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Exploring the utility of drought indicators to assess climate risks to agricultural productivity in a humid climate

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ABSTRACT

Drought indices have been extensively used by the hydrological research community and practitioners involved in understanding and managing drought risks to water resources systems in both semi-arid and humid environments. They have also proved particularly useful for monitoring drought onset and severity and the spatio-temporal extent and duration of meteorological and hydrological droughts. In a humid climate such as in England, most agricultural crop production is rainfed and highly dependent on summer rainfall. Whilst supplemental irrigation is used on high value crops to buffer the impacts of drought, knowledge of drought risks in terms of their occurrence and potential agronomic impacts on rainfed productivity remains limited. This paper evaluated the utility of integrating data from three well established drought indices including the standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI) and the Palmer drought severity index (PDSI) with simulated yield outputs from a biophysical crop model for potato, a drought sensitive and high value crop. The relationships between drought onset and yield response were statistically evaluated. The SPEI-3 drought indicator was found to be most suited to monitoring water availability and hence drought conditions for both rainfed and irrigated production. 'Heat maps' were produced to illustrate the strength of the correlation between the modelled SUBSTOR-Potato yields and SPEI for different aggregation periods and monthly lags. Finally, the outputs were used to assess alternative ways in which decision-making could be improved regarding adaptation strategies to reduce agricultural system vulnerability to future drought events. The approach was applied to a large rural catchment in Eastern England with a high concentration of rainfed and irrigated farming and acute levels of water resource stress. The broader implications for managing future climate variability and drought risk in agricultural cropping are discussed.

Keywords: England; model; potato; SUBSTOR-Potato; water resources.

INTRODUCTION

Droughts are recognised as being one of the dominant causes of global environmental, agricultural and economic damage (Vicente-Serrano et al. 2009). Despite accounting for just 5% of natural disasters between 1994 and 2013, drought affected more than one billion people (CRED, 2015) and is one of the world's costliest extreme weather-related natural hazard (Wilhite, 2000). Although droughts affect all sectors, their impacts are usually more evident in the agricultural sector, with dried crops, abandoned farmland, and desiccated pastures being common signs of drought. Crop failure, low productivity and pasture losses represent the principal direct economic impacts of drought within agriculture (Ding et al. 2010). Moreover, drought-induced production losses spread from primary production through the supply chain, causing a reduction in supply, loss of revenue and price increases. In addition, drought impacts on agriculture can be aggravated by poor farming habits, deforestation, over-exploitation, and other anthropogenic activities that can reduce water resources availability.

Drought differs from other natural hazards because of its slow onset, with temporal and spatial dimensions difficult to determine accurately. In addition, the lack of a universal definition for drought normally introduces inconsistencies in terms of understanding the magnitude and severity of a specific drought event (Kim et al. 2002), often leading to confusion. In general, droughts are classified into four widely accepted categories depending on the variable used to describe them: (i) meteorological, when a lack of precipitation occurs over a given region for a period of time; (ii) hydrological, related to a period with insufficient surface water flow in a river basin; (iii) agricultural, defined by declining soil moisture and subsequent crop failure; and (iv) socio-economic, related to the failure of water resources systems to meet water demands for established water uses. In the absence of heavy modification of the water cycle by human activities, hydrological and agricultural drought are caused by the propagation of meteorological anomalies according to catchment characteristics such as land cover, soil and geology (van Loon et al. 2016). In order to monitor the severity, propagation and extent of drought, several drought indices have been derived in recent years. For example, the World Meteorological Organization (WMO) and Global Water Partnership (GWP) conducted an extensive synthesis and evaluation of most existing drought indices (WMO-GWP, 2016). A drought index can be described as a variable that assesses the effect of a drought and determines different drought parameters, which include magnitude, intensity, duration and spatial extent (Mishra and Singh 2010). It is a measure for establishing information in relation to droughts through the comparison of current prevailing conditions to the historical record using statistical methods (Fuchs 2012). Regarding agricultural drought, in England, the water regulatory agency, the Environment Agency defines drought as a period with inadequate precipitation and soil moisture to support crop production or irrigated farming (EA, 2015). Thus, it is reasonable that any drought monitoring efforts should focus on these two variables for agriculture.

Although the climate is humid in England, and most agricultural cropping is rainfed, drought is an intrinsic characteristic of the climate, and a recurrent threat to crop productivity (Rey et al. 2017). The farming sector has been negatively impacted by a series of relatively recent droughts including 1988-92, 1995-96, 2003, 2010 and 2012, although the 1975-76 drought is still widely regarded as being the most severe and iconic (Burke et al. 2010). Droughts can also cause severe economic impacts; for example, an estimated £400 million in farming losses was reported from the most recent 2010-2012 drought (Anglian Water and University of Cambridge 2013). In the UK agriculture accounts for a relatively small proportion of the national economy and employment, but it occupies almost 75% of the total land surface area (Angus et al. 2009). It is also strategically important for national food security, providing over half of all food consumed in the UK (Knox et al. 2010). In a typical dry year, about 150,000 ha are irrigated in England supplying the food market (principally retailers or supermarkets) with substantial quantities of high-quality vegetables and horticultural produce. In this context, and given increasing concerns regarding the impacts of drought and rainfall uncertainty on the sustainability of UK agriculture (Rey et al. 2017) the aim of this paper was to explore the utility and relevance of selected drought indices to inform knowledge of the risks and impacts of drought in high-value cropping. A better understanding of how drought indices might be integrated with yield data would also support decision-makers in developing appropriate strategies to increase the agricultural sectors' resilience to future drought.

MATERIALS AND METHODS

In summary, a three stage methodology was developed. Firstly, two recently published national long-term climatic datasets were processed and aggregated to catchment level for the period 1900-2014 in order to derive an equivalent time series dataset for the three selected drought indices (SPI, SPEI and PDSI). A previously calibrated and validated biophysical crop model, termed SUBSTOR-Potato (Jones et al. 2003) was then used to simulate the annual yield and irrigation needs for a maincrop potato (*Solanum tuberosum*) variety (Maris Piper) grown under both rainfed and fully irrigated conditions. The results from the crop modelling were then correlated against the derived drought indices to evaluate their utility in assessing future drought risk and supporting implementation of appropriate adaptation responses. A brief description of each methodological stage, followed by discussion of the results and implications for the case study catchment and humid regions internationally is presented.

Case study catchment

Due to the very favourable agroclimate, fertile soils, low lying topography and dominance of large scale intensive farming systems, more than half the cropped area in eastern England is dedicated to agricultural and horticultural production. High-value irrigated vegetable cropping typically abstracts 160 Mm^3 in a dry year (Weatherhead et al. 2015) with half the total irrigated area and 57% of the volume of water applied being concentrated in Anglian region. The region is also recognised as being one of the driest and most water-stressed (Figure 1a) with over half of all catchments being defined by the water regulator, the Environment Agency (EA) as being either over-abstracted and/or over-licensed (Hess et al. 2010). Indeed, in many catchments, summer water resources are over-committed and additional licences for either surface or groundwater irrigation abstraction are no longer available. Average annual rainfall in the region is around 600 mm (less than 70% of the national average) and annual reference evapotranspiration (ETo) averages 530 mm. The spatial distribution in aridity (agroclimate) across Anglian region is shown in Figure 1a. For many crops including potatoes and field-scale vegetables, supplemental irrigation is used to buffer the effects of rainfall variability and critically to meet the quality assurance standards demanded by the major retailers (supermarkets) who require consistent supplies of premium quality produce (Knox et al 2000).

One of the largest and most intensively farmed catchments in Anglian region is the Cam and Ely Ouse. This extends to an area of approximately 3600 km^2 and has a rural pattern of land use including extensive areas of drained agricultural land with high yield potential. There are more than 184,000 ha cultivated for crop production, with 11,600 ha being irrigated, representing a quarter (23%) of the total irrigated area in Anglian region. The most commonly irrigated crops in the catchment include potatoes (40%), vegetables (36%) and sugar beet (11%). Most irrigation in the catchment is via mobile overhead hose reels fitted with rain guns or booms, since these provide the flexibility required to cope with rotational cropping, and varying irrigation needs between different crop types. Sub-irrigation is also practiced but only in selected areas where Fenland silt soils allow the drainage network to be actively managed to control in-field soil water levels. Rey et al. (2016) estimated the total gross financial benefit (£) in a theoretical dry year in the Cam and Ely Ouse catchment to be £91m. The significant majority of the financial benefit related to field vegetable (55%) and potato (35%) production. It is therefore classified as one of the 'irrigation hotpots' in England where demand for irrigation abstraction is in competition with public water supply and environmental flows (Figure 1b). The Cam and Ely Ouse catchment was therefore selected on the basis of its high intensity of agricultural production and its susceptibility to meteorological, hydrological and agricultural drought.

Climate datasets for drought indicator and crop modelling

Two recently developed long-term weather datasets for the 20th Century were used in this study to derive datasets for the three drought indices and as a climate variable input for the biophysical crop model. The datasets were termed CEH-GEAR (Keller et al. 2015) and Hindcast (1851-2014) (Guillod 2016). The CEH-GEAR dataset contains 1 km gridded estimates of daily and monthly rainfall for the UK landmass (Great Britain and Northern Ireland) from 1890 through to 2014. It was derived from the UK Met Office historical weather observations. The Hindcast is a time specific model-based reconstruction of past climatology derived with the Met Office HadRM3P model driven by the 20th Century Reanalysis (Compo et al. 2011) at its lateral boundaries and run at a 25 km grid resolution over Europe. The Hindcast time series runs from 1851 through to 2014. For calculating the drought indices and for crop modelling, the precipitation data was retrieved from CEH-GEAR dataset and reference evapotranspiration (ETo) then calculated using the Penman-Monteith formula (Allen et al. 1994) from the Hindcast climatology. The rationale for using these two different data sources was due to the lack of an equivalent time series dataset to the CEH-GEAR containing gridded estimates of ETo for the UK; for example, the CEH CHESS-PE dataset (Robinson et al. 2016) only contains data from 1961. Given the different spatial resolutions of each dataset, the average of all the grid cells within the catchment area was derived using a GIS to produce a time series of daily precipitation and ETo for the Cam and Ely Ouse catchment for the period 1900 to 2014.

Deriving drought indicators

Boken (2005) noted that soil moisture availability is the basic and fundamental contributor to attaining crop growth and yield and thus agricultural drought monitoring efforts should focus on this variable. However, Boken (2005) also reported that data regarding this variable is not as readily available as it is for precipitation. More recent studies have shown the reliability of meteorological drought indices for predicting soil moisture droughts in arid and semi-arid environments (Halwatura et al. 2016; Moorhead et al. 2015). For this reason, this study explored the utility of three most widespread meteorological drought indices, including the Standardised Precipitation Index (SPI), Standardised Precipitation-Evapotranspiration Index (SPEI) and Palmer Drought Severity Index (PDSI). Each of these indices was derived using the time series of precipitation and ETo derived from the above climatic products.

SPI is a drought index designed to primarily define and monitor droughts where precipitation is the only input parameter. It is a versatile index that is useful in analysing both dry and wet periods (WMO & GWP 2016; WMO 2012; McKee et al. 1993). The SPI identifies a drought when its value is continuously negative and reaches -1.0 or less (McKee et al. 1993), although this is not a standard in place but varies among researchers (WMO & GWP 2016). Drought monitoring systems have widely used the SPI either as a standalone indicator (e.g. Stagge et al. 2015) or as part of a wider set of indicators (e.g. European Drought Observatory (EDO) and US Drought Monitor). The WMO (2012) have recommended the use of the SPI indicator for drought identification. In this study, the SPI values were derived following the computational procedure described in Edwards and McKee (1997) and implemented by the National Drought Mitigation Centre as described in WMO (2012). Due to the length of the available data, the SPI was calculated for accumulated periods of 1, 3, 6, 9, 12, 24 and 36 months.

SPEI is a relatively new index that uses the basis of SPI but includes a temperature component to account for its variability in drought assessment (Vincente-Serrano et al. 2010). Considered as being as versatile as SPI, several authors have suggested that SPEI is a more reliable drought indicator since it contains more information and can take changes in climate into account in a more comprehensive way (Vincente-Serrano et al. 2010; Stagge et al. 2014; Beguería et al. 2014). In this study, the SPEI was calculated for the same accumulation periods as the SPI using code provided by Vincente-Serrano et al. (2010) at http://sac.csic.es/spei/

Also included in the analysis was the Palmer Drought Severity Index (PDSI), a much older drought indicator which quantifies the departure of the moisture supply based on the computation of a soil water balance (Palmer 1965). It is calculated based on precipitation, temperature and locally available data on the water content of the soil. By drawing on the wider set of variables included in the climatology described above, the basic terms of the water balance equation were determined. PDSI is considered most effective in measuring impacts sensitive to soil moisture conditions, such as agriculture production, but it is also useful for drought monitoring (it constitutes one of the key indicators included in the US

Drought Monitor). In this study, PDSI values were calculated using the computer algorithm developed by Wells (2003).

Biophysical crop yield and irrigation modelling

In a humid environment such as England, the irrigation needs (depths applied) for a particular crop vary from month to month and year to year depending on the summer weather and distribution of rainfall. Potato is acknowledged as being a high-value commodity crop for both the fresh (supermarket) and processing markets and is very sensitive to drought stress (Daccache et al., 2012). Specifically, shortages of water at key growth stages can have major deleterious impacts on both yield and tuber quality (size, shape, skin finish) with consequences on crop price. In this study, the annual variation in irrigation need and yield for both a 'typical' rainfed and irrigated potato crop were modelled using SUBSTOR-Potato, a biophysical crop growth model which is embedded within the Decision Support System for Agrotechnology Transfer (DSSAT) program (Jones et al. 2003). The SUBSTOR-Potato model simulates the growth and development of the potato crop on a daily time-step using data relating to the local climate, soil characteristics, farm management practices and cultivar. The model includes four sub models to simulate phenological development, biomass formation and partitioning, and soil water and nitrogen balances to provide a conceptual representation of the plant-soil-atmosphere system. The phenological development is controlled by cumulative temperature whilst the growth rate is calculated as the product of absorbed radiation, which is a function of leaf area, using a constant ratio of dry matter yield per unit radiation absorbed. Cultivar specific coefficients known as 'genetic coefficients' are used by the model to control tuber initiation, leaf area development and tuber growth rate (Daccache et al., 2012). Readers interested in a detailed description of the SUBSTOR-Potato model are referred to Griffin et al. (1993).

The model has been previously calibrated for UK conditions to simulate the impacts of climate change on potato production in eastern England where half the national potato cropped area is concentrated. Daccache et al (2011) calibrated and validated the SUBSTOR-Potato model using field data from an experimental research station at Cambridge University Farm (CUF) (Lat: 52°22' N; Lon: 0°10'E) where long-term potato trials have been undertaken since 1989. Regarding soil type, most potatoes are cropped on free draining soils with low moisture holding capacity; this helps to reduce disease risk, limit tuber damage during lifting and avoids soil compaction and trafficability issues during harvest, particularly in a wet summer. A typical sandy loam soil which is most commonly used for potato production was therefore selected for the crop modelling. Using this typical soil type, representative site (Cambridge) which is located within the Cam and Ely Ouse catchment, and the daily time-step weather data from the 20th Century reanalysis dataset, the SUBSTOR-Potato model was used to simulate annual rainfed and irrigated yields (t ha^{-1}) for maincrop potato (*cv* Maris Piper) between 1900 and 2014. The variables used to parameterise the model matched those described in Daccache et al. (2011). The local climate was represented by the same time series of precipitation and ETo derived from the climate products described above and used to derive the various drought indicators. The SUBSTOR-Potato model outputs included annual data relating to yield (t ha^{-1}) for both rainfed and irrigated crops and irrigation water requirements (depths applied, mm). These were then correlated to the drought indicators to assess relationships between drought, water use and agricultural productivity.

RESULTS AND DISCUSSION

Historic droughts in the Cam and Ely Ouse catchment

Figure 2 shows the annual summary of derived drought indicators for the Cambridge site in the Cam and Ely Ouse catchment between 1900 and 2014, including PDSI, and the 3-, 9- and 12-monthly SPI and SPEI values. According to PDSI, the main drought episodes occurred in the 1900s, 1920s, 1930s, 1940s, 1970s, 1990s and 2010 decade. Calculated PDSI also identifies the drought events of 1976, 1993 and 2012. The same episodes can also be identified from the SPI and SPEI values. These results are consistent with those reported by Vicente-Serrano et al. (2010) for climate conditions with low inter-annual variability in temperature in which the indices respond mainly to changes in precipitation.

A correlation analysis between the calculated drought indicators and their different aggregation periods (Table 1) confirms the strong correlation between SPI and SPEI for any monthly aggregation. PDSI showed a stronger correlation with SPI-9 and SPEI-9. This is due to PDSI being calculated using a time scale of nine months thus being more directly comparable to the defined SPI and SPEI accumulation periods. Regarding the intensity and duration of droughts in the Cam and Ely Ouse catchment, the results for ‘severe’ and ‘moderate’ drought events did not show large differences between the three indices with similar results obtained for both the number of events and their duration. Moderate droughts are the most prevalent episodes in the catchment. For the extreme drought category, the SPI identified a larger number of events compared to the other two indices, with a larger average and maximum duration for any aggregation scale. These extreme drought events took place mostly over longer aggregation scales, with SPI-24 showing the poorest results (6 identified drought events of 7 months average duration with a maximum of 16 months). However, the results from the SPEI analysis show drier 1990 and 2000 decades compared to PDSI and SPI. This may mask a change in the climate conditions in the Cam and Ely Ouse catchment, and Anglian region more generally. Climate observations show that there has been a gradual warming over the UK since 1960, with warmer temperatures in summer than in winter (Met Office, 2011). In addition, climate projections for the UK show that the average global temperature increases would imply even larger increases for the UK, especially in southern regions such as the case study catchment (CCC, 2016). Thus, despite the SPI appearing to be a useful index to assess historic drought events in the Cam and Ely Ouse catchment, the SPEI might be a better indicator for the future.

Modelled annual crop yields and irrigation

The outputs from the SUBSTOR-Potato model include annual estimates of irrigation need (mm) and crop yield (t ha^{-1}). A comparison of the simulated yields for rainfed and irrigated maincrop potatoes and irrigation needs for the reference site at Cambridge are shown in Figure 3. The data shows how inter-annual climate variability strongly impacts on both yield and irrigation need. The impacts of specific drought years on productivity are shown in Figure 4 where rainfed yields have been ranked and compared against the equivalent irrigated yield. The data highlight the impacts of a number of extreme dry (1921, 1975-76, 1990, 1995-96, 2010 and 2013) and wet (1987, 2007-08, 2012, 2014) years on crop yield, and the buffering effect that irrigation can have on production in very dry years (as evidenced by very low inter annual variability in yield). The simulated average irrigated yield was 84 t ha^{-1} compared to 34 t ha^{-1} for the rainfed crop; more significant, however, is the large reduction in yield in drought years with rainfed yields in the lowest quartile reducing by nearly two thirds to only 13 t ha^{-1}. It should be noted that these simulated yields are much higher than reported on-farm yields (Daccache et al. 2011) but the relative differences between rainfed and irrigated yield are consistent with observations on-farm. The modelling outputs serve to illustrate the major impact that any shortfall in summer rainfall even in a humid climate can have on crop productivity and the agronomic benefits that can accrue from supplemental irrigation, particularly in drought years when the returns from irrigation are highest (Knox et al. 2000). The drought impacts shown here only relate to a yield penalty, but the financial impacts would be even higher given that quality assurance is a major determinant of crop profitability.

Correlating drought indicators with yield and irrigation

The modelled yields (Figure 3) have been correlated against the derived drought indicators. Due to the similar results obtained for SPI and SPEI, here we show the relationship between this latter drought indicator, PDSI and modelled yields. The so-called 'heat maps' shown in Figure 5 (a, b and c) illustrate the strength of the correlation between the three modelled outputs from SUBSTOR-Potato and SPEI for different aggregation periods and monthly lags. In addition, Figure 5d shows the correlation between the three modelled outputs from the SUBSTOR-Potato model and PDSI.

As expected, for rainfed potatoes, the correlation between yield and SPEI is strong in the summer months for aggregation periods of between 1 and 6 months, although the strongest correlation occurs for the 3-month aggregation between July and August. This confirms that the weather in late spring and the beginning of summer is a key determinant in crop productivity. It also matches the key development periods for scheduling irrigation to avoid potato yield and quality losses attributable to common scab (*Streptomyces scabies*) The strength of this relationship also means that the period for anticipating a drought effect on rainfed production is very short, with little available time to activate suitable mitigation measures. Regarding irrigated yields, since the crop modelling assumed no constraint on water resources availability for irrigation abstraction, yield does not show, as expected, any direct correlation to SPEI. However, irrigation need has a strong inverse correlation to SPEI. Since the summer months are usually the driest, the SPEI-3 and SPEI-6 indicators show the strongest correlation to total annual irrigation water requirement (IWR). Drought episodes reduce yield and may impair crop growth due to a shortage of water availability and soil moisture to the crop (Martin and Gilley 1993). Therefore, failing to supply irrigation in those months would probably compromise productivity to levels observed for rainfed production. Potato production potential is influenced not only by the availability of water, but also other factors including the correct timing and availability of fertiliser and nutrients (Daccache et al. 2011). From the analysis presented here, the SPEI-3 drought indicator is considered to be most suited to monitoring water availability and hence drought conditions for both rainfed and irrigated production. Finally, despite containing greater uncertainty due to its lower correlation values, the SPEI-6 index could also provide useful information in support of developing catchment scale drought early warning measures and drought management actions for the case study.

Similarly, the PDSI shows a strong correlation with rainfed yield; no correlation with irrigated yield; and a strong negative correlation with IWR. The correlation is also stronger during the summer months. However, PDSI is not as flexible as SPEI to analyse aggregation periods because the definition of the index already includes a nine month aggregation. For example, in the case of rainfed yield the maximum correlation is obtained in June, but the correlation in May is very low. PDSI captures the drought conditions for a longer period than is relevant for the crop, masking the development of negative conditions until it is too late. Similarly, the maximum correlation of PDSI with IWR is in August, when the irrigation period is close to finishing and most irrigation for tuber bulking has been applied. These results demonstrate that PDSI has a limited utility to monitor drought conditions under both rainfed and irrigated potato production conditions in a humid climate.

Methodological limitations

Whilst this was explicitly stated to be a scoping or exploratory study, there are a number of methodological limitations that need to be recognised; these present opportunities for further work to develop our understanding of the application of drought metrics for UK agriculture. Firstly, the lack of a long-term reported data on potato (or other crop) yields for the catchment required the adoption of a crop modelling approach to create a suitably long yield time-series. Although the SUBSTOR-Potato model has been previously calibrated and validated for the Cambridge site (Daccache et al. 2011) over a period of 10 years, ideally the simulated outputs for the longer-term (1900-2014) modelled time series could have been further validated, drawing on either industry or government published statistics, or reported farm yields from selected growers in the catchment. National crop yield statistics were available but their granularity was too coarse (regional scale) for use in this study. Secondly, the modelling assumed irrigation was unconstrained with no restrictions on water availability, which meant we were not able to assess the impacts of possible abstraction restrictions on irrigation during drought periods. However, potatoes are a high-value crop with production tightly specified through grower contracts so farmers have limited flexibility in adapting to partial restrictions other than to reprioritise their irrigation onto high value crops. Under these circumstances, potatoes would continue to receive irrigation, even if actual application depths were less than scheduled requirements. Thirdly, the crop development analyses were conducted on a daily time-step but the outputs then presented on a monthly temporal resolution to compare them against the drought indicators, which were calculated on a monthly time-step. For other short season, and shallow rooting crops including lettuces and salads, it would be useful to evaluate the sensitivity of the drought indicators at a finer temporal resolution (weekly). Finally, the use of different climatic datasets for precipitation (CEH-GEAR) and ETo (20CR) might introduce inconsistencies in the results. Whilst this was partially mitigated in this study by using a monthly time-scale, it could be a limiting factor should the same datasets be used in future finer scale applications. However, there are currently no datasets that facilitate calculation of daily ETo equivalent to the CEH-GEAR dataset in terms of their spatial resolution. In addition, the spatial variability of ETo is much lower than that for precipitation (Hess et al 2015).

CONCLUDING REMARKS

Further work and implications for drought management in agriculture

Further work could investigate the relationships between drought indicators and the spatial and temporal timing of abstraction restrictions for irrigation. This could be useful for farmers and agricultural stakeholders in helping to understand better the thresholds or probabilities of abstraction restrictions occurring and their geographical extent. Further research could also focus on modelling climate variability impacts and drought events across a much larger network of sites and crop types and then correlating yields spatially against selected drought indicators, to estimate the productivity impacts of drought at regional and national scales. The crop modelling could also assess the sensitivity of the potato yields and drought indicator relationships to changes in soil type and rooting depth; lower soil available water capacities (via either soil texture and/or rooting depth) would not only potentially increase the impacts of drought but would also extend the period over which a drought would pose a threat to yield. Modelling could also be extended to consider other shorter season, shallow rooting (e.g. salad) crops to assess the utility of using drought indicators with shorter monthly lags. It would also be interesting to evaluate the effects of climate change including rainfall and evapotranspiration on both the intensity and duration of droughts and consequent yield impacts. Finally, a more comprehensive assessment of alternate drought indicators as reported by the WMO-GWP (2016) could provide further insights into whether the choice of drought indicators selected here were most suited for application in a humid climate and whether multivariate drought indicators might be more appropriate.

Historically, most rainfed farming enterprises in England have not considered the risks associated with increased rainfall variability and drought on their business. However, the situation is changing rapidly, particularly as retailers start to recognise the potential water-related risks to their supply chains. With increased costs of production, rising demands for quality assurance and lower margins, growing high-value commodity crops under rainfed conditions is becoming a more challenging and higher-risk activity. Farming businesses are recognising and reassessing the returns from irrigation investment even for non-food crops such as grassland (Perez-Ortola et al., 2016) and there is growing industry demand for the research community to provide decision-support tools and guidance to help farmers in setting risk thresholds or triggers for initiating drought management actions, and importantly a need for contingency planning. Of course, the strategies available depend on a number of factors including the scale of the businesses, cropping mix and extent to which irrigation might be available to mitigate drought impacts. In particular, there is a need to consider how drought indicators, such as those considered here, could be embedded into existing farmer and/or water regulatory decision-making, and if improved weather forecasting skill could be combined with indicator-yield response functions to assess seasonal yield predictions to guide investments in drought mitigation. Recent drought experiences in England have highlighted how drought is a real and emergent risk for high-value rainfed agriculture, even in a humid climate, impacting both on yield and quality, as well as water resource availability for irrigated production. The challenge lies in integrating sufficiently high resolution geo-spatial knowledge on the onset of a drought and its likely magnitude and severity with evidence on crop responses to changing soil moisture availability, considering not only the impact on yield but also on quality, a key determinant for profitability for many crop types in a humid climate.

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Figure 1 Spatial distribution of aridity and irrigation water demand in EA Anglian region. The Cam and Ely Ouse catchment is identified.

(a) Aridity expressed as potential soil moisture deficit (PSMD)

(b) Irrigation demand (m^3 per km^2) for agricultural crops based on 2010 land use

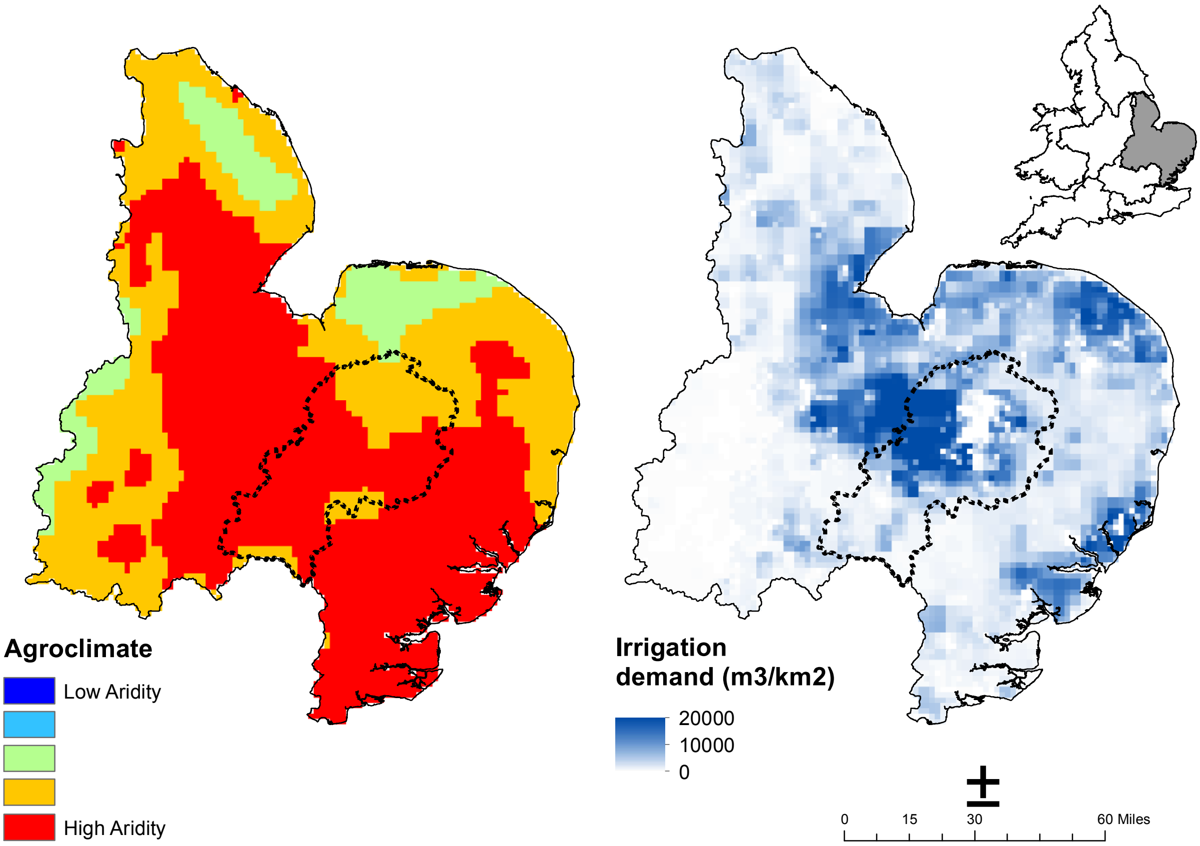

Figure 2 Derived drought indicator values from 1900 to 2014 for PDSI; 3-, 9-, and 12-month SPI, and SPEI for the Cambridge site in the Cam and Ely Ouse catchment.

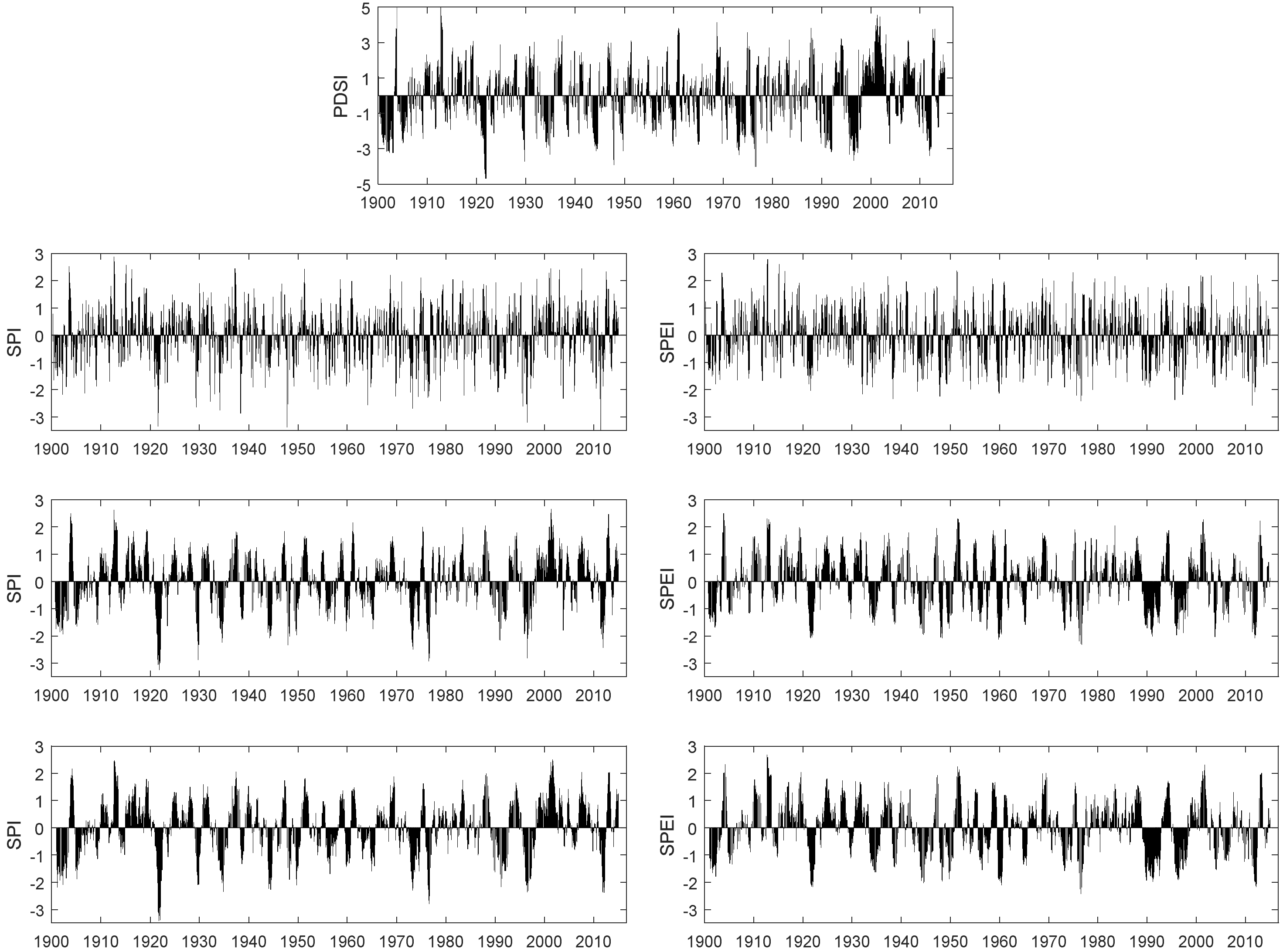

Figure 3 Modelled yield (t/ha) for rainfed potatoes and yield (t/ha) and IWR (mm) for unconstrained irrigated potatoes

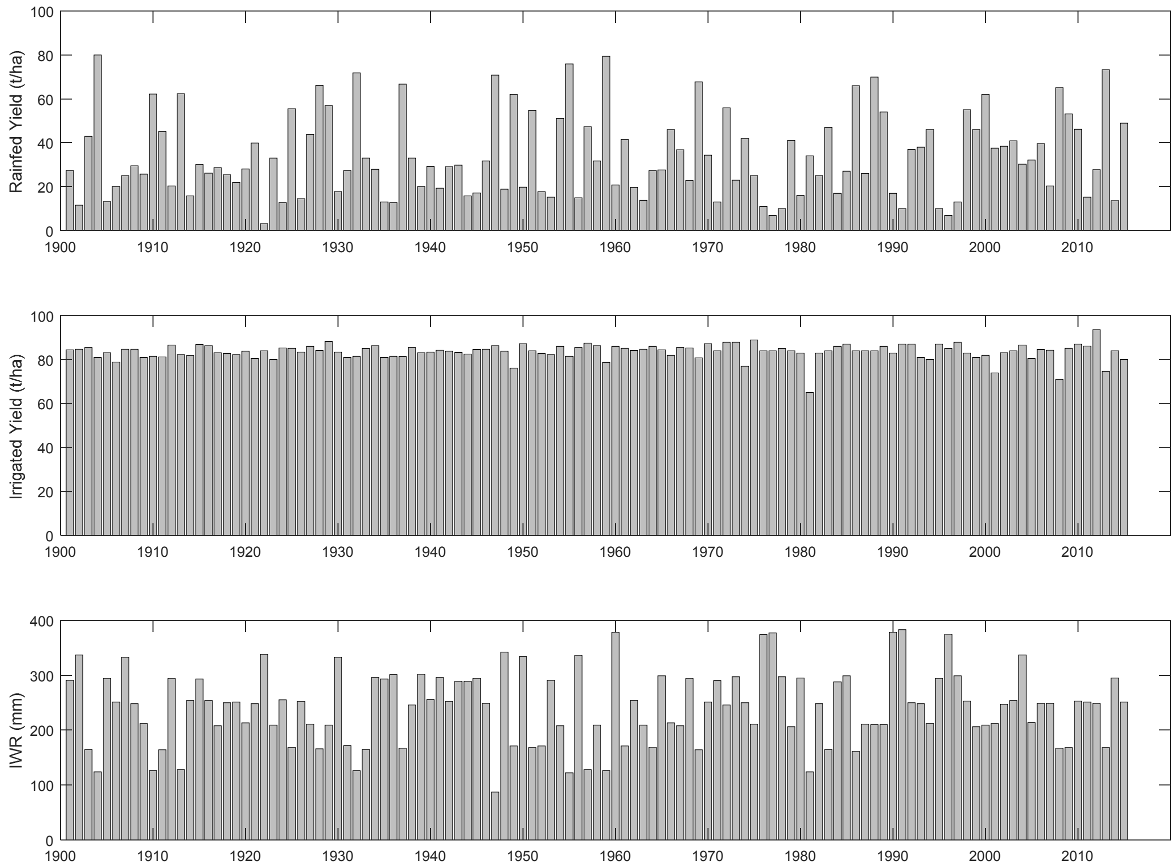

Figure 4 Ranked SUBSTOR-Potato simulated rainfed and irrigated yield (t ha^{-1}) for maincrop potatoes grown at Cambridge (UK), based on 20th Century reanalysis data from 1900 to 2014. Average yields for both rainfed and irrigated potato crops are shown.

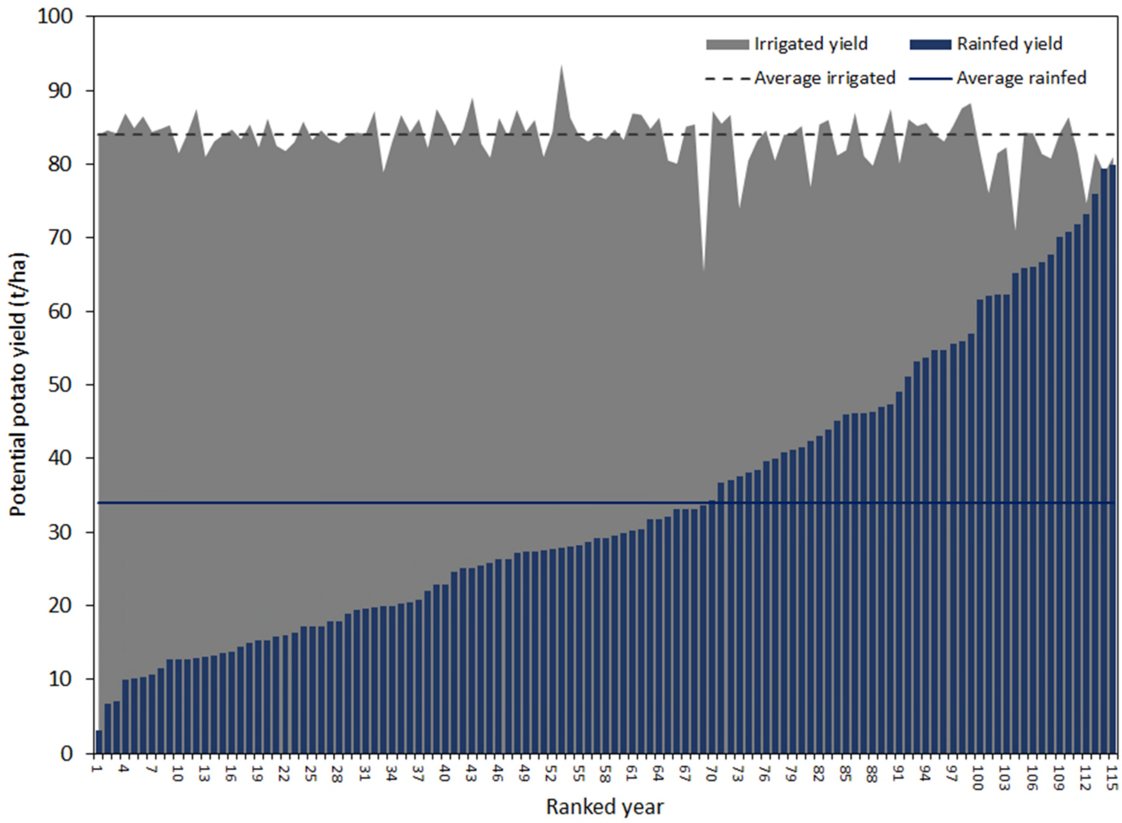

Figure 5 Correlation heat maps for SPEI versus (a) rainfed potato yield (t ha^{-1}), (b) irrigated potato yield,(c) irrigation water requirements (IWR, mm) for potatoes and (d) a correlation graph for PDSI versus rainfed and irrigated potato yield (t ha^{-1}) and IWR (mm).

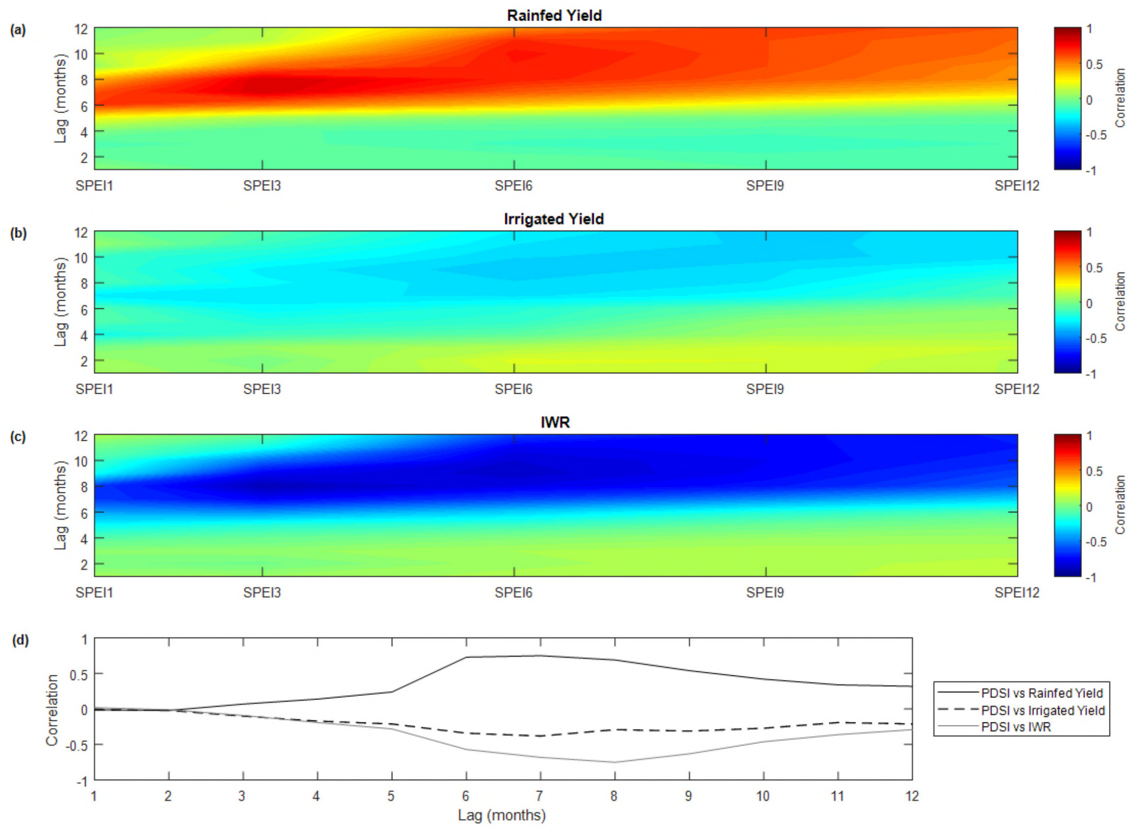

Table 1 Cross-correlation between calculated drought indicators (SPI, SPEI and PDSI) in the Cam and Ely Ouse catchment. Bold values correspond to indicators with the same aggregation period.

Drought indicator	SPI-3	SPI-6	SPI-9	SPI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12	PDSI
SPI-3	1.0000								
SPI-6	0.6645	1.0000							
SPI-9	0.5457	0.7642	1.0000						
SPI-12	0.3618	0.5319	0.7777	1.0000					
SPEI-3	**0.9063**	0.6371	0.5102	0.3185	1.0000				
SPEI-6	0.5795	**0.8609**	0.6422	0.4209	0.6949	1.0000			
SPEI-9	0.5054	0.7189	**0.6903**	0.3656	0.5954	0.8315	1.0000		
SPEI-12	0.3686	0.5205	0.6888	**0.8268**	0.4263	0.6052	0.6530	1.0000	
PDSI	0.6257	0.7392	**0.7598**	0.6544	0.6001	0.6142	**0.6502**	0.5726	1.000