Cole and Marsh, 2006a)
1921	-2.2	-2.9	-6.2	-2.2	-2.9	-2.0	-2.4	458	(Cole and Marsh, 2006a)
1929	-1.5	-1.6	-2.4	-1.4	-1.2	-1.1	-1.2	324	(Cole and Marsh, 2006a)
1933	-1.7	-1.6	-2.5	-1.4	-0.7	-1.6	-1.0	339	(Cole and Marsh, 2006a)
1934	-2.0	-2.7	-6.3	-1.4	-1.3	-1.3	-0.9	361	(Cole and Marsh, 2006a)
1935	-0.7	-0.1	-3.0	-1.2	-1.0	-1.4	-0.8	321	
1938	-1.3	-1.6	-2.6	-1.4	-2.0	-0.7	-1.1	331	(Cole and Marsh, 2006a)
1940	-1.0	-0.6	-2.0	-1.0	-0.6	-1.3	-1.4	325	
1942	-1.0	-1.0	-2.1	-1.0	-0.8	-0.6	-0.5	289	
1943	-1.3	-1.1	-3.4	-1.6	-1.8	-0.9	-1.1	372	(Cole and Marsh, 2006a)
1944	-1.5	-2.0	-6.0	-1.1	-1.3	-0.2	-0.5	330	(Cole and Marsh, 2006a)
1945	-1.3	-1.4	-3.0	-1.1	-1.0	-0.4	-0.5	301	
1947	-0.5	-0.1	-1.6	-0.6	0.1	-1.0	-0.6	328	(Cole and Marsh, 2006a)
1949	-1.4	-0.9	-0.7	-1.0	-0.4	-1.0	-0.3	288	(Cole and Marsh, 2006a)
1952	-1.0	-0.5	-1.5	-0.7	0.0	-0.6	-0.4	291	
1955	-0.8	-0.6	-1.4	-1.0	-0.8	-1.1	-0.8	287	(Cole and Marsh, 2006a)
1957	-0.9	-0.6	-2.3	-1.0	-1.0	-0.2	0.0	282	
1961	-0.6	-0.5	-1.8	-1.1	-1.3	-0.6	-0.6	298	
1972	-0.8	-1.6	-2.0	-0.6	-1.3	-0.6	-1.4	252	(Cole and Marsh, 2006a)
1973	-1.1	-1.1	-4.5	-0.6	-0.4	-0.7	-0.4	244	(Cole and Marsh, 2006a)
1975	-0.5	0.1	-1.7	-0.1	0.4	-1.8	-1.7	326	(Cole and Marsh, 2006a)
1976	-2.2	-2.9	-6.6	-2.0	-2.2	-2.2	-1.5	450	(Cole and Marsh, 2006a)
1983	0.3	0.1	-0.8	0.3	0.3	-1.1	-1.4	233	(Wreford and Adger, 2011)
1989	-1.4	-0.9	-2.6	-1.2	-0.5	-1.3	-0.7	339	(Cole and Marsh, 2006a)
1990	-1.1	-0.5	-3.6	-1.9	-2.8	-1.6	-2.0	405	(Cole and Marsh, 2006a)
1991	0.0	-0.4	-2.8	0.3	0.0	0.5	0.5	181	(Cole and Marsh, 2006a)
1994	-0.3	-0.1	-1.9	-0.8	-1.0	-1.6	-2.2	308	
1995	-1.4	-1.0	-3.5	-1.9	-2.4	-2.0	-2.5	417	(Cole and Marsh, 2006a)
1996	-1.0	-1.2	-3.5	-1.2	-1.8	-0.9	-0.5	336	(Cole and Marsh, 2006a)
1997	-0.7	-0.3	-2.3	-0.2	0.4	1.0	1.4	229	(Cole and Marsh, 2006a)
2000	0.3	0.2	0.6	0.4	0.2	-0.5	-1.0	179	
2003	-0.9	-0.6	-1.8	-1.4	-1.4	-0.9	-0.7	338	(Wreford and Adger, 2011)
2005	-0.9	-1.1	-2.4	-0.5	-0.6	-0.2	-0.1	244	(Wreford and Adger, 2011)
2006	-1.1	-1.1	0.5	-0.6	-0.3	-0.9	-0.3	263	(Wreford and Adger, 2011)
2011	-1.5	-1.5	-3.2	-1.5	-1.6	0.0	0.1	353	(Kendon et al., 2013)

Classification	%	%	%	%	%	%	%
Extreme	2.9	3.8	4.8	1.9	4.8	2.9	3.8
Severe	3.8	4.8	6.7	3.8	2.9	3.8	1.9
Moderate	13.5	7.7	12.5	15.4	9.6	8.7	8.7
Total	20.2	16.3	24	21.2	17.3	15.4	14.4

(SPI,SPEI and PDSI)
Extreme drought
Severe drought
Moderate drought
No drought reported
(PSMD)
PSMD outside 75th percentile
PSMD inside 75th percentile

3.2 Sirius crop modelling

3.2.1 Model validation

Table 19 shows the observed yields from the RLT compared against Sirius simulated yields for 1.5 m and 1 m maximum rooting depths (MRD). The statistical analysis presented in Table 20 shows the results for all yield records (n=9), just the Cambridge records (n=5), just the St Neots records (n=4) and when average observed yield is compared to the average simulated yield for years when more than one record is available (2003, 2004 and 2005) (n=6). Figure 11 shows the relationship between the observed and simulated yields for n=9, n=6, n=8 and with a significant outlier removed (St Neots; 19/10/2005) (n=8) for 1.5 m and 1 m MRD.

Table 19 Site, sowing date, observed (RTL) yield and simulated yield ($t\ ha^{-1}$) at 1.5 and 1m maximum rooting depth (MRD) for the Evesham 3 soil series

Site	Sowing date	Observed yield ($t\ ha^{-1}$)	1.5 m MRD simulated yield ($t\ ha^{-1}$)	1 m MRD simulated yield ($t\ ha^{-1}$)
Cambridge	12/10/1999	10	10.4	10.4
Cambridge	20/10/2000	10.1	10.8	10.5
Cambridge	01/10/2003	10.7	11.6	11.5
Cambridge	09/10/2004	10.4	10.2	9.70
Cambridge	04/10/2005	9	10	9.1
St Neots	11/12/2002	8.5	10.2	9.6
St Neots	17/10/2003	10	10.9	10.8
St Neots	05/11/2004	8.8	10	9.5
St Neots	19/10/2005	11.8	9.9	9

Table 20 Root Mean Square Error (RMSE), Mean Bias Error (MBE), Mean Absolute Error (MAE) and Relative Root Mean Square Error (RRMSE) for RLT data (t ha^{-1}) and simulated yields (t ha^{-1}) for the cv. Claire for 1.5m and 1m maximum rooting depth (MRD)

Site	MRD	n	RMSE (t ha^{-1})	MBE (t ha^{-1})	MAE (t ha^{-1})	RRMSE (%)	R^2
All sites	1.5m	9	1.11	0.51	0.99	11.22	0.05
Cambridge	1.5m	5	0.7	0.3	0.64	6.93	0.49
St Neots	1.5m	4	1.48	0.47	1.43	15.12	0.01
Excluding outlier	1.5m	8	0.97	0.81	0.87	10.01	0.51
Average	1.5m	6	0.88	0.61	0.77	8.98	0.12
All sites	1m	9	1.14	0.08	0.87	11.49	0.03
Cambridge	1m	5	0.55	0.1	0.48	5.48	0.59
St Neots	1m	4	1.6	-0.05	1.35	16.34	0.01
Excluding outlier	1m	8	0.69	0.44	0.62	7.15	0.55
Average	1m	6	0.82	0.21	0.67	8.29	0.10

For the Evesham 3 soil (MRD 1.5m) Sirius can be described as simulating yield to a 'good' level of accuracy for all sites (n=9) with a RRMSE of 11.2%. Simulations are of a greater accuracy for the RLT sites at Cambridge (RRMSE=6.93,'excellent') compared to St Neots (RRMSE=15.12%,'Good'). It is important to note that the St Neots records are located further from the weather stations used in the climate record and situated on a slightly different soil series. Therefore it can be expected simulations are likely to differ from measured yields. The average (n=6) RRMSE shows that simulated yields are 'excellent' at all sites. Sirius significantly underestimates (1.91 t ha^{-1} less than observed yield) a yield record at St Neots. The exclusion of this outlier significantly improves the accuracy of the simulations (n=8).

Although Sirius provides statistically 'good' simulations of wheat yields on an Evesham 3 soil series with a 1.5 m MRD, the model shows a bias towards the overestimation of yields (MBE=0.51 t ha^{-1}), this increased to (0.81 t ha^{-1}) once the outlier is excluded (Table 20). One possible explanation for this is the way Sirius define rooting depth. The MRD in Sirius is defined as the deepest depth

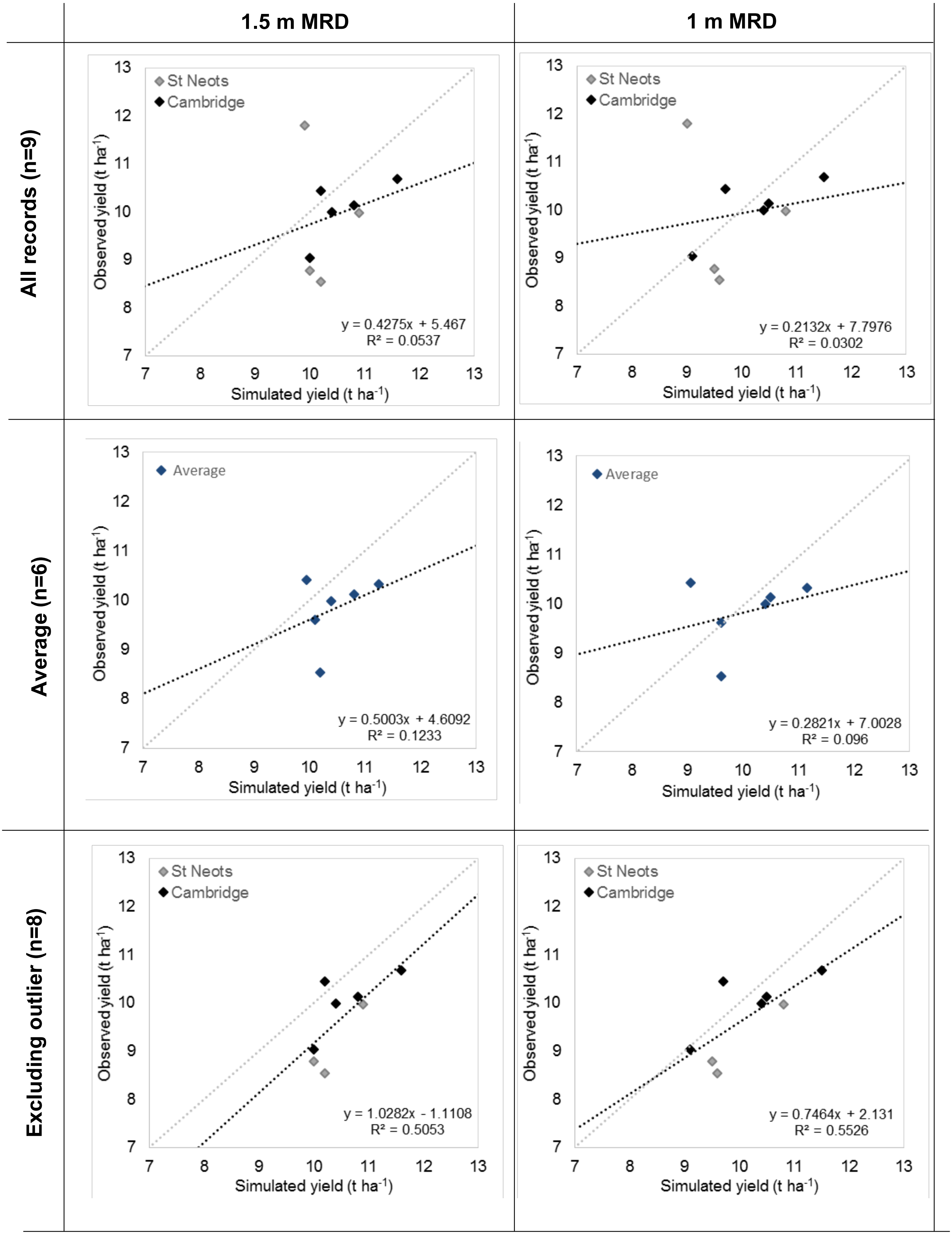


Figure 11 Comparison between observed yields (RLT) (t ha^{-1}) and Sirius simulated yields (t ha^{-1}) at 1.5 m and 1 m MRD for all records, the average yields for years with multiple records and excluding the 19/10/2005 St Neots outlier. Dashed grey line=1:1 line. Black line=linear regression line

parameters of the soil profile, with a maximum rooting depth of 1.5 m to cease at anthesis. Although the Soil Horizon Hydraulic data for Evesham 3 provides soil profile characteristics to 1.5m in the Series Agronomy Data set the average depth to rock is defined as 0.8 m. Therefore, by using the standard values of Evesham 3 with a MRD of up to 1.5m Sirius may be overestimating root growth and therefore soil profile available water capacity. Reducing the maximum soil depth to 1m with the same clay, sand, silt and organic matter content reduces the soil profile AWC for the Evesham 3 soil series to 118 mm in Sirius. Table 20 shows that by reducing the soil depth to 1 m improves the accuracy of the validation. Although the RRMSE (11.49%), for n=9 does not change significantly the overestimation of yield has been reduced. The MBE and MAE for all n values (n=9, n=5, n=4,n=8 and n-6) improves with the 1m soil profile. The yield record for St Neots (sowing date 19/10/2005) is still underestimated (-2.8 t ha^{-1}) compared to the observed yield. The improved accuracy of the simulation is shown when this outlier is removed (n=8) with the RRMSE of 7.15% demonstrating 'excellent' model accuracy.

3.2.2 Simulated historic yield (Evesham 1m)

Figure 12 shows the simulated PO and WL yields for the Evesham 3 soil series with a MRD of 1m (1912-2015). Table 21 provides the supporting statistical analysis.

The average yield loss due to water limitation was 6.1%. The average yield loss however is less than that of the estimated national average (10%) (Foulkes, et al., 2007). The 3 major growing season droughts (1921, 1934 and 1976) identified both in DSI analysis and as major droughts in the literature (Table 18) show significant yield loss due to water limitations. The lowest simulated WL yield occurred in 1921, where yields fell to 7.3t ha^{-1} (38% yield loss). The second lowest simulated WL yield occurred in 2010 (7.5 t ha^{-1}, 32% yield loss). The growing season does fall into a documented UK drought (2010-2012, Kendon et al., 2013), however is not identified in the DSI analysis in Table 18. The 1976 drought showed a significantly reduced yield of 7.9 t ha^{-1}, the third overall lowest simulated yield. The 1976 drought is one of the most documented droughts in the UK, with substantial agricultural losses reported and is identified in the DSI analysis as an extreme drought year (Table 18).

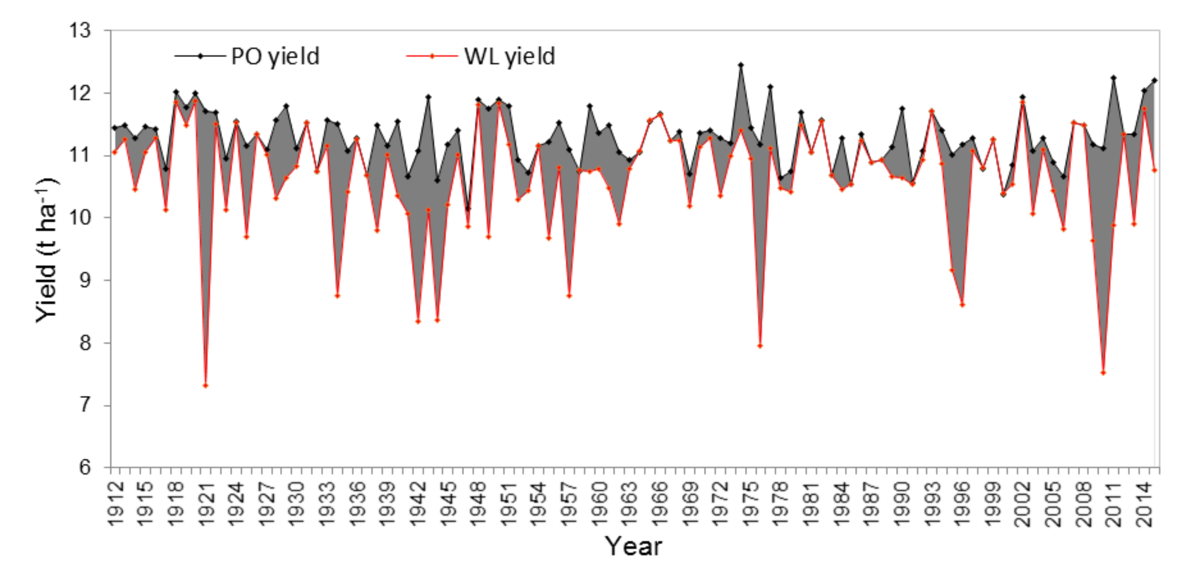


Figure 12 Simulated potential (PO) and water limited (WL) yields (t ha^{-1}) for Cambridge (1912-2015) for the Evesham 1m soil series

The 2011, 1996, 1995, 1957, 1949, 1944, 1943, 1942 and 1934 seasons also led to significant yield loss (<15%) based on the Sirius simulations. The 1934, 1943, 1944, 1949, 1995, 1996 and 2011 growing seasons all fall under drought episodes reported in the DSI analysis (Table 18) and drought literature. There is a strong link between identified droughts and yield loss for a medium AWC soil at Cambridge.

3.2.3 Sensitivity analysis

Figure 13 shows the simulated WL yield and standard deviations of the WL and PO yield for the Badsey, Evesham 3 and Handsworth soil series at 1m and 1.5m MRD, 1912-2015. Table 21 shows the statistical analysis of the historic simulated yield records presented in Figure 13. The sensitivity analysis demonstrates that soil properties affects a wheat crop's vulnerability to drought in East Anglia.

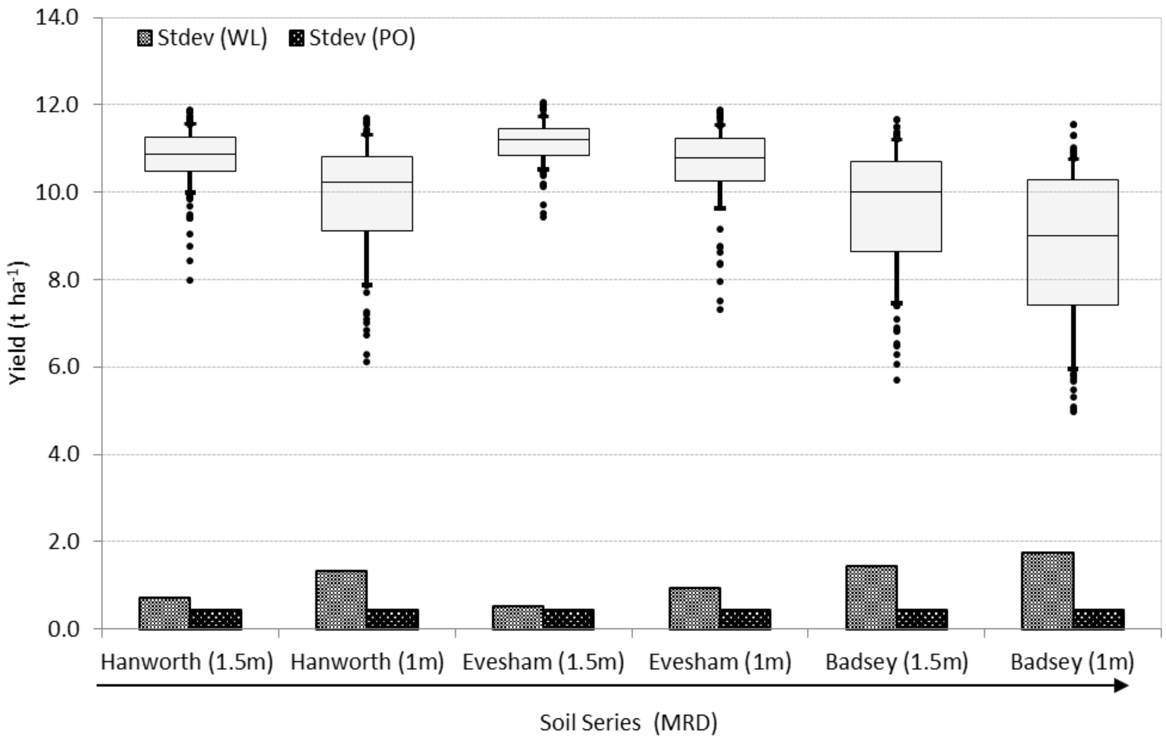


Figure 13 Box and whisker of simulated yield for the 3 soil series at 1.5m and 1m MRD (whiskers: 10th and 90th percentile; box: 25th and 75th percentiles; horizontal line: median; black dots: outliers) and Bars displaying the standard deviation of the WL yield and PO

Table 21 Statistical analysis of simulated historic yield for the Evesham, Hanworth and Badsey soil series at 1.5m and 1m maximum rooting depths (STDEV = standard deviation)

Soil Type	AWC	Percolation coefficient	Median yield (t ha^{-1})	Average yield (t ha^{-1})	Average potential yield (t ha^{-1})	Average yield loss (t ha^{-1})	Average yield loss (%)	Max yield (t ha^{-1})	Minimum yield (t ha^{-1})	Max yield loss (t ha^{-1})	Max yield loss (%)	WL yield STDEV (t ha^{-1})	PO STDEV (t ha^{-1})
Hanworth (1.5m)	H	H	10.9	10.8	11.3	0.5	4.4	11.9	8	3.3	28.2	0.7	0.4
Hanworth (1m)			10.2	9.8	11.3	1.5	12.8	11.7	6.1	5.4	46.4	1.3	0.4
Evesham (1.5m)	M	L	11.2	11.1	11.3	0.2	1.5	12.1	9.4	2.3	19.6	0.5	0.4
Evesham (1m)			10.8	10.6	11.3	0.7	6.1	11.9	7.3	4.4	37.7	0.9	0.4
Badsey (1.5m)	L	H	10	9.6	11.3	1.7	14.9	11.7	5.7	5.7	48.8	1.4	0.4
Badsey (1m)			9	8.7	11.3	2.6	22.7	11.6	5	6.6	56.6	1.8	0.4

The low AWC Badsey soil series was the most affected by water limitations with an average yield loss of 1.7 t ha^{-1} and 2.6 t ha^{-1} for 1.5m and 1m rooting depths respectively. Despite the higher AWC of the Hansworth soil series it showed larger average yield losses than the Evehsam 3 soil series at both rooting depths. This is likely a result of the higher percolation coefficient. Sirius describes soil in terms of it is capacity to hold water in various states. Of these the plant can use immobile plant available water (the root zone AWC) and mobile plant water (water that can drain from one layer to the next and may be extracted unhindered) (Jamieson et al., 1998b). The percolation coefficient is a rate parameter, determining the downward flow of this mobile water through the soil (Addiscott and Whitmore, 1991). A higher percolation coefficient increases the rate that water is lost through the soil, reducing the mobile plant available water.

Reducing the rooting depth to 1m increased the vulnerability to drought on all soil types. By subtracting the PO standard yield deviation from the WL standard yield deviation the standard yield deviation that can be wholly attributed to water limitations is calculated. The Badsey (1m) soil produced the highest yield deviation (1 t ha^{-1}) with the Evesham 1.5m soil producing the smallest (0.1 t ha^{-1}). All soils showed the potential to suffer considerable yield loss due to water limitations in years with extreme water limitations. Even the least droughty Evesham 3 (1.5m) soil experienced a maximum yield loss of 19.6% (2.3 t ha^{-1}).

3.3 Relationship between DSI and simulated wheat yield

Figure 14 shows the Spearman's Rho correlation coefficients (r) between the monthly DSI at their computed time steps (lags) and the simulated wheat yields at Cambridge 1913-2015. Figure 15 shows the difference in the correlation coefficients between the SPI and SPEI. In Figure 15 the negative values (blue) are time steps where the SPI has a stronger correlation, the positive values (yellow) are time steps the SPEI is stronger. Figure 15 indicates there is very little difference between the strength of the correlations between the SPI and SPEI at various time steps. The SPI shows a slightly stronger (0.05-0.07) correlation at various time steps between February and June, with the SPEI showing very slightly stronger (0.06-0.09) correlations at the 1-2 and 2-3 month lags for July and August, respectively. Therefore, the results for the SPI and SPEI depicted in Figure 14 are described together.

SPI	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.00	-0.07	-0.08	-0.09	-0.07	-0.06	-0.05	-0.05	-0.07	-0.11	-0.08	-0.09
OCT (S)	0.06	0.01	-0.03	-0.03	-0.03	0.00	-0.01	-0.01	-0.03	-0.07	-0.04	-0.07
NOV	-0.03	0.04	0.00	-0.05	-0.05	-0.04	-0.02	-0.01	-0.03	-0.04	-0.08	-0.06
DEC	0.00	0.02	0.02	0.07	0.00	-0.04	-0.02	-0.03	0.00	0.00	0.00	-0.01
JAN	-0.12	-0.08	-0.07	-0.08	-0.03	0.01	0.02	0.01	0.00	-0.01	-0.02	-0.01
FEB	0.04	0.11	0.08	0.06	0.09	0.06	0.00	-0.01	-0.01	0.01	0.02	0.02
MAR	0.02	0.05	0.09	0.06	0.05	0.07	0.03	-0.01	-0.01	-0.02	0.00	0.01
APR	**0.35**	**0.25**	**0.26**	**0.28**	**0.23**	0.18	0.21	0.14	0.10	0.09	0.09	0.09
MAY	**0.25**	**0.43**	**0.37**	**0.38**	**0.38**	0.33	**0.25**	0.26	**0.22**	0.15	0.14	0.13
JUN	**0.39**	**0.46**	**0.57**	**0.49**	**0.49**	0.51	0.47	**0.37**	**0.37**	0.31	**0.24**	**0.24**
JUL	**0.32**	**0.51**	**0.53**	**0.62**	**0.58**	0.57	0.60	0.57	0.46	0.46	0.41	0.34
AUG (H)	0.19	**0.36**	0.49	0.53	0.65	0.62	0.60	0.62	0.58	0.51	0.50	0.45

SPEI	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.00	-0.09	-0.09	-0.10	-0.09	-0.08	-0.05	-0.04	-0.04	-0.06	-0.04	-0.05
OCT (S)	0.05	-0.02	-0.05	-0.04	-0.06	-0.03	-0.01	-0.01	-0.01	-0.02	-0.01	-0.04
NOV	-0.03	0.04	-0.02	-0.06	-0.07	-0.07	-0.04	-0.02	-0.01	-0.02	-0.03	-0.01
DEC	0.00	0.02	0.01	0.05	-0.04	-0.07	-0.06	-0.06	-0.03	-0.01	0.01	-0.01
JAN	-0.07	-0.06	-0.05	-0.05	0.01	0.05	0.04	0.05	0.03	0.00	-0.01	-0.01
FEB	0.00	0.06	0.03	0.03	0.05	-0.02	-0.04	-0.04	-0.05	-0.03	-0.01	0.00
MAR	-0.01	-0.02	0.04	0.00	0.01	0.03	-0.01	-0.05	-0.05	-0.06	-0.03	0.00
APR	**0.36**	**0.24**	**0.23**	**0.25**	**0.21**	0.16	0.17	0.11	0.07	0.04	0.04	0.04
MAY	**0.21**	**0.39**	**0.32**	**0.31**	**0.33**	**0.30**	**0.22**	**0.23**	0.16	0.12	0.10	0.08
JUN	**0.41**	**0.44**	**0.53**	**0.46**	**0.45**	**0.46**	**0.42**	**0.35**	**0.33**	**0.27**	**0.22**	**0.20**
JUL	**0.41**	**0.58**	**0.58**	**0.65**	**0.60**	**0.58**	**0.59**	**0.56**	**0.48**	**0.48**	**0.40**	**0.34**
AUG (H)	**0.24**	**0.42**	**0.56**	**0.57**	**0.63**	**0.60**	**0.58**	**0.59**	**0.57**	**0.52**	**0.51**	**0.46**

PDSI	
SEP	-0.02
OCT (S)	0.03
NOV	0.02
DEC	0.08
JAN	0.06
FEB	0.08
MAR	0.15
APR	**0.33**
MAY	**0.37**
JUN	**0.46**
JUL	**0.53**
AUG (H)	**0.55**

$PSMD_{Month}$	
SEP	-0.03
OCT (S)	-0.05
NOV	-0.13
DEC	0.16
JAN	0.13
FEB	0.01
MAR	-0.05
APR	**0.18**
MAY	**0.32**
JUN	**0.51**
JUL	**0.66**
AUG (H)	**0.63**

$PSMD_{Max}$
0.64

Key
-0.1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Figure 14 Spearman's Rho correlation coefficient (r) between monthly SPI 1-12 , SPEI 1-12, PDSI, $PSMD_{Max}$ and $PSMD_{Month}$ and simulated wheat yields at Cambridge. Correlation coefficients in bold represent those that are statistically significant (p-0.05)

SPEI-SPI	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.00	-0.03	-0.01	-0.01	-0.02	-0.01	0.00	0.01	0.03	0.05	0.04	0.04
OCT (S)	-0.01	-0.03	-0.02	-0.01	-0.03	-0.03	0.00	0.00	0.02	0.04	0.03	0.04
NOV	0.00	0.00	-0.02	-0.01	-0.02	-0.03	-0.02	-0.02	0.02	0.02	0.05	0.05
DEC	0.00	0.00	0.00	-0.02	-0.04	-0.03	-0.03	-0.03	-0.03	-0.02	0.01	0.00
JAN	0.04	0.02	0.01	0.03	0.05	0.03	0.03	0.04	0.02	0.01	0.02	0.00
FEB	-0.04	-0.06	-0.05	-0.03	-0.05	-0.07	-0.04	-0.04	-0.04	-0.04	-0.04	-0.02
MAR	-0.03	-0.07	-0.05	-0.05	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03	-0.02
APR	0.01	-0.01	-0.03	-0.03	-0.02	-0.03	-0.05	-0.04	-0.04	-0.05	-0.06	-0.05
MAY	-0.04	-0.05	-0.05	-0.07	-0.05	-0.03	-0.03	-0.04	-0.06	-0.04	-0.04	-0.04
JUN	0.02	-0.02	-0.04	-0.04	-0.04	-0.06	-0.04	-0.02	-0.04	-0.04	-0.02	-0.03
JUL	0.09	0.07	0.05	0.02	0.01	0.01	-0.01	-0.01	0.01	0.01	0.00	0.00
AUG (H)	0.05	0.06	0.07	0.04	-0.02	-0.02	-0.02	-0.03	-0.01	0.01	0.01	0.02

Figure 15 The Spearman's Rho correlation coefficients (r) between simulated wheat yield and the SPEI 1-12 subtracted from the equivalent spearman's Rho correlation coefficient (r) for the SPI 1-12

Figure 14 shows no significant correlations (p-0.05) between historic weather expressed as the SPI, SPEI (regardless of the time step), $PSMD_{Month}$ and the PDSI between October (sowing) and March although not significant (0.15, *P= 0.13*) The PDSI shows small correlation for March. From April all the DSI show an increased relationship with simulated yields as a drought event extends through the production and construction phases. Figure 14 highlights (black box) the strongest correlating time step for the SPI and SPEI each month from April. Correlations are strongest for time steps that incorporate weather from April to the month of calculation. The strongest correlations occur either in July (SPEI 4 and $PSMD_{Month}$) or August (SPI 5 and PDSI). However, for all DSI there is very little difference in the strongest correlation in July and August. The $PSMD_{Max}$ does show a strong correlation (0.64) to simulated wheat yields. However, the $PSMD_{Max}$ has no fixed time step and can occur in different months depending on that seasons weather, therefore it is not linked to a specific month in the growing season.

In Figure 14 the highlighted correlations for the SPI and SPEI show the strongest correlation in each month. However, other time steps also show significant correlations to simulated wheat yield. Such as the SPI and SPEI 1-5 for April, SPI 1-9 and SPEI 1-8 for May, SPI and SPEI 1-12 June and July and the SPI 2-12 and SPEI 1-12 for August. The $PSMD_{APR}$ shows a noticeably weaker correlation (0.18) compared to the strongest correlating time step of the other DSI (0.33-0.36). The strongest correlation of the PDSI (0.55) is weaker than the strongest of the other DSI (0.65-0.66)

Figure 16 shows the linear relationship between the SPI 4, SPEI 4 and PDSI for July and the $PSMD_{JUL}$. It is recognised that the SPI and PDSI have a slightly stronger correlation (r) in August than July (Figure 14), but this is minimal and as a large part of August weather occurs after harvest, the DSI in July seems more appropriate. Figure 16 demonstrates that there is a relationship (R^2 0.36-0.47) between a low SPEI, SPI, PDSI in July, high $PSMD_{JUL}$ and simulated wheat yields. The $PSMD_{JUL}$ shows the strongest regression and the PDSI the weakest. There are however outliers in all of the plots. The 1942 season saw noticeably depressed yields yet the SPI and SPEI classified weather as near normal. An opposing trend can be seen for the 1990 season, which saw a drought classified by all the DSI, however, no significant impact on yield was simulated in Sirius.

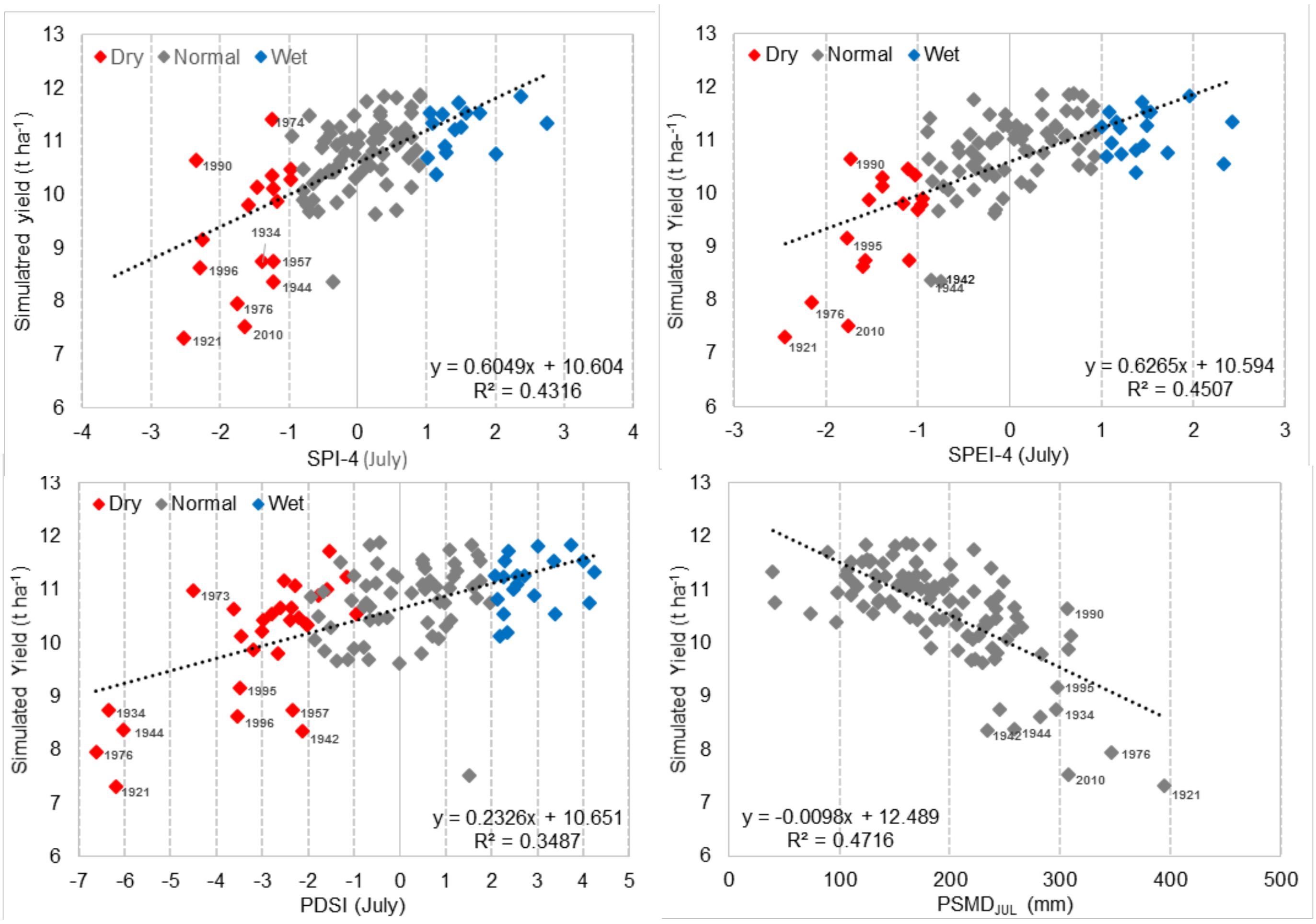


Figure 16 Linear relationships between the SPI-4 and SPEI-4 July, the PDSI July and the $PSMD_{JUL}$ and simulated wheat yields. For the SPI, SPEI and PDSI years that are classified as a moderate, severe or extreme drought are coloured red (labelled 'Dry'), years that fall in the normal range are coloured grey (labelled 'Normal'), and years that are classified as moderately, severely or extremely wet are coloured blue (labelled 'Wet'). The $PSMD_{Jul}$ has no classification system therefore all years are coloured grey.

4 Discussion

This chapter discusses the context of historic droughts identified through DSI analysis and their effects on simulated wheat yields, the potential application for DSI in agricultural drought monitoring, the methodological limitations, and finally, the implications of the research for science, the UK wheat and agricultural industry and drought management policy.

4.1 Historic droughts

Despite it is humid climate it is recognised that the UK and some regions (notably eastern England) are vulnerable to drought (Cole and Marsh, 2006a; b). The DSI analysis (Figure 10) showed that ‘moderate-extreme’ droughts were identified across the winter wheat growing season. At least one of the SPI-9,6,3, SPEI-9,6,3 and PDSI drought indicators highlight a ‘moderate’ drought in nearly a third (30 of 104) growing seasons (1911-2015). This is comparable to the results of Cole and Marsh (2006a) who used a range of sources to classify 12 ‘notable’ and 6 ‘major’ UK drought episodes, featuring 35 years from 1912-2000. Of the 18 notable and major drought episodes identified by Cole and Marsh, (2006a), 14 of these had a coinciding growing season identified for the Cambridge site (Table 18). It is therefore unsurprising that growers rank unpredictable weather highly in assessment of risks to wheat production (Ilbery et al., 2013), emphasising the need for better understanding of droughts and their impacts. With 14 of the 18 droughts reported by Cole and Marsh, (2006a) shown to have occurred during the winter wheat growing season, Cambridge provides a good representative site for exploring the drought/yield relationships and likely adaptation responses.

The DSI’s used in this study were in close agreement with each other both through the statistical analysis (Table 17), via visual appraisal (Table 18), and with previous observations (Vicente-Serrano et al., 2010; Paulo et al., 2012). There are years where the DSI differ in their drought classification, such as 1972 and 1990 on a 9-month time step which justifies the need to compare all four DSI with simulated wheat yields. For example, depending on the DSI used , agricultural stakeholders could be advised that the 1990 winter wheat growing season was either ‘near normal’, a ‘moderate’ or ‘severe’ drought. This highlights the difficulty in selecting one representative drought index for a specific purpose (Vicente-Serrano et al., 2012).

There were a number of ‘notable’ drought episodes (1919, 1941, and 1962-1965) reported by Cole and Marsh (2006a) that were not identified by the DSI analysis. Of potentially greater significance, however, is the absence of the ‘major’ 1959 drought episode, reported as an ‘intense 3 season drought’ (February-November) which was particularly severe in Eastern England (Cole and Marsh, 2006a). The SPI 1-12 for each month in 1959 (Figure 17) shows that although dry months are present in February, May and July these were preceded by a wet March and July, thus preventing any serious drought episode from taking hold. The main expression of the 1959 drought occurred at the end of (August), and after (September/October) the winter wheat growing season, resulting in a ‘severely’ dry SPI-4 for November. Therefore, this was unlikely to have affected wheat yields. Wilhite et al., (2007) noted that the economic impacts of drought are highly variable within and between economic sectors. The 1959 drought at Cambridge highlights this, with it is main expression outside a typical wheat growth season. However, it is late summer/autumn expression threatened crops such as grasslands supporting livestock. This reinforces the need for drought

1959	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
JAN	1.2	1.1	0.7	0.5	0.7	0.7	1.0	1.8	2.0	1.8	1.7	1.9
FEB	-2.5	-0.1	0.3	0.0	0.0	0.2	0.3	0.6	1.5	1.6	1.5	1.3
MAR	1.1	0.0	0.6	0.8	0.5	0.4	0.5	0.6	0.8	1.6	1.7	1.6
APR	0.4	0.9	0.1	0.6	0.8	0.5	0.4	0.5	0.6	0.8	1.6	1.7
MAY	-1.7	-0.8	0.1	-0.7	-0.1	0.1	0.0	-0.1	0.1	0.2	0.5	1.2
JUN	0.3	-0.9	-0.5	0.1	-0.5	0.0	0.2	0.0	0.0	0.1	0.2	0.5
JUL	1.3	1.1	0.3	0.4	0.7	0.3	0.6	0.7	0.5	0.4	0.6	0.6
AUG	-1.1	0.3	0.3	-0.3	-0.2	0.2	-0.3	0.1	0.3	0.1	0.1	0.2
SEP	-3.2	-2.6	-0.7	-0.5	-1.1	-0.9	-0.5	-0.9	-0.6	-0.4	-0.5	-0.5
OCT	-0.3	-1.6	-2.1	-0.8	-0.7	-1.2	-1.0	-0.7	-1.1	-0.7	-0.5	-0.6
NOV	-0.6	-0.7	-1.8	-2.2	-1.0	-0.9	-1.3	-1.2	-0.8	-1.2	-0.9	-0.7
DEC	1.2	0.5	0.1	-0.9	-1.4	-0.5	-0.4	-0.9	-0.8	-0.4	-0.8	-0.5

Key	
Value	Classification
2.0+	Extremely wet
1.5 to 1.99	Severely wet
1 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2 and less	Extreme drought

Figure 17 SPI1-12 for 1959 at Cambridge

monitoring and reporting to be not only industry specific (e.g. agriculture) but also sector specific (e.g. wheat).

The most recent 2010-2012 drought was identified by being ‘severe’ with dry conditions for the 9 and 6 months (SPI-SPEI-6,9 and PDSI) prior to harvest in 2011. The lack of expression over the production phase (SPI/SPEI-3) can be explained by Kendon et al., (2013) who noted an exceptionally dry March and April persisting into May, with much of the UK experiencing a cool above-average rainfall during the summer. Kendon et al. (2013) also reported that in 2010,

2010	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-1.4	-0.7	0.5	0.4	0.1	-0.3	-0.3	-0.1	-0.2	-0.5	-0.4	-0.3
OCT (S)	-0.4	-1.4	-0.9	0.2	0.1	-0.2	-0.5	-0.6	-0.3	-0.4	-0.7	-0.6
NOV	1.7	0.9	0.1	0.1	0.8	0.7	0.5	0.2	0.1	0.3	0.2	-0.1
DEC	1.1	2.0	1.3	0.5	0.5	1.2	1.0	0.8	0.5	0.4	0.6	0.5
JAN	0.0	0.8	1.6	1.1	0.4	0.4	1.1	1.0	0.7	0.4	0.4	0.5
FEB	1.3	0.9	1.2	1.9	1.4	0.8	0.8	1.3	1.2	1.0	0.7	0.7
MAR	-0.4	0.6	0.4	0.8	1.5	1.1	0.5	0.5	1.1	1.0	0.8	0.5
APR	-1.3	-1.4	-0.3	-0.3	0.3	1.0	0.7	0.2	0.2	0.8	0.7	0.5
MAY	-0.5	-1.4	-1.6	-0.6	-0.6	-0.1	0.7	0.4	-0.1	0.0	0.6	0.5
JUN	0.0	-0.6	-1.2	-1.4	-0.7	-0.7	-0.2	0.6	0.3	-0.1	-0.1	0.5
JUL	-1.1	-0.9	-1.1	-1.6	-1.8	-1.1	-1.1	-0.6	0.2	-0.1	-0.5	-0.4
AUG (H)	1.9	1.1	0.9	0.6	0.1	-0.1	0.3	0.3	0.6	1.1	0.8	0.4

Key	
Value	Classification
2.0+	Extremely wet
1.5 to 1.99	Severely wet
1 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2 and less	Extreme drought

Figure 18 SPI-1-12 month time steps for the 2010 winter wheat growing season at Cambridge

England received less than 70% of it is average spring rainfall followed by a warm and dry July. Considering this, and the documented impacts of water limitations on wheat in 2010 (DEFRA, 2010a) it raises the question of why this drought episode was not identified in Table 18? Kendon et al., (2013) provide a possible explanation. August was used as the base month for the DSI analysis (Table 18) and was described as being cool and wet month, with over twice the monthly rainfall in parts of East Anglia. The SPI evolution (Figure 18) shows this expression with a very dry April continuing through to July were the SPI-4 and SPI-5 classify this as a ‘severe’ drought. However, the exceptionally wet August wipes out the expression of the previous drought episode. The failure of the DSI on time steps used in Table 18 to identify the 2010 drought highlights the varying temporal and spatial scales that droughts can extend over. Therefore, classifying a drought episode into a single value, such as SPI-9 for August can be misleading, particularly if the time step includes periods after the drought has ended. This emphasises that DSI should be used in conjunction with the specific sector of interest and should be monitored at varying time steps.

The DSI analysis (Table 18) identified growing season droughts that did not fall into previously reported drought episodes. Some of these appear to be minor deviations from the normal weather, acknowledged by just one DSI (1952 and 2000). More pronounced events (1935, 1940, 1942, 1957 and 1961) are classified as 'moderate' droughts by more than one DSI at various time steps. A significant event however occurred over the 1994 production phase, with the SPI-3 and SPEI-3 classifying an 'extreme' and 'severe' drought respectively. Considerable attention has been given to the 1988-1992 (Marsh et al., 1994; Marsh, 1998) and 1995-1997 (Marsh, 1995) droughts, with little attention given to a potentially dry summer in 1994. Spinoni et al., (2015) report of a 1994 drought across North Eastern Europe. Whether the significant drought reported at Cambridge was experienced more widely requires further research and highlights the importance of studies such as this that attempt to analyse the complexity of drought event and their impacts at a local scale (Wilhite et al., 2007).

4.2 Wheat yield simulation

4.2.1 Model performance

Before the effects of drought on yield could be simulated, Sirius was first validated for the Cambridge site. The observed yields at Cambridge were simulated with an 'excellent' level of accuracy (Table 20). Nevertheless, the range (9-10.7 t ha^{-1}) and sample size (n = 5) was relatively small (Table 19), although, not dissimilar to the 8.3-11 t ha^{-1} range of for an identical sample size (n = 5) used by Vanuytrecht et al., (2015) to validate Sirius in the Flemish Region of Belgium. As the weather over central England is nearly uniform (Butterfield et al., 1998 cited in Jamieson et al., 1999; Hess et al., 2015) and the RLT data featured 4 additional sites near St Neots (~40 km) grown on similar soil characteristics the validation was extended to include these sites. Unsurprisingly the model simulated yields more accurately at the Cambridge site (RRMSE = 5%) compared to St Neots (RRMSE = 16%). When combined (n = 9) the simulated yields were still to a ‘good’ level of accuracy over an increased range (8.6-11.8) and sample size. There is a noticeable outlier for the St Neots site (19/10/2005), where yield is under-estimated by 2.8 t ha^{-1}. If excluded from the data set the model was shown to simulate yields to an excellent (RRMSE=7%) level of accuracy. The underestimation in yield for the outlier was not considered important for validation as the record for that year at the Cambridge site was simulated almost perfectly (0.1 t ha over estimation) (Table 19). In addition, when the average yield from all the RLT observations from Cambridge (n = 22) was compared to the Sirius simulated yield there was no major difference (Figure 19) confirming that the Sirius model provided a good yield simulation in East Anglia for that year.

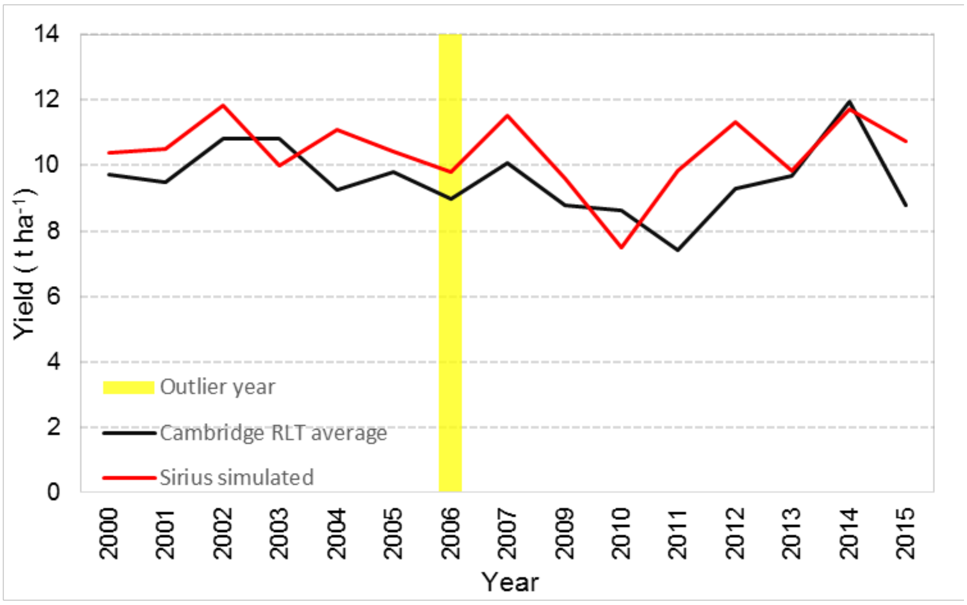


Figure 19 Average yield across all RLT observations for all cultivars and all soil types in Cambridge, 2000-2015 (no records 2008), range of annual observations (12-74) and Sirius simulated yield (cv. Claire, Soil: Evesham 3 1m MRD)

4.2.2 Historic yield simulations

Simulated wheat yields on a medium AWC soil with a 1m MRD were supressed through water limitations (Figure 12). However, the simulated average yield loss of 6.1% (0.7 t ha^{-1}), is not high. El Chami et al. (2015) simulated an average yield loss (irrigated yield-rainfed yield) of 24.6% (1.9 t ha-1) on a light sandy loam soil at Silsoe, Bedfordshire using the Aquacrop model. The ‘heavier’ soil type (Evesham 3; clay / loam-clay) used in this study helps explain the lower average yield loss. The standard deviations of the PO and WL yield suggest that around half of the simulated yield deviation is a result in water limitations, and half due to temperature and radiation levels (Figure 13 and Table 21).

El Chami and Daccache (2015) reported that rainfed winter wheat grown on lighter soils (sandy loam AWC 120 m/mm) produced 14% less yield than on heavier soils (silty clay loam –AWC 220mm/m, 4m MRD). The results from the sensitivity analysis (Figure 13 and Table 21) support El Chami and Daccache (2015) findings with the low AWC Badsey soil (MRD 1.5m) resulting in a 14% reduced yield compared to the medium (MRD 1.5m) AWC soils. The high AWC Hanworth soil demonstrated a lower median yield and a greater yield variance compared to the medium AWC Evesham soil at both 1m and 1.5m rooting depths; this can be explained by the soil characteristics increasing the rate at which the soil drains and dries.

The average day of anthesis across the simulated record was 12th June which is comparable to the average anthesis date 15-19th June for East Anglia for a baseline climate scenario 1960-1990 reported by Madgwick et al., (2011), confirming that the site chosen for this study was representative for wheat production in East Anglia. The slightly later anthesis date reported by Madgwick et al. (2011) can be explained by lower CO_2 concentration (334 ppm) used, the different location, differences in cultivar parameters and sowing dates.

Although yield loss was small compared to more droughty soils, assuming an average UK milling wheat price (2016-2010) of £150 (Nix, 2016), the annual average loss equates to £105 per ha. El Chami et al. (2015) reported that wheat typically occupies 50 ha per farm in East Anglia, which would therefore equate to an average annual farm loss of £7500. Based on El Chami et al., (2015) cheapest cost for irrigation of £915.9 ha and assuming all yield losses could be mitigated by supplemental irrigation , on average irrigation is still not financially viable for the soil type at Cambridge. This confirms El Chami et al., (2015) findings that a significant increase in grain price or a major reduction in irrigation cost would be needed before wheat is widely irrigated in the UK.

4.2.3 Extreme yield limiting years

Crop simulation models can help predict crop responses to large variations in weather (Jamieson et al., 1998a), but are less effective in predicting smaller yield fluctuations (Porter et al., 1993). Therefore discussion will focus on years where Sirius predicts significant yield loss due to water limitations (>15% yield loss) (Table 22).

Table 22 Years when water limitations simulated yield loss of >15% compared to potential yield

Year	Yield loss (%)
1921	37.7
1934	24.1
1942	24.7
1943	15.2
1944	21.2
1949	17.6
1957	21.3
1976	28.9
1995	17.0
1996	23.0
2010	32.4
2011	19.4

The simulated yield limiting years (Table 22) correspond with growing seasons identified as experiencing drought through the DSI analysis (Table 18). The simulated loss during the more recent drought episodes (from 1976 onwards) can be corroborated with regional and national yield records, industry reports and newspaper or magazine articles.

The 1976 drought had significant reported impacts on agriculture (Table 3). Sirius simulated a 32% yield loss in 1976, with the SPI showing drought months throughout the growing season (October, December, February and June (Figure 31, Appendix D). As a result, the time steps incorporating the complete growing season (SPI-6 to SPI-12) identify an ‘extreme’ drought.

The SPI for the 1995 growing season at Cambridge (Figure 31 in Appendix D) identified a wet winter/early spring followed by a dry April that progressed through the summer to an extremely dry August. Substantial impacts were reported with £180 million losses in agriculture mainly to damage to root crops, vegetables and livestock (Palutikof et al., 1997). However, UK national wheat yields were above the 5 year running mean (Wreford and Adger, 2011). Despite this, there were reports of yield loss in Cambridgeshire;

> "Wheats on heavy land with some rain topped 4 t/acre, while on dry light land they have come in below 3t", says store manager Phil Darke. "We have averaged about a quarter tonne down on last year" (“Almost the last gasp" Farmers Weekly, 25th August 1995, vol 123 (8), p 46)

The more recent 2010 drought had documented impacts in the Eastern region. Wheat yields were reported to be 6% below the previous 5 year average and 11% below the record up to 2010 (2008) (Figure 20) It was reported that crops were adversely Affected by the prolonged dry spell in April and May with continued dry weather during grain filling (June and July) causing stress to crops on all soil types (DEFRA, 2010a); this description is supported by the SPI for Cambridge (Figure 31, Appendix D). A report in Farmers Weekly quoted a Lincolnshire farmer describing the drought impacts:

> “the drought caught us out and did a lot of crop damage……the wheat suffered, especially JB Diego, which died in patches’’ (Farmers Weekly, 3rd September 2010,

Sirius simulated a 19.4% yield loss in 2011. It was reported that the drought in spring and early summer having the greatest affect on light soils in the South and

Eastern regions (DEFRA, 2011); this corresponds with the SPI which identified a dry March, April and May over the growing season. This is also evident in the regional yield time series for East Anglia where yields were 10% below the 1999-2015 average, and considerably below the high yielding years (2008, 2014 and 2015) (Figure 20). An East Anglian farmer reported:

"…yields are so far low, about where we feared they would be and nowhere near the 9-10 t ha I have heard about further west" (Farmers Weekly, 12th August 2011,

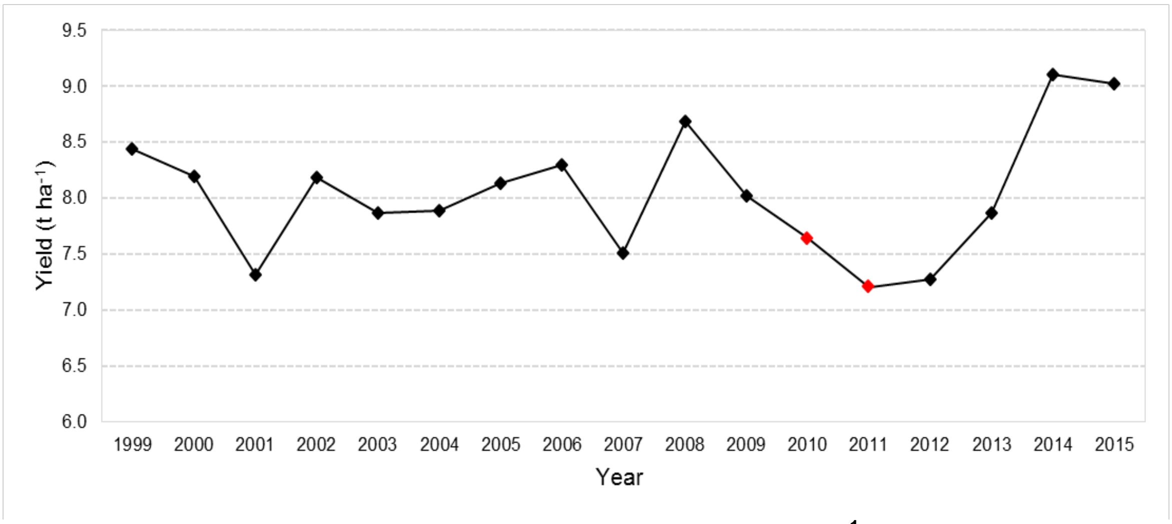


Figure 20 Eastern region average wheat yield (t ha^{-1}) 1999-2015

Prior to 1976 documented impacts of droughts on wheat are harder to identify. Evidence from newspaper articles and yield records suggests yields were not considerably affected, and in some cases may have benefitted (Table 23). It is recognised that a drought event today may be of comparable intensity and duration as a historical event, but the impacts can be expected to differ markedly because of changes in societal characteristics (Wilhite et al., 2007). Therefore, it must be acknowledged that simulations were for a modern wheat cultivar, under a modern wheat production system and that pressures on yield were different prior to the adoption of fertiliser application, plant growth regulators and crop breeding programs. An explanation as to why wheat may have performed better during droughts in the first half of the 20th Century was not the purpose of this study. However, some explanation may be evident in anecdotal evidence from the 1921 and 1944 seasons (Table 23). The reduced length in the straw appears

Table 23 Summary of reported drought impacts prior to 1976 and comparison of 5 year moving average yield deviation(excluding drought year, see Wreford and Adger, (2011) **against Sirius modelled yield loss**

Year	UK yield deviation (%)	Simulated yield loss (%)	Documented impacts
1921	+20%	-37.7%	Department of Agriculture report 'fields of winter wheat were described as excellent' the straw was barely a foot in length in southern counties (Weekly Freeman's Journal, 6th August 1921) / Autumn-sown wheat has stood the dry weather well. Though in some cases the straw is short" (Sussex Agricultural Express 15th July 1921)
1934	+11%	-24.1%	In the Feltwell area crops on lighter land are described in perfect condition (Thetford and Watton Times 25th August 1934)
1942	+8%	-24.7%	Given sunshine and good weather Bedfordshire harvest this year may be the best for many years……it can be said wheat is the crop of the year (Bedfordshire Times and Independent-Friday 21st August 1942
1944	0%	-21.2%	Essex farmers, greatly concerned about the poor prospects of the wheat harvest, on account of prevailing drought conditions-Abnormally short straw will not allow the use of mechanical harvesters.
1949	+13%	-17.6%	In my experience this is the worst year for crops since 1921…..if drought continues for another week or so farmers will be facing heavy losses…there should be a bumper wheat crop this year, but barley, root and oats badly need rain (Shropshire farmer) (Bury Free Press, July 1st 1949)
1957	-3%	-21.3%	N/A

to be a common consequence of a drought stricken harvest, implying that in an era prior to PGR and the selective breading of wheats drought formed a natural resistance to lodging. Lodging is the permeant displacement of stems from the vertical through interactions plant wind, rain and soil (Sterling et al., 2003). Great progress in reducing the risk of lodging in the UK was made in the 1960s and 1970s through the use of plant growth regulators and the breeding of shorter stemmed crops (Berry et al., 2004). The anecdotal evidence suggests that the drought in the first half of the 20th Century may have acted as a natural growth regulator stunting stem growth (see 1921, 1944 in Table 23) and reducing losses from lodging. Other possibilities include higher levels of radiation experienced during drought aided yield formation and the fast on field drying experienced during drought minimised post-harvest losses.

Despite the ability of the Sirius model to be able to accurately simulate yields across a wide range of environments including drought, it is important to note that modelling yield in response to extreme events, particularly when they correspond to sensitive growth stages, remains a challenge (Craufurd et al., 2013 Semenov et al., 2014). It was not however the purpose of this study to quantify the yield loss of a historic drought if it occurred today. It was to identify historic droughts by their potential to cause yield loss to a modern wheat production system. Such studies are important a farmer's changing perception of risk influences their decision around this risk (e.g. what cultivar should be grown). This perception is often shaped through personal experiences and memories (Ilbery et al., 2013). For example, a farmer at Cambridge is likely to be aware of drought risk from recent drought events (2010 or 1976) however, it is important to be aware that these may not be the worst case scenario. The crop modelling shows that historic weather patterns such as that of 1921 may be very detrimental to yield were they to reoccur.

This study also showed that varying types of droughts can dramatically reduce yield (Figure 31, Appendix D). These included droughts that showed a strong expression over the entire growing season (1921, 1934, 1944, 1976 and 2011), those that formed over key growth stages only (1957 and 1996) even if preceding a wet winter and or spring (1990, 1995, 2010) and even those that had a single month expression after a serious of near normal months precipitation (1947).

4.2.4 Clustering of potentially yield limiting droughts

It is reported that droughts can cluster (Marsh et al., 2007), occurring in successive years or in a number of years in close proximity. The causes of such clustering is poorly understood (Folland et al., 2015) although it is recognised that their impacts can exceed that of a single extreme event (Benton et al., 2012). The 5 year running mean simulated yield (Figure 21) showed that when droughts appeared in close proximity, such as those during the early 1940s (Table 18) the impact on half decadal yield average can be greater than that of a single extreme yield reducing event, such as 1921. The recent 2010-2012 drought event was simulated to cause the second lowest 5 year average yield supporting reports that the multi-year 2010-2012 drought/flooding event led to compounding impacts on agriculture (Kendon et al., 2013). There is little knowledge on how temporal patterns of droughts will change, with some studies suggesting a clustering of droughts likely to become more common (Ping et al., 2012). However there is currently very limited understanding on how multi-seasonal (2010-2012) and drought clusters (1940-45) might change with climate change. The crop simulation results here reinforce the need for a better understanding of such events, as the potential impacts of these droughts can far outweigh single events.

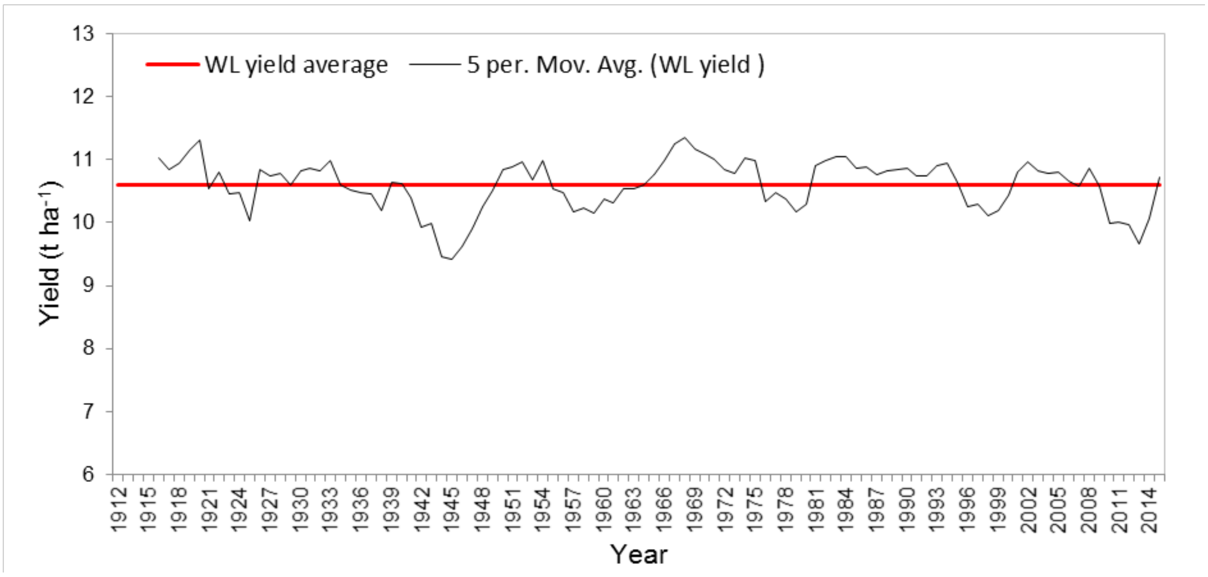


Figure 21 Simulated 5 year moving average WL yields and average WL yield (1912-2015)

4.3 DSI and simulated yield relationship

Despite the documented impacts of drought on UK wheat (Foulkes, et al., 2007; Ober et al., 2011) studies investigating the relationship between national wheat yields and DSI have failed to show significant correlations (Vicente-Serrano et al., 2012; Naumann et al., 2015). The use of national yield records has two major limitations. Firstly, the regional variation in yield caused by the spatial variability in intensity and duration of droughts in the UK (Marsh, 2007) is excluded. Secondly, although de-trending removes the effects of advances in technological and management practices on yield (Vicente-Serrano et al., 2012) it fails to remove other causes of yield loss including lodging (Sterling et al., 2003), disease (Fones and Gurr, 2015) and pest (Millet and Miner, 2009) outbreaks. These limitations were overcome by modelling wheat yield response to historic (1912-2015) water limitations, disregarding the effects of other pressures on yield. The results show that commonly used DSI have a significant relationship to simulated wheat yields (Figure 14 and Figure 16). There is however variance in the strength and timing of the correlations between DSI.

On time steps before April, the DSI showed no significant correlation to simulated yields, which is consistent with understanding that water stress is typically minimal up to this period (El Chami et al., 2015). Although not significant ($p=0.13$), the PDSI showed a stronger correlation in March than the other DSI. Paulo et al. (2012) reported that the PDSI calibrated for a Mediterranean climate might help identify the onset of drought earlier providing it with an advantage in classifying agricultural drought. Any advantage the PDSI possesses is likely the result of it is ability to take into account runoff and soil moisture through soil AWC (Guttman, 1998). Any potential for the PDSI to earlier identify agricultural drought in the UK requires further attention as the early warning of drought provides a foundation allowing well-timed decisions to be made at all levels (e.g. farmers and policy makers) (Wilhite et al., 2000). Such decisions for growers in the UK could include considering if irrigation provides economic sense based on the criteria set out by El Chami et al., (2015).

The correlations for all DSI strengthen as drought continues from April peaking in July and August, on time steps that include the entire construction and production phase for wheat (SPEI/SPI-4 July, SPI/SPEI-5 August, $PSMD_{JUL}$, $PDSI_{July}$ and $PDSI_{August}$). This pattern of correlation corresponds with how Sirius simulates yield, and with the current understanding of yield-drought interactions in the UK. In Sirius, grain yield is dependent on biomass at anthesis and new biomass formed after the start of grain filling. In addition during unstressed conditions the decline in LAI and end of grain filling coincide, however during water stressed conditions senescence is accelerated, restricting grain filling, and reducing yield (Jamieson et al., 1998b). The correlations are consistent with Dodd et al's, (2011) conclusions, that early stem extension (April), flowering (June) and grain filling (June-July) are particularly drought sensitive stages. In addition, this correlation matches those of similar DSI yield relationship studies in Europe. Potopová et al., (2015) report that the SPEI and regional winter wheat yields in the Czech Republic correlate strongest in May and June (anthesis) at 1-7 month lags. They also find a less pronounced correlation in April (shooting stage). Potopová et al., (2015b) demonstrate a short-term drought (1-2 month) during wheat emergence (October) also correlates to yield. No such significant correlation was found in UK wheat. This is likely to be due to the fact that poor establishment due to weather in the UK tends not to reduce establishment enough that compensatory root growth or tillering fails to compensate (AHDB, 2015a).

The SPI and SPEI do not differ considerably in their correlations (Table 17). This contradicts Vicente-Serrano et al. (2012) who reported that SPEI shows the strongest maximum correlation to wheat yields. However it is consistent with Bachmair et al., (2016b) who showed that the two DSI perform similarly when correlated with documented UK drought impacts. Such findings are consistent with Paulo et al. (2012) who reported that in humid environments the SPI and SPEI do not deviate considerably. It is therefore likely that the SPI may be the more suitable over the SPEI for drought M&EW in the UK wheat sector due to it is reduced input parameters. However with climate change evapotranspiration

(ET) rates are likely to increase (Richter and Semenov, 2005) meaning the suitability of the SPEI in drought monitoring may increase.

Despite the possible ability of the PDSI to identify yield-limiting droughts earlier, it fails to maintain it is advantage over other DSI during the sensitive growth stages. It is strongest correlation, August (0.55) is noticeably weaker than the strongest correlation of the other DSI (SPI 5 August (0.65), SPEI 4 July (0.65) and the $PSMD_{JUL}$ (0.66). Supporting previous studies who showed that multi-scalar indices such as the SPI and SPEI outperform indices with fixed time step indices such as the PDSI in identifying agricultural impacts (Paulo et al., 2012; Vicente-Serrano et al., 2012; Wang et al., 2016). Although some studies have found the PDSI to be better linked to agricultural impacts (Tunaloglu and Durdu, 2012). This highlights the need for location and sector specific studies. It is important to recognize that the $PSMD_{Max}$/$PSMD_{JUL}$ are also calculated on a fixed time step (in the case of this study October-August) yet show the strongest correlation to simulated wheat yields. The reality is however that PSMD in the UK is normally accumulated over the spring and summer months (Figure 7) therefore is more a reflection of the drought situation from March to August, a time step featuring the key yield limiting growth stages (Dodd et al., 2011). The $PSMD_{Month}$ shows that the timing of the $PSMD_{Max}$ has an impact on the effect on yield, agreeing with previous research (Richter and Semenov, 2005).

Figure 16 shows the linear regression plots for the SPI 4, SPEI 4, PDSI and $PSMD_{JUL}$. The substantial yield limiting years of 1921, 1976 and 2010 are all accompanied by ‘extreme’ or ‘severe’ drought classifications by the SPI and SPEI. Therefore, the monitoring of these DSI through the growing season would have provided the industry with the knowledge that a severe yield limiting drought was developing. The shortcomings of the fixed temporal scale of the PDSI is demonstrated in 2010. The SPI shows an extremely wet November, December and February (Figure 31, Appendix D). Which are not included in the calculation of the SPI 4 and SPEI 4 for July, However, the PDSI incorporates these months, potentially diminishing the effects of the summer drought episode. Highlighting the importance of evaluating drought severity on different time steps, continuously (Wilhite, 2005).

There are also examples when yields were noticeably depressed despite drought not being identified by the DSI at the highest correlating time step. The 1942 season was not identified as a drought by the SPI-4 or the SPEI-4 for July, but experienced a 24.7% yield loss. For the SPI, June was the only month classified as a drought (Figure 31 in Appendix D). However, it coincided with certain sensitive growth stages in wheat (e.g. stem extension, anthesis and early grain filling) therefore, short intense precipitation deficits such as those seen in the SPI-1 in June 1942 can reduce yield. Both the SPI and SPEI show a significant (0.39-0.41) correlation for a single month drought identified in June. This emphasises the need for drought monitoring not only across multi-month times steps, but also across individual months including sensitive growth stages. Finally, for the 1990 growing season (which demonstrates a contrasting trend to 1942) the SPI and SPEI classified the year as being a 'severe' and 'extreme' drought respectively and a $PSMD_{JUL}$ over 300 mm; however, the simulated yield loss was only 9.5%. The SPI (Figure 31, Appendix D) showed precipitation deficiencies in May, July and August after a wet winter.

4.4 Methodological limitations

The availability of weather data covering a large temporal resolution was limited. The absence of recorded mean wind speed, VP and radiation data for Cambridge meant estimates had to be derived from other variables. However long-term records for temperature and precipitation, the important variables influencing drought formation were available. In addition, estimates of absent variables were derived from other, available variables (i.e. minimum temperature (VP), sunshine hours (radiation) and monthly mean daily wind speed (daily mean wind speed).

The RLT data provided sufficient information (sowing date and yield) to validate the cultivar *cv.* Claire in Sirius. However, to validate more recent, widely grown cultivars such as *cv.* Skyfall (Table 12) the timing of key growth stages was required (e.g. anthesis, ripening date). These observations are required in the RLT protocol (AHDB, 2015b). In addition, observations of grain protein content would have allowed the effects of historic drought on grain quality to be investigated. Unfortunately, neither of these data could be obtained.

The UK experiences significant spatial heterogeneity in climate (Figure 4), soil characteristics (Haygarth and Ritz, 2009), wheat production and productivity (Table 2). Therefore, to investigate the spatial variability of yields in response to historic droughts across different UK soils and climate, Sirius would need to be validated across a number of sites. Semenov (2009) simulated the impacts of climate change at 18 sites across England and Wales. For this study to be replicated, long-term climate data and soil parameters for sites with sufficient RLT yield observations for validation would be needed.

The DSI also provide classifications of wet episodes (Table 5 and Table 6) and these have been shown to correlate with yield loss in Europe (Potopová et al., 2015b). The UK is expected to experience an increase in excessive wet periods between sowing and anthesis increasing the risk from waterlogging (Trnka et al., 2014). Unfortunately, the Sirius CSM does not simulate the effects of waterlogging on yield therefore no relationship between classified wet periods and yield response could be made. However, although waterlogging has been demonstrated to limit yields in the UK (Dickin et al., 2009) periods of winter flooding of up to 21 days have limited impact (Watts et al., 2016) .

Finally, it is important to recognise the inherent limitations of DSI. A main limitation is the monthly time-step that DSI are often calculated on may not be a sufficiently high temporal resolution. A heavy precipitation event early on in the month may cause a month to be classed as normal, however in reality much of this is lost as run off or deep percolation and could be followed by 28 days of no rain, which (especially on droughty soils) may have caused a significant soil moisture deficit (Nain et al., 2005).

4.5 Research implications

4.5.1 Implications for science

It is accepted that there is little empirical evidence as to which DSI best represents drought impacts to a given sector, mainly due to the lack of information on drought impacts (Bachmair et al., 2016). However, the method presented in this study demonstrates that the use of models to simulate impacts can be used as substitute for limited and unsuitable recorded data, e.g. national or regional crop yields. Droughts pose a substantial threat to a multitude of UK sectors. Projects such as the UK droughts and Water Scarcity programme (NERC, 2016) (http://www.nerc.ac.uk/research/funded/programmes/droughts/), intend to support improved decision-making in relation to droughts through research that 'identifies, predicts and responds' to drought and their impacts. The outputs of this study, particularly the long term daily climate data set (1912-2015) and subsequent DSI record, as well as the identification of historic droughts whose timing and intensity prove most detrimental to East Anglian wheat production contribute towards a number of the programmes projects. Including, the Historic Drought project (http://historicdroughts.ceh.ac.uk/) who intend to build a drought inventory of past drought characteristics, impacts and responses. Also to the Marius project (http://www.mariusdroughtproject.org/) which intends to analyse the frequency of drought at local and national scales in present climates. The yield simulations presented here provide valuable insights into the occurrence rate of potentially significant yield limiting droughts. In addition, commonly used DSI were shown to correlate to simulated wheat yield highlighting there potential for introducing alternative drought management arrangements and agricultural drought monitoring.

Field studies are important in agricultural science; they represent a more realistic representation of agricultural practices with much more variable results (compared to controlled environments). Therefore it is important that environmental factors (particularly water stress) are monitored (Lawlor and Mitchell, 1991). This study demonstrates that the monitoring of commonly used

DSI, particularly over key growth stages can provide an indication of water stress to wheat. This could assist in improving the understanding and validity of field experiments by forming a basis of comparison between years or experiments.

4.5.2 Implications for industry

There is no nationwide drought M&EW system for the UK. This study shows that for certain time steps the DSI could be used by the wheat industry in monitoring potentially yield-limiting droughts. In addition to the monthly water situation reports produced by the Environment Agency (Section 1.2.2) the AHDB provide monitoring tools for leaf spot, wheat bulb, aphid disease and weather https://cereals.ahdb.org.uk/monitoring.aspx. The weather and soil-monitoring tool provides weekly information on rainfall, temperature and wind speed. If a weekly or monthly SPI, SPEI or PSMD were provided growers would have more informed information on potential drought risk. Other actors could also benefit from a more targeted drought monitoring system. Using Ilbery et al, (2013a) separation of the UK wheat sector. 'Upstream' input providers supplying seed, fertilisers and chemicals may be able to make estimates on demand products. 'Intermediates' such as grain merchants will be able to gauge supply scenarios, and output from upfront contracts. Downstream stakeholders such as mills, retailers and consumers may also find use in monitoring drought risk as reductions in UK production may increase the need for imports by millers resulting in a prize rise for wheat based products (Neate, 2012).

Drought can increase risk to certain diseases in the UK. Foot rot (*Cochliobolus sativus*) although rare, can be found in very dry seasons. In dry seasons, Bunt (*Tilletia tritici*) may survive in the soil affecting following crops. Growers could also potentially use DSI to monitor risks from disease.

Choosing drought tolerant varieties could yield an extra 1.3 t ha^{-1}. However, the recommended list does not provide data on individual varieties yield stability (Henley, 2012). Meaning growers have little guidance on which varieties perform best in dry conditions (Ober, 2012). The SPI requires only precipitation data, therefore could be potentially calculated at a large number of RL trial sites. The findings of this study suggesting that the SPI between April and August provides a good indicator of yield loss due to water restrictions potentially allowing for the comparative performance of varieties under drought stress.

Studies have demonstrated that a single DSI can identify yield limiting droughts across a wide variety of agricultural crops (Potopová et al., 2015a Potopová et al., 2015b). The production of other UK crops is also often considerably limited by drought; including sugar beet (Jaggard et al., 1998; Ober et al., 2005), potatoes (Onder et al., 2005; Daccache et al., 2012) and oilseed rape (Wreford and Adger, 2011). Here DSI have been shown to correlate with simulated wheat yields in East Anglia. There is potential therefore, for DSI to be applied across UK agriculture if studies similar to this were replicated on other drought vulnerable UK crops. This could provide an inventory of DSI-yield relationships to aid farmer and stakeholder decision making.

The UK is often one of the first regions to experience drought across Europe (Hannaford et al., 2010). Therefore, a tool that identifies agricultural drought in the UK could potentially be a useful early warning for other parts of Europe. For example although for the UK a drought in March and February has no correlation to wheat, a drought in March or April in the UK may manifest later, over key growth stages in Europe. It is important to note however that despite some broad patterns between drought in Europe, there tends to be few commonalities between major drought episodes (Hannaford et al., 2010). Therefore, other stakeholders in other countries could use the situation in the UK as an exemplar to monitor the situation in their country.

There are a number of training programs for agricultural stakeholders in the UK. The outputs of this study could contribute to programs such as the AgriFood Advanced Training Partnerships Soil (ATP) and Water Management Course. This course offers a technical overview of the key factors in effective soil and water management. The DSI yield relationship tables (**Figure 14**) could be used in training to inform how water limitations over key growth stages can be detrimental to yield, and how DSI can be used to monitor possible crop stress.

4.5.3 Implications for policy

National drought policy should include comprehensive M&EW systems (Wilhite et al., 2014). In England, the Environment Agency decides when a drought is happening by setting up and monitoring drought indicators, based on meteo-hydrological thresholds or environmental indicators (Environment Agency, 2015). The production of monthly water situation reports supports and disseminates these situations. This study demonstrates that DSI, particularly the SPI and SPEI could provide a more sector targeted drought M&EW system. Emphasising that drought policy should attempt to direct research priorities to establishing a greater understanding between the tools used in drought M&EW and it is impacts on a sector.

5 Conclusions

The aim of this research has been to assess the impacts of historical drought on a modern wheat production system and the performance of DSI in quantifying drought risk to UK wheat. The subsequent conclusions will focus on the three research objectives that form the major contributions to knowledge:

1. To parameterise and validate a suitable crop growth model for wheat using existing industry field trials and published scientific data

2. To simulate the impacts of historic climate variability on UK wheat, and;

3. To assess the performance of selected drought indices for drought M&EW for the UK wheat industry and agricultural applications

Three main conclusions can be drawn from this study. The first conclusion is that Sirius was shown to simulate wheat yields to an 'excellent-good' level of accuracy (RRMSE 5.48-16.34) demonstrating it is use as a valuable tool for modelling wheat yields in the UK.

The second conclusion is that simulated yield limiting droughts generally coincide with major reported droughts in the UK. With the 1921, 1976 and 2010 droughts being the most devastating in terms of yield loss simulated at Cambridge (1911-2015). This yield reconstruction emphasises that historically droughts may be more damaging (1921) than those that shape growers or actors perceptions (1976 and 2010). In addition, years in which yield was limited by water restrictions are shown to potentially cluster together, compounding the impacts over a number of years. Simulations identified periods in the early 40s and over the more recent 2010-2012 drought as the most extreme examples.

The third conclusion and arguably most significant is that the SPI, SPEI, PDSI, and the $PSMD_{Month}$ all showed significant correlations to simulated wheat yields (0.18-0.66) between April to August with a strengthening of correlation as drought extends over the key growth stages. Previous studies have failed to find a significant relationship between DSI and UK national wheat yields. By using local simulated yields, confounding factors such as disease and lodging were removed. Presenting a method that may be taken forward an applied to other UK field crops and internationally.

The SPI and SPEI showed little difference in their correlations, In agreement with other studies investigating DSI and impact relationships. The PDSI showed the weakest maximum correlation to wheat yields (0.55), in agreement with other previous comparative studies. However although not statistically significant (*P=0.13*) the PDSI may provide an earlier warning of yield limiting drought. This may require further investigation.

Collectively, this new knowledge and insights can be taken forward and used in a more directed and sector specific drought M&EW system in the UK. Aiding farmers, grain merchants, miller's retailers and consumers of potential production risks. Field studies and trials can use DSI to monitor drought stress allowing for more informed information on drought tolerance between modern wheat varieties.

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APPENDICES

Appendix A - Sirius simulation accuracy

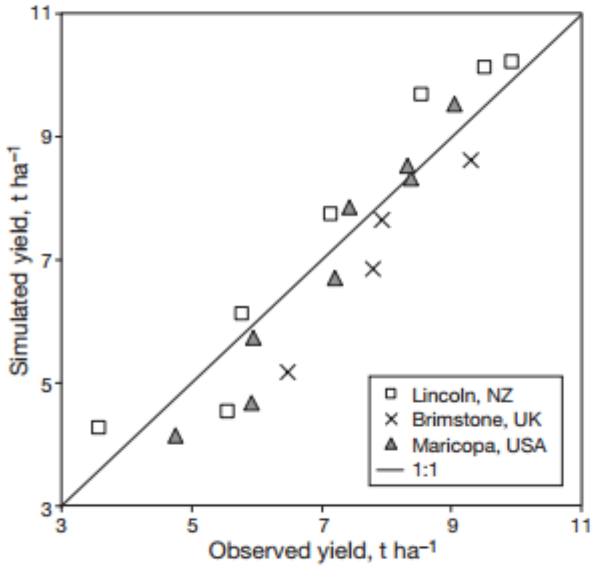

Figure 22 Comparison between Simulated yields in Sirius and wheat yields in contrasting environments: rain shelter experiment, Lincoln, NZ; nitrogen experiment, Brimstone, UK; and nitrogen and water experiment, Maricopa, USA (Semenov and Doblas-Reyes, 2007)

Appendix B - Weather data comparison

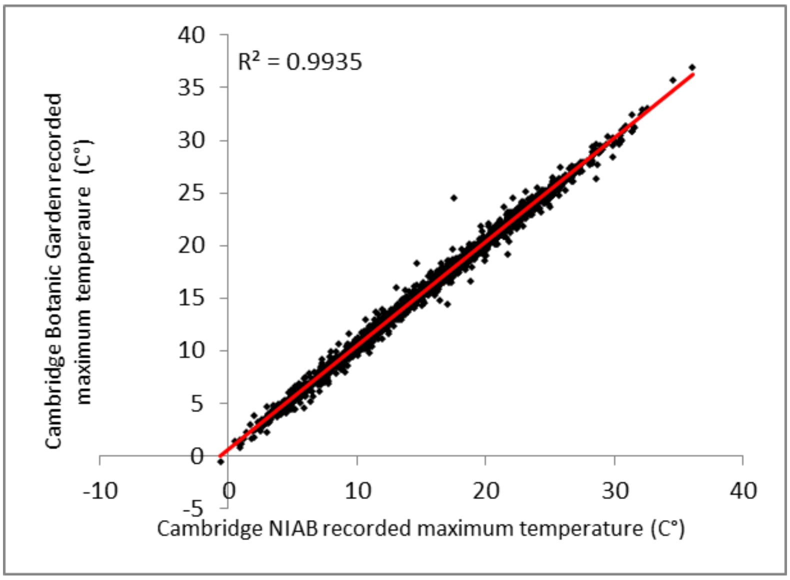

Figure 23 Comparison of daily maximum temperature (C°) at the Cambridge Botanic Gardens and Cambridge NIAB Met office weather stations 1959-2005

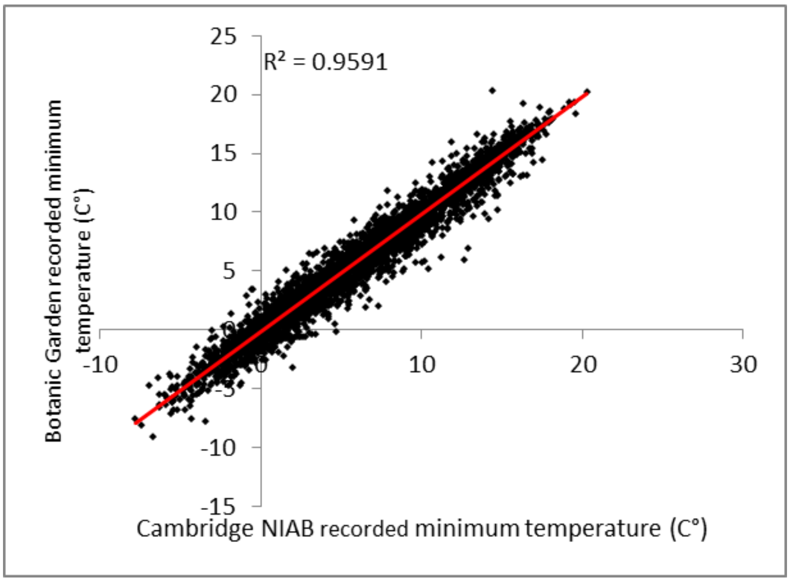

Figure 24 Comparison of daily minimum temperature (C°) at the Cambridge Botanic Garden and Cambridge NIAB Met office weather stations 1959-2005

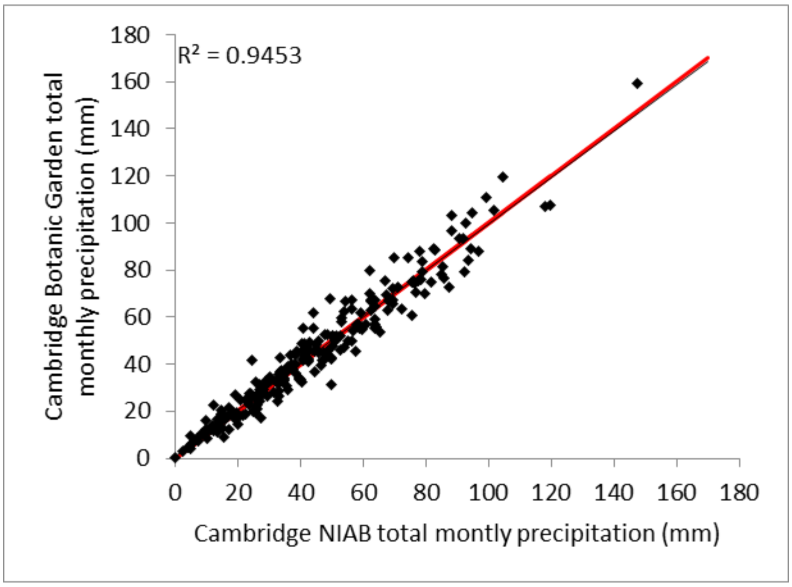

Figure 25 Comparison of Monthly precipitation (mm) totals at Cambridge NIAB and Cambridge Botanic Garden (1961-1969 and 1990-1999)

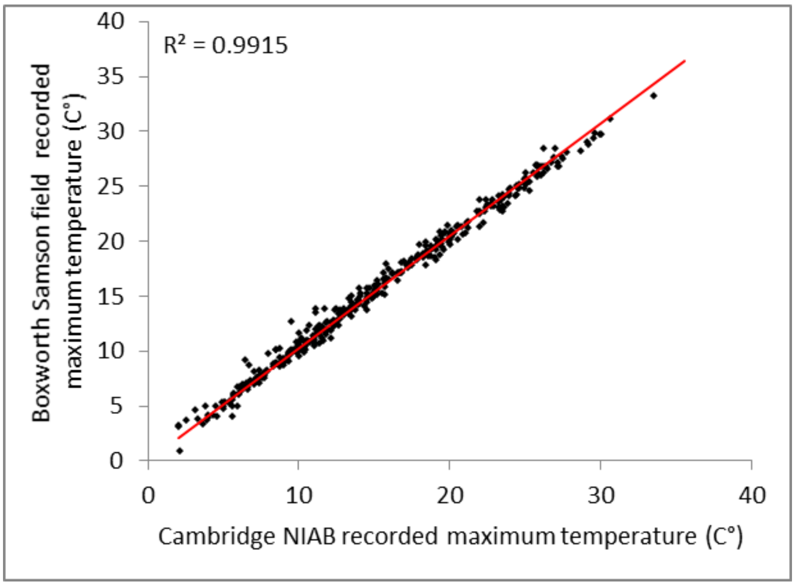

Figure 26 Comparison of daily maximum temperature (C°) at the Cambridge NIAB and Boxworth Samson Field Met stations 1977-1989

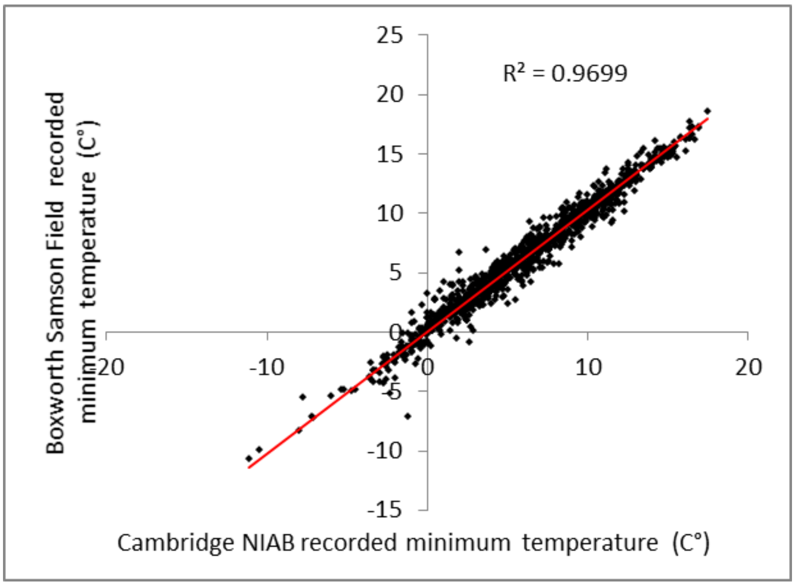

Figure 27 Comparison of daily minimum temperature (C°) at the Cambridge NIAB and Boxworth Samson Field Met stations 1977-1989

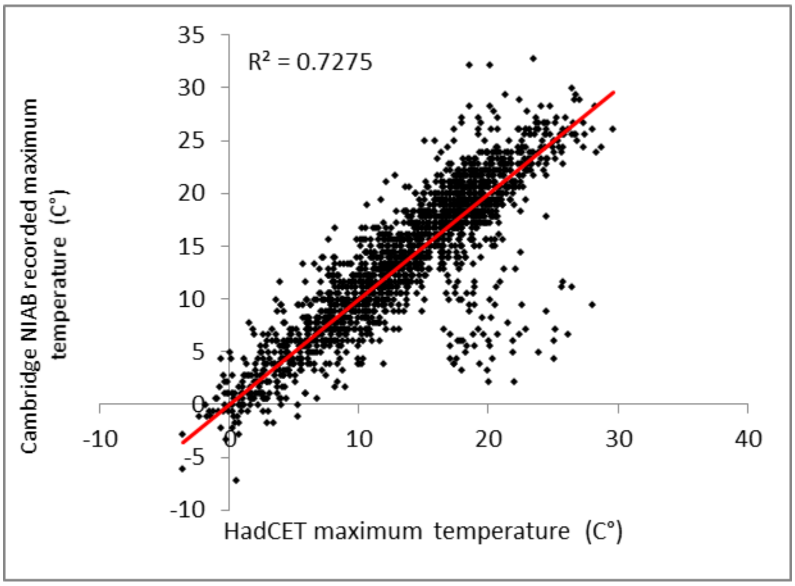

Figure 28 Comparison of daily maximum temperature (C°) at the Cambridge NIAB and Hadley Centre Central England Temperature data (HadCET) 1959-1963

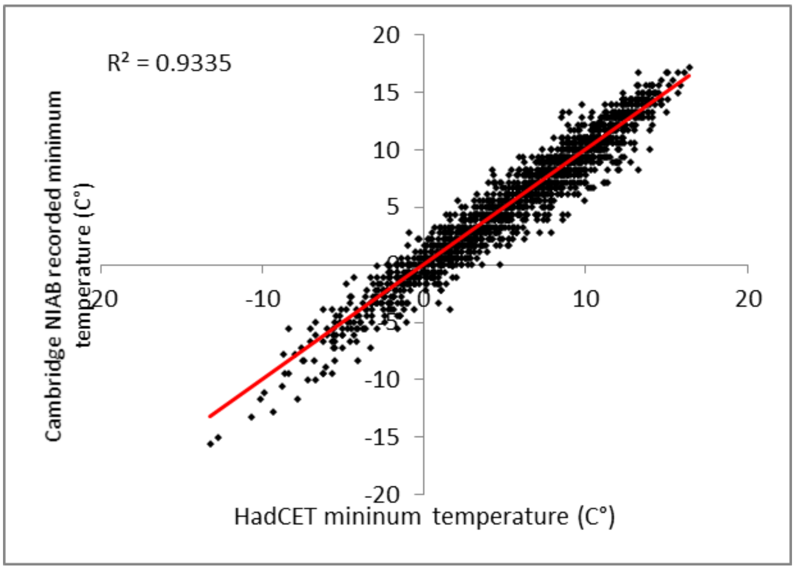

Figure 29 Comparison of daily minimum temperature (C°) at the Cambridge NIAB and Hadley Centre Central England Temperature data (HadCET) 1959-1963

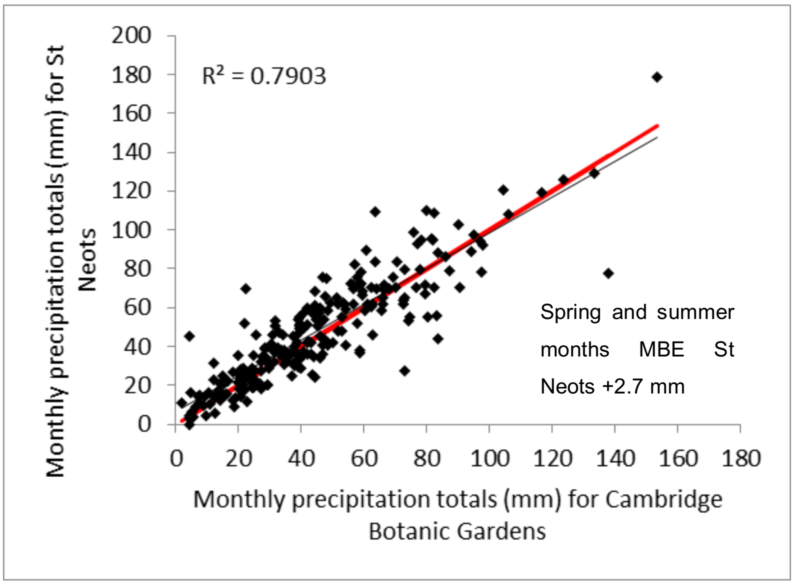

Figure 30 Comparison of monthly precipitation totals for St Neots and Cambridge Botanic Garden Met station (1930-1949)

Appendix C - RLT soil classification

Table 24 Soil classification system used for the AHDB RLT(DEFRA, 2010b; AHDB, 2015b)

Descriptor	Soil type	Definition
L	Light sand soils	Soils which are sand, loamy sand or sandy loam to 40 cm depth and are sand or loamy sand between 40 and 80 cm, or over sandstone rock.
	Shallow	Soils over chalk, limestone or other rock where the parent material is within 40 cm of the soil surface. Sandy soils developed over sandstone rock should be regarded as light sand soils.
M	Medium	Medium textured soil that does not fall into other category.
H	Deep clay soils	Soils with predominantly sandy clay loam, silty clay loam, clay loam, sandy clay, silty clay or clay topsoil overlying clay subsoil. Deep clay soils normally need artificial field drainage.
	Deep fertile soils	Soils of sandy silt loam, silt loam to silty clay loam textures to 100 cm depth or more. Silt soils formed on marine alluvium; warp soils (formed on river alluvium) and brickearth soils (formed on windblown material) will be in this category.
O	Organic soils	Soils that are predominantly mineral with between 6 and 20% organic matter. These can be distinguished by darker colouring that stains the fingers black or grey and gives the soil a silty feel.
	Peaty soils	Soils that contain more than 20% organic matter derived from sedge or similar peat material.
C (L)	Chalky soil.	Specific chalky soil within the L group described above.
B (L)	Limestone brash soil.	Specific limestone brash within the L group described above.
W (L)	Wold	Wold soil over chalk within the L group described above.
F (O)	Black Fen soil.	Black fen within the O group described above.
S (H)	Silts	Silty soils that are within the H group described above.

Appendix D - SPI for years of significant simulated yield loss

1921	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.7	-0.2	0.2	-0.1	-0.2	0.5	0.6	0.2	0.3	0.8	0.5	0.1
OCT (S)	-1.7	-0.4	-1.0	-0.4	-0.7	-0.7	0.0	0.1	-0.3	-0.2	0.3	0.1
NOV	-2.3	-2.8	-1.3	-1.8	-1.1	-1.2	-1.2	-0.5	-0.5	-0.8	-0.7	-0.1
DEC	-0.1	-1.6	-2.5	-1.5	-1.9	-1.2	-1.3	-1.3	-0.6	-0.5	-0.9	-0.8
JAN	0.3	0.0	-1.0	-1.8	-1.2	-1.6	-1.0	-1.2	-1.2	-0.5	-0.5	-0.8
FEB	-1.7	-0.8	-0.7	-1.5	-2.2	-1.5	-1.9	-1.3	-1.4	-1.5	-0.8	-0.7
MAR	-0.8	-1.8	-1.2	-1.1	-1.8	-2.4	-1.7	-2.1	-1.5	-1.6	-1.6	-1.0
APR	0.0	-0.6	-1.5	-1.2	-1.1	-1.7	-2.3	-1.7	-2.1	-1.5	-1.6	-1.6
MAY	-1.4	-1.0	-1.4	-2.1	-1.8	-1.6	-2.2	-2.7	-2.1	-2.4	-1.8	-1.8
JUN	-1.2	-2.2	-1.8	-2.0	-2.6	-2.3	-2.1	-2.5	-3.0	-2.5	-2.7	-2.1
JUL	-2.2	-2.6	-3.0	-2.5	-2.8	-3.2	-2.9	-2.7	-3.1	-3.5	-3.0	-3.2
AUG (H)	-0.7	-2.0	-2.4	-2.8	-2.7	-2.9	-3.3	-3.0	-2.9	-3.2	-3.6	-3.1

1934	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.1	-0.6	-1.2	-0.9	-0.7	-0.8	-0.7	-0.7	-1.0	-1.5	-1.6	-1.0
OCT (S)	-0.1	-0.2	-0.7	-1.2	-1.0	-0.8	-0.8	-0.8	-0.8	-1.1	-1.6	-1.7
NOV	-0.7	-0.7	-0.6	-1.0	-1.4	-1.2	-1.0	-1.0	-1.0	-1.0	-1.3	-1.7
DEC	-2.5	-2.1	-1.8	-1.5	-1.8	-2.1	-1.9	-1.6	-1.6	-1.5	-1.5	-1.8
JAN	-1.5	-2.5	-2.4	-2.2	-1.9	-2.2	-2.4	-2.1	-1.8	-1.9	-1.8	-1.7
FEB	-2.2	-2.6	-3.2	-3.0	-2.6	-2.3	-2.5	-2.7	-2.4	-2.2	-2.2	-2.1
MAR	-0.1	-1.3	-2.0	-2.8	-2.6	-2.4	-2.2	-2.4	-2.6	-2.3	-2.1	-2.1
APR	0.4	0.1	-0.8	-1.4	-2.1	-2.2	-2.1	-1.9	-2.2	-2.3	-2.1	-1.9
MAY	-1.5	-0.7	-0.7	-1.5	-2.1	-2.7	-2.6	-2.5	-2.3	-2.5	-2.6	-2.4
JUN	-0.9	-2.0	-1.2	-1.2	-1.9	-2.4	-3.0	-2.9	-2.8	-2.6	-2.8	-2.9
JUL	-0.6	-1.2	-1.9	-1.4	-1.4	-2.0	-2.4	-3.0	-2.9	-2.8	-2.7	-2.8
AUG (H)	0.0	-0.5	-0.9	-1.5	-1.3	-1.3	-1.8	-2.2	-2.7	-2.7	-2.6	-2.6

1942	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-1.6	0.2	0.0	-0.3	-0.3	-0.6	0.0	0.1	0.3	0.1	1.1	0.8
OCT (S)	0.0	-1.0	0.0	-0.1	-0.4	-0.4	-0.6	-0.1	0.1	0.2	0.0	1.0
NOV	0.2	0.0	-0.8	0.0	0.0	-0.3	-0.3	-0.5	0.0	0.1	0.2	0.0
DEC	-0.9	-0.5	-0.5	-1.3	-0.3	-0.4	-0.6	-0.6	-0.8	-0.3	-0.2	-0.1
JAN	0.3	-0.4	-0.3	-0.4	-1.1	-0.3	-0.3	-0.5	-0.5	-0.7	-0.2	-0.1
FEB	0.0	0.1	-0.5	-0.3	-0.4	-1.0	-0.3	-0.3	-0.6	-0.6	-0.7	-0.3
MAR	-0.1	-0.3	-0.2	-0.6	-0.4	-0.5	-1.1	-0.4	-0.4	-0.6	-0.6	-0.8
APR	-0.4	-0.6	-0.7	-0.5	-0.9	-0.7	-0.7	-1.2	-0.6	-0.6	-0.7	-0.7
MAY	0.2	-0.3	-0.5	-0.6	-0.4	-0.8	-0.6	-0.7	-1.2	-0.5	-0.5	-0.7
JUN	-1.3	-0.9	-1.1	-1.1	-1.2	-1.0	-1.3	-1.1	-1.1	-1.5	-0.9	-0.9
JUL	0.8	-0.1	-0.1	-0.4	-0.5	-0.6	-0.5	-0.8	-0.7	-0.7	-1.1	-0.6
AUG (H)	-0.6	0.1	-0.5	-0.4	-0.7	-0.8	-0.8	-0.8	-1.0	-0.9	-0.9	-1.3

1944	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-0.2	-0.7	-1.6	-1.3	-1.3	-1.5	-1.9	-2.1	-1.3	-1.2	-1.7	-1.2
OCT (S)	-0.1	-0.4	-0.7	-1.4	-1.2	-1.2	-1.5	-1.8	-2.0	-1.3	-1.3	-1.8
NOV	-0.6	-0.5	-0.7	-1.0	-1.5	-1.4	-1.4	-1.6	-2.0	-2.1	-1.5	-1.4
DEC	-0.9	-1.2	-1.1	-1.3	-1.5	-2.0	-1.8	-1.7	-1.9	-2.3	-2.4	-1.7
JAN	-0.9	-1.2	-1.5	-1.4	-1.5	-1.7	-2.1	-1.9	-1.9	-2.1	-2.4	-2.5
FEB	-0.7	-1.3	-1.5	-1.6	-1.5	-1.6	-1.8	-2.2	-2.0	-2.0	-2.2	-2.5
MAR	-1.9	-1.8	-2.1	-2.2	-2.1	-2.0	-2.0	-2.2	-2.5	-2.3	-2.2	-2.4
APR	0.2	-0.8	-1.2	-1.7	-1.9	-1.9	-1.8	-1.9	-2.0	-2.3	-2.1	-2.1
MAY	-0.8	-0.5	-1.3	-1.6	-2.0	-2.2	-2.2	-2.1	-2.1	-2.2	-2.5	-2.3
JUN	-1.2	-1.8	-1.3	-1.9	-2.2	-2.5	-2.6	-2.5	-2.4	-2.5	-2.5	-2.8
JUL	-0.3	-1.1	-1.5	-1.2	-1.8	-2.0	-2.3	-2.5	-2.5	-2.4	-2.4	-2.5
AUG (H)	0.6	0.1	-0.5	-0.8	-0.8	-1.3	-1.5	-1.8	-2.0	-2.0	-2.0	-2.1

1957	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-0.2	1.3	1.7	1.6	1.1	1.0	0.7	0.4	0.7	0.6	0.3	0.6
OCT (S)	-0.6	-0.7	0.8	1.2	1.2	0.8	0.6	0.4	0.2	0.5	0.3	0.1
NOV	-1.3	-1.4	-1.3	0.3	0.7	0.7	0.4	0.3	0.0	-0.2	0.1	0.0
DEC	0.6	-0.4	-0.9	-1.0	0.4	0.9	0.9	0.5	0.4	0.1	-0.1	0.2
JAN	-0.9	0.0	-0.8	-1.1	-1.2	0.1	0.6	0.6	0.3	0.2	-0.1	-0.2
FEB	1.0	0.2	0.5	-0.2	-0.5	-0.7	0.4	0.8	0.8	0.5	0.4	0.2
MAR	0.4	0.8	0.3	0.5	-0.1	-0.4	-0.6	0.4	0.8	0.8	0.5	0.4
APR	-2.6	-0.9	-0.2	-0.6	-0.3	-0.7	-1.0	-1.1	0.0	0.4	0.4	0.1
MAY	-1.1	-2.5	-1.6	-0.8	-1.2	-0.7	-1.1	-1.3	-1.4	-0.4	0.1	0.1
JUN	-0.2	-1.2	-2.1	-1.6	-1.0	-1.3	-0.9	-1.2	-1.4	-1.5	-0.5	0.0
JUL	0.5	0.1	-0.5	-1.2	-1.0	-0.6	-0.9	-0.6	-1.0	-1.1	-1.3	-0.3
AUG (H)	0.1	0.3	0.0	-0.5	-1.1	-1.0	-0.6	-0.9	-0.6	-0.9	-1.1	-1.2

1976	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.7	-0.1	-0.6	-1.1	-0.8	-0.1	0.6	0.5	0.5	0.3	1.1	1.3
OCT (S)	-2.2	-0.5	-1.0	-1.3	-1.7	-1.4	-0.7	0.1	-0.1	0.0	-0.2	0.6
NOV	-0.4	-1.6	-0.7	-1.1	-1.4	-1.8	-1.5	-0.8	-0.1	-0.2	-0.2	-0.4
DEC	-1.0	-1.1	-2.2	-1.3	-1.6	-1.8	-2.1	-1.9	-1.2	-0.4	-0.5	-0.4
JAN	-0.9	-1.2	-1.3	-2.3	-1.4	-1.8	-2.0	-2.2	-2.0	-1.3	-0.6	-0.7
FEB	-1.1	-1.5	-1.7	-1.7	-2.5	-1.7	-2.0	-2.1	-2.4	-2.2	-1.5	-0.8
MAR	-0.8	-1.5	-1.8	-2.0	-1.9	-2.6	-1.9	-2.1	-2.2	-2.5	-2.3	-1.6
APR	-0.5	-1.1	-1.7	-2.0	-2.2	-2.0	-2.7	-2.0	-2.3	-2.4	-2.5	-2.4
MAY	-0.4	-0.9	-1.3	-1.8	-2.1	-2.3	-2.2	-2.8	-2.2	-2.4	-2.4	-2.6
JUN	-1.8	-1.8	-1.9	-2.1	-2.5	-2.8	-2.9	-2.7	-3.2	-2.6	-2.8	-2.9
JUL	-0.4	-1.5	-1.6	-1.8	-2.0	-2.4	-2.6	-2.9	-2.7	-3.1	-2.7	-2.8
AUG (H)	-0.5	-0.8	-1.5	-1.6	-1.9	-2.2	-2.4	-2.7	-2.9	-2.7	-3.2	-2.7

1990	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-1.0	-1.3	-1.3	-1.3	-1.9	-1.1	-1.0	-0.7	-1.0	-1.3	-1.4	-1.4
OCT (S)	-0.4	-1.1	-1.4	-1.4	-1.4	-1.9	-1.2	-1.1	-0.9	-1.2	-1.4	-1.5
NOV	-0.5	-0.8	-1.3	-1.6	-1.5	-1.5	-2.0	-1.3	-1.3	-1.0	-1.3	-1.5
DEC	2.4	1.7	1.1	0.4	-0.1	-0.2	-0.3	-0.8	-0.3	-0.2	0.0	-0.3
JAN	0.0	1.9	1.3	0.9	0.3	-0.1	-0.2	-0.3	-0.8	-0.3	-0.3	-0.1
FEB	1.5	1.1	2.2	1.7	1.3	0.7	0.4	0.2	0.1	-0.3	0.1	0.1
MAR	-0.3	0.8	0.6	1.8	1.4	1.0	0.5	0.2	0.1	0.0	-0.4	0.0
APR	-0.2	-0.5	0.4	0.3	1.5	1.1	0.8	0.4	0.1	-0.1	-0.1	-0.5
MAY	-2.4	-1.6	-1.6	-0.5	-0.6	0.9	0.5	0.3	-0.1	-0.4	-0.5	-0.5
JUN	-0.7	-2.2	-1.9	-1.9	-0.9	-0.9	0.5	0.2	0.0	-0.4	-0.6	-0.7
JUL	-1.4	-1.6	-2.6	-2.4	-2.4	-1.4	-1.4	-0.1	-0.2	-0.4	-0.8	-1.0
AUG (H)	-1.0	-1.9	-2.0	-2.7	-2.7	-2.8	-1.8	-1.8	-0.5	-0.6	-0.8	-1.1

1995	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.8	-0.1	-0.9	-1.3	-1.2	-0.6	-0.6	-0.6	-0.3	0.1	0.2	0.6
OCT (S)	0.9	1.1	0.4	-0.3	-0.7	-0.6	-0.2	-0.2	-0.2	0.1	0.4	0.4
NOV	-1.0	0.2	0.6	-0.1	-0.6	-1.0	-0.9	-0.5	-0.5	-0.5	-0.2	0.1
DEC	-0.1	-0.9	0.0	0.4	-0.2	-0.7	-1.1	-1.0	-0.6	-0.6	-0.6	-0.3
JAN	1.5	0.8	0.1	0.6	0.9	0.3	-0.2	-0.5	-0.5	-0.1	-0.1	-0.2
FEB	1.3	1.9	1.3	0.7	1.0	1.2	0.7	0.2	-0.1	-0.1	0.2	0.2
MAR	0.8	1.3	1.8	1.4	0.9	1.1	1.3	0.8	0.4	0.1	0.1	0.3
APR	-1.3	-0.2	0.5	1.1	0.8	0.4	0.7	0.9	0.5	0.0	-0.2	-0.2
MAY	-0.8	-1.6	-0.7	0.0	0.7	0.4	0.0	0.4	0.6	0.2	-0.2	-0.4
JUN	-1.1	-1.6	-2.2	-1.3	-0.5	0.1	0.0	-0.4	0.0	0.3	-0.1	-0.5
JUL	-0.8	-1.5	-1.8	-2.3	-1.6	-0.9	-0.3	-0.4	-0.7	-0.3	0.0	-0.4
AUG (H)	-2.4	-2.1	-2.5	-2.6	-3.1	-2.4	-1.6	-1.0	-1.0	-1.2	-0.8	-0.6

1996	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	1.5	0.3	-0.2	-0.7	-1.0	-1.4	-1.1	-0.6	-0.1	-0.2	-0.5	-0.2
OCT (S)	-1.6	0.5	-0.4	-0.8	-1.3	-1.5	-1.9	-1.6	-1.1	-0.6	-0.7	-0.9
NOV	-0.9	-1.8	0.1	-0.8	-1.1	-1.5	-1.7	-2.1	-1.8	-1.3	-0.9	-0.9
DEC	0.8	0.0	-1.0	0.4	-0.5	-0.8	-1.2	-1.4	-1.8	-1.5	-1.1	-0.6
JAN	-0.6	0.2	-0.3	-1.1	0.1	-0.7	-1.0	-1.3	-1.5	-1.9	-1.6	-1.2
FEB	0.8	0.1	0.5	0.0	-0.7	0.3	-0.4	-0.7	-1.0	-1.2	-1.6	-1.4
MAR	-0.5	0.1	-0.3	0.1	-0.3	-0.9	0.0	-0.6	-0.9	-1.1	-1.3	-1.6
APR	-2.1	-1.7	-0.9	-1.2	-0.6	-0.9	-1.5	-0.4	-1.1	-1.3	-1.5	-1.7
MAY	-1.0	-2.2	-2.2	-1.5	-1.7	-1.0	-1.3	-1.8	-0.8	-1.3	-1.5	-1.7
JUN	-1.4	-2.1	-2.9	-2.9	-2.1	-2.3	-1.6	-1.7	-2.2	-1.2	-1.7	-1.9
JUL	-0.2	-1.1	-1.6	-2.3	-2.4	-1.9	-2.1	-1.6	-1.7	-2.1	-1.2	-1.7
AUG (H)	0.5	0.1	-0.5	-0.9	-1.6	-1.8	-1.4	-1.6	-1.2	-1.4	-1.8	-1.0

2010	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	-1.4	-0.7	0.5	0.4	0.1	-0.3	-0.3	-0.1	-0.2	-0.5	-0.4	-0.3
OCT (S)	-0.4	-1.4	-0.9	0.2	0.1	-0.2	-0.5	-0.6	-0.3	-0.4	-0.7	-0.6
NOV	1.7	0.9	0.1	0.1	0.8	0.7	0.5	0.2	0.1	0.3	0.2	-0.1
DEC	1.1	2.0	1.3	0.5	0.5	1.2	1.0	0.8	0.5	0.4	0.6	0.5
JAN	0.0	0.8	1.6	1.1	0.4	0.4	1.1	1.0	0.7	0.4	0.4	0.5
FEB	1.3	0.9	1.2	1.9	1.4	0.8	0.8	1.3	1.2	1.0	0.7	0.7
MAR	-0.4	0.6	0.4	0.8	1.5	1.1	0.5	0.5	1.1	1.0	0.8	0.5
APR	-1.3	-1.4	-0.3	-0.3	0.3	1.0	0.7	0.2	0.2	0.8	0.7	0.5
MAY	-0.5	-1.4	-1.6	-0.6	-0.6	-0.1	0.7	0.4	-0.1	0.0	0.6	0.5
JUN	0.0	-0.6	-1.2	-1.4	-0.7	-0.7	-0.2	0.6	0.3	-0.1	-0.1	0.5
JUL	-1.1	-0.9	-1.1	-1.6	-1.8	-1.1	-1.1	-0.6	0.2	-0.1	-0.5	-0.4
AUG (H)	1.9	1.1	0.9	0.6	0.1	-0.1	0.3	0.3	0.6	1.1	0.8	0.4

2011	No. months lag											
	1	2	3	4	5	6	7	8	9	10	11	12
SEP	0.4	1.7	1.1	0.9	0.6	0.2	0.0	0.4	0.3	0.6	1.1	0.9
OCT (S)	0.4	0.4	1.5	1.0	0.9	0.6	0.3	0.1	0.4	0.4	0.6	1.1
NOV	-1.0	-0.4	-0.2	1.1	0.6	0.5	0.3	-0.1	-0.3	0.1	0.1	0.3
DEC	-1.0	-1.6	-1.0	-0.7	0.8	0.3	0.2	0.0	-0.4	-0.5	-0.2	-0.2
JAN	0.8	-0.1	-0.7	-0.5	-0.3	1.0	0.5	0.4	0.2	-0.2	-0.3	0.0
FEB	0.1	0.5	-0.2	-0.7	-0.5	-0.3	0.9	0.4	0.3	0.1	-0.2	-0.3
MAR	-2.3	-1.2	-0.5	-0.9	-1.3	-1.0	-0.8	0.4	0.0	0.0	-0.2	-0.5
APR	-2.6	-3.6	-2.3	-1.4	-1.7	-1.9	-1.6	-1.3	-0.1	-0.4	-0.4	-0.6
MAY	-1.3	-2.6	-3.5	-2.8	-2.0	-2.2	-2.3	-2.0	-1.7	-0.4	-0.7	-0.7
JUN	0.8	-0.1	-1.1	-1.8	-1.7	-1.2	-1.5	-1.7	-1.5	-1.3	-0.2	-0.5
JUL	-0.4	0.2	-0.5	-1.2	-1.8	-1.7	-1.4	-1.7	-1.8	-1.6	-1.4	-0.3
AUG (H)	0.1	-0.4	0.1	-0.4	-1.1	-1.6	-1.6	-1.3	-1.5	-1.7	-1.5	-1.4

Key

Value	Classification
2.0+	Extreme drought
1.5 to 1.99	Severe drought
1 to 1.49	Moderate drought
-.99 to .99	Near normal
-1.0 to -1.49	Moderately wet
-1.5 to -1.99	Severely wet
-2 and less	Extremely wet

Figure 31 SPI1-12 for the winter wheat growing season of significant yield limiting years