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Regional variations in the link between drought indices and reported agricultural impacts of drought

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ABSTRACT

Drought has wide ranging impacts on all sectors. Despite much effort to identify the best drought indicator to represents the occurrence of drought impacts in a particular sector, there is still no consensus among the scientific community on this. Using a more detailed and extensive impact dataset than in previous studies, this paper assesses the regional relationship between drought impacts occurrence in British agriculture and two of the most commonly used drought indices (SPI and SPEI). The largest qualitative dataset on reported drought impacts on British agriculture for the period 1975–2012 spanning all major recent droughts was collated. Logistic regression using generalised additive models was applied to investigate the association between drought indices and reported impacts at the regional level. Results show that SPEI calculated for the preceding six months is the best indicator to predict the probability of drought impacts on agriculture in the UK, although the variation in the response to $SPEI_6$ differed between regions. However, this variation appears to result both from the method by which SPEI is derived, which means that similar values of the index equate to different soil moisture conditions in wet and dry regions, and from the variation in agriculture between regions. The study shows that SPEI alone has limited value as an indicator of agricultural droughts in heterogeneous areas and that such results cannot be usefully extrapolated between regions. However, given the drought sensitivity of agriculture, the integration of regional predictions within drought monitoring and forecasting would help to reduce the large on-farm economic damage of drought and increase the sector's resilience to future drought.

1. Introduction

In recent decades the severity and frequency of extreme climatic events, including droughts, have increased significantly, causing severe damage, casualties and injuries around the world (FAO, 2008; Giddens, 2011). Climate change is expected to contribute to this increasing trend, posing greater risks to society, the environment and those sectors dependant on precipitation and water resources (IPCC, 2014).

A drought is normally defined as a natural hazard caused by a period of abnormally low precipitation. Drought differs from other natural disasters in the slowness of onset and its usual lengthy duration (European Commission, 2007a). Its effects accumulate slowly over time, so it is difficult to determine the onset, duration and termination of a drought event (European Commission, 2007b; Parry et al., 2016; Wilhite, 2007). Drought has wide-ranging impacts on the environment, economy and society. The agricultural sector is particularly sensitive to drought and water scarcity (Wilhite et al., 2014) as it is directly dependent on precipitation and evapotranspiration. Droughts can decrease crop yields and quality (Rey et al., 2016), and affect livestock by reducing grass and feed availability. Drought impacts do not depend only on the severity of the hazard, but also on the sensitivity of a sector or activity. Thus, as agriculture varies spatially, the vulnerability to the same drought is different, and so are the associated impacts.

There are several papers on the relationship between drought severity (usually measured as some form of standardized index) and the associated impacts using statistical methods with data such as time series of crop yields (Gunst et al., 2015; Potopová et al., 2015; Vicente-Serrano et al., 2012). In Europe, since the multi-sectoral European Drought Impacts Inventory (EDII) was released (containing impact entries for all countries in Europe, ranging from one entry for Ukraine to 278 for Germany), this qualitative dataset has been used to assess the association between drought indicators and reported impacts at different scales: continental (Blauhut et al., 2015), national (Stagge et al., 2015) and regional (Bachmair et al., 2015, 2016, 2017). Still, there is

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no consensus on which indicator best represents drought impact occurrence for any given sector, including agriculture (Zargar et al., 2011). As stated by Bachmair et al. (2016), the main limitation for evaluating commonly used drought indicators is the lack of information on drought impacts. While most previous papers looking at the relationship between drought indicators and agricultural impacts in Europe used the EDII, or a proxy, such as remote sensing data (Bachmair et al., 2018), this paper uses a more comprehensive dataset: the United Kingdom (UK) Agricultural Drought Inventory, which covers a wider range of agricultural impacts reported during past droughts. It contains text-based reports on 1480 agricultural impacts between 1975 and 2012, compared with 202 for the same period in the EDII. This period captures all major recent UK droughts, with the exception of a limited duration heatwave and drought in 2018. This allows for a more accurate and nuanced evaluation of national and regional drought indicators against reported impacts.

There are numerous proposed drought indices (Dalezios et al., 2016a, 2016b; Svoboda and Fuchs, 2016) of which > 20 have been reviewed for various purposes by other authors (e.g. Pedro-Monzonís et al., 2015; Zargar et al., 2011). These may be broadly grouped by the types of data used to construct the indices. The simplest use meteorological data only, and will be discussed further below. These lack any explicit consideration of retention of water in the soil or the responses of crops. To overcome the first of these limitations, several indices include a soil water balance model; one of the earliest examples was the Palmer Drought Severity Index (PDSI) (Palmer, 1965). These indices are better suited to application at scales where soil conditions are relatively uniform. In non-uniform regions, there may be considerable variations in the index within a region. More sophisticated agricultural drought indices, such as the Crop Specific Drought Index (Meyer et al., 1993), include explicit modelling of crop water use. These may be able to give better predictions for specific crops, but are not suitable for large-scale forecasting where cropping is not uniform. Other methods use crop monitoring via remote sensing, for example Normalized Difference Vegetation Index (Tucker, 1979). Although these can be applied at large spatial scales by utilising satellite imagery, they are more appropriate for monitoring than forecasting and planning. Finally, composite indices such as the US Drought Monitor (Svoboda et al., 2002) combine several existing indices to try to improve their predictions. The use of multiple indices, which are likely to be correlated, makes these unsuitable as the basis for further statistical modelling.

As the emphasis of this work was on the potential use of indices for forecasting drought impacts at large scales using readily available data, purely meteorological indices were the most appropriate. The simplest of these, such as the Effective Drought Index (Byun and Wilhite, 1999) and the more commonly used Standardized Precipitation Index (SPI) (McKee et al., 1993) are derived from precipitation only, comparing precipitation in the period of interest with the long-term mean and standard deviation. For use in agriculture, a potentially important limitation of these indices is the omission of evapotranspiration, as the available water may be significantly reduced by evaporation in hot weather.

This is addressed by several indices such as the Standardized Precipitation Evapotranspiration Index (SPEI), which extends the SPI method to include evapotranspiration, and the Potential Soil Moisture Deficit (PSMD). These can use evapotranspiration calculated from temperature alone in the simplest cases, or uses more sophisticated models when the necessary variables are available period (Vicente-Serrano et al., 2009). Other indices that include evapotranspiration, such as the PDSI for determining long-term drought and the Crop Moisture Index (Palmer, 1968) for short-term moisture deficits require additional soil data, so are less suitable for use at regional scales.

This paper aims to assess the probability of drought impacts on agriculture for each region of the UK using regional drought indices based on meteorological data, so Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) were chosen as representative indices that are easily derived from readily-available data. Reported drought impacts were taken from the UK Agricultural Drought Inventory. The paper explores which drought index best represents the historical regional drought impacts pattern and identifies the relative sensitivity of regional agricultural systems to drought. The outputs of this study should inform improved sectorally-relevant drought monitoring and early warning for British agriculture, increasing the resilience of the sector. The same approach could be applied to any other country/region where reported impact data are available.

2. Data and methods

2.1. Drought indices

SPI, as originally defined by McKee et al. (1993), is a drought index based on the probability of precipitation for a given accumulation period. A positive SPI represents a surplus of precipitation in comparison to the long-term average for the region where it is assessed whereas negative values represent rainfall deficit. SPI calculated for short accumulation periods allows the identification of short drought events, whereas SPI for longer accumulation periods will detect longer, multi-year droughts.

SPEI is similar to SPI, but also takes into account the evaporative demand, as it is based on the probability of Climatic Water Balance, which is equivalent to the amount of precipitation minus the amount of potential evapotranspiration, for a given accumulation period (Vicente-Serrano et al., 2009). Generally, precipitation in the UK is not strongly seasonal, in contrast to evapotranspiration. Although precipitation in the UK normally exceeds evapotranspiration for periods over 1 year, the converse is usually the case through the spring and summer, especially in drier eastern regions, leading to significant soil water deficits in some years, so SPEI is potentially a better indicator of agricultural drought in these periods.

Gridded datasets of SPI and SPEI were acquired from the Environmental Information Data Centre[1] (Tanguy et al., 2015a,b). The standard period which was used in these two datasets to fit the gamma distribution for SPI and the generalised logistic distribution for SPEI was 1961–2010, and the different accumulation periods available for both indicators were 1, 3, 6, 12, 18, 24 months. Time series of area-averaged SPI and SPEI for all accumulation periods at a monthly time-step from 1961 to 2012 were extracted from the gridded datasets for European NUTS1 administrative regions (NUTS = Nomenclature of Territorial Units for Statistics, map version 13 used).

In addition to the two standardized indicators, Potential Soil Moisture Deficit (PSMD) was also calculated for the same period. This agroclimatic indicator has been extensively used to reflect the relationship between aridity and irrigation needs (e.g. Knox et al., 1997; Rodríguez Díaz et al., 2007). It takes into account the distribution of rainfall and potential evapotranspiration (PET) amounts throughout the year to provide an absolute measure of moisture deficits that can be compared across regions (unlike with standardized indices), and is used to support the discussion of the results from our analysis. The PSMD in each time-step was calculated from

$$PSMD_i = PSMD_{i-1} + PET_i - P_i$$

where $PSMD_i$ = potential soil moisture deficit at timestep i, mm, PET_i = potential evapotranspiration of short grass in timestep i, mm, P_i = rainfall in timestep i, mm. Rainfall was extracted for NUTS1 regions from the GEAR dataset (Keller et al., 2015; Tanguy et al., 2016) and PET from the CHESS-PE dataset (Robinson et al., 2016; Robinson et al., 2017) and historic gridded data for Northern Ireland (Tanguy et al., 2018). In timesteps where $P_i > (PSMD_{i-1} + PET_i)$, $PSMD_i$ was

[1] http://eidc.ceh.ac.uk/

returned to 0. The estimation of PSMD from monthly data started with January as month $i = 1$ and PSMD was set to zero each year to avoid the unrealistic carry-over of soil moisture deficits from the previous year. For comparison with the drought indices calculated over periods of months, the maximum PSMD within a number of preceding months (N) of accumulation ($PSMD_{maxN}$) was used.

2.2. Agricultural impacts

The agricultural drought inventory for the UK is a subset of data from the UK Drought Inventory.[2] It contains qualitative text-based drought data related to UK agriculture based on an extensive review of two weekly farming periodicals in the UK: Farmers Weekly and Farmers Guardian. These represent the most widely-read industry periodicals with weekly circulations of > 50,000 and > 35,000 copies, respectively. From 2004 onwards, the issues are in electronic format. For items before 2004 (not available electronically), issues in paper format were consulted. The search terms were: drought, dry weather/spell, rainfall/precipitation, soil moisture, water scarcity/stress/deficit. After all the text containing one or more of these terms were collected, the content was screened and only the relevant ones were included in the inventory. The agricultural inventory contains a total of 2565 text entries, of which 1480 relate to impacts. The collected data were classified using spatial (unspecified, NUTS1, NUTS2, NUTS3, location), date (day, month, year, season) and DPSIR framework categories (Driver, Pressure, State, Impacts and Responses), among others (Lange et al., 2017). For the purpose of the paper, only the text entries regarding drought impacts that could be associated with a particular NUTS1 region were considered (839 references). The data was aggregated by NUTS1 region (Fig. 1) and month-year to get the number of reported impacts in each region (Table 1).[3]

2.3. Data analysis

2.3.1. Probability of impacts

Logistic regression and generalised additive models (GAM) were used to investigate the association between drought indices and reported impacts. This is similar to the method used by other authors to model impacts at national level for several economic sectors (Bachmair et al., 2017; Stagge et al., 2015). Logistic regression is generally used to model the relationship between a binary response variable (in this case the occurrence of an impact) and continuous predictor variables (see e.g. Hosmer and Lemeshow, 2013). The frequency of occurrence is treated as the sample observation of the probability of occurrence ($p(X)$), which is transformed to the range $(-\infty, \infty)$ using the logit transform:

$$\text{logit}\,(p(X)) = \log\left(\frac{p(X)}{1 - p(X)}\right) \tag{1}$$

This can then be used as the dependent variable for regression in a generalised linear model (GLM). GAMs extend the approach to allow the linear predictor variables to be replaced by smoothed functions of the variables using, for example, spline functions (Hastie and Tibshirani, 1986).

All the statistical analysis was conducted in R (R Core Team, 2017) and model fitting was performed using the *mgcv* package (Wood, 2011). The predictor variables considered were: drought indices (SPI and SPEI for the 1, 3, 6 or 12 preceding months), month number (treated as a continuous variable) and year. The response variable was the binary impact/no impact status for each month, with the number of impacts in the month used as a weight.

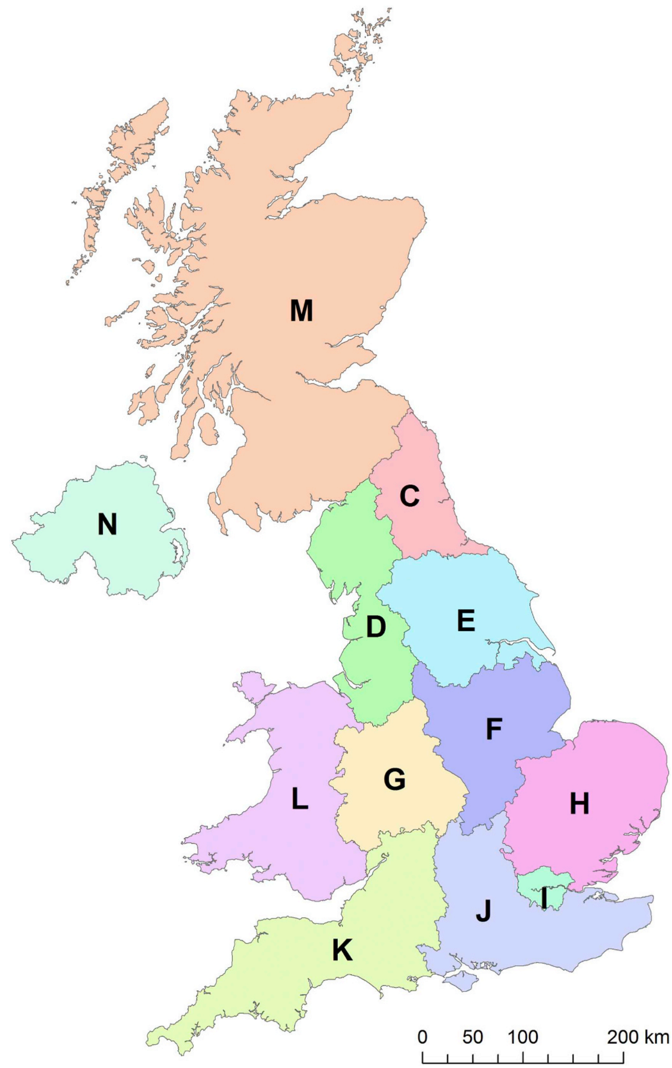

Fig. 1. NUTS 1 regions of the UK (prefix letters by UK for the NUTS1 code). © EuroGeographics for the administrative boundaries.

Only one drought index was considered in each model, because drought indices for overlapping periods would be correlated due to the data from the common period being used in both. After fitting GAMs using each of the drought indices alone, with and without smoothing, to find the best predictor, month and year were then introduced into the models. A smoothing function was always applied to the month, as the effect was expected to be seasonal rather than linear. Conversely, no smoothing was applied to the year, as the intention was to test for a temporal trend. The GAMs were examined for signs of overfitting, such as responses to one of the variables with multiple minima and maxima, indicating that the model was effectively generating different parameters for every data point.

Each model was fitted to the complete data set and to the data for each NUTS1 region separately. The models were assessed using the McFadden pseudo-R^2, the adjusted R^2, the Akaike information criterion (AIC), where appropriate, and the receiver operating characteristic (ROC) curve, using the *ROCR* package (Sing et al., 2005). The McFadden pseudo-R^2 (or proportion of deviance explained) is one minus the ratio of the log-likelihood of the model to the log-likelihood of the null model (McFadden, 1973). The adjusted R^2 is the proportion of the variance explained by the model. The AIK is derived from the log-

[2] http://historicdroughts.ceh.ac.uk/content/task-3-drought-inventory

[3] Note that Scotland, Wales and Northern Ireland are constituent countries of the United Kingdom, whereas the other NUTS1 regions are subdivisions of England, but all will here be referred to as regions in the sense of NUTS1. Due to the very low number of reported impacts in Northern Ireland, it was omitted from most of the analyses.

Table 1
NUTS1 regions of the United Kingdom: mean annual rainfall and potential evapotranspiration (PET) and total number of reported agricultural drought impacts.

NUTS1 code	Name	Description	Mean annual rainfall, mm	Mean annual PET, mm	Number of impact periods	Number of impacts
UKC	North East	Tees Valley & Durham, Northumberland & Tyne and Wear	875	479	16	19
UKD	North West	Cumbria, Cheshire, Greater Manchester, Lancashire, Merseyside	1254	482	12	18
UKE	Yorkshire and the Humber	East Yorkshire & Northern Lincolnshire (Humberside), North Yorkshire, South Yorkshire, West Yorkshire	871	498	27	40
UKF	East Midlands	Derbyshire, Nottinghamshire, Leicestershire, Rutland, Northamptonshire, Lincolnshire	706	516	44	109
UKG	West Midlands	Herefordshire, Worcestershire, Warwickshire, Shropshire, Staffordshire, West Midlands	765	509	26	46
UKH	East of England	East Anglia, Bedfordshire, Hertfordshire, Essex	634	529	86	276
UKI	Greater London	Inner London – West, Inner London – East, Outer London – East and North East, Outer London – South, Outer London – West and North West	663	514	2	2
UKJ	South East	Berkshire, Buckinghamshire, Oxfordshire, Surrey, East Sussex, West Sussex, Hampshire, Isle of Wight, Kent	787	511	58	136
UKK	South West	Gloucestershire, Wiltshire, Bristol, Dorset, Somerset, Cornwall and Isles of Scilly, Devon	1042	519	50	138
UKL	Wales	West Wales, The Valleys, East Wales	1444	495	11	13
UKM	Scotland	Scotland including islands	1547	422	24	42
UKN	Northern Ireland	Northern Ireland	1097	470	6	5
					356	839[a]

[a] The total number impact records in the UK Agriculture Drought Inventory is 1480. However, this analysis only considers those associated with particular NUTS1 regions, excluding records on impacts across the whole UK, Great Britain or England, or without spatial information.

likelihood, penalised by the number of parameters to allow comparisons between models; where the number of parameters is constant, minimising AIK is equivalent to maximising log-likelihood. The ROC shows the trade-off between false positive and true positive responses. A successful classifier deviates as far as possible from a 1:1 straight line, and it is useful to calculate the area under the curve (AUC): a perfect classifier has an AUC of 1, whereas an AUC of 0.5 indicates a prediction that is no better than random (Bradley, 1997). As explained in Section 3.1, SPEI calculated over six months was chosen for more detailed analysis.

2.3.2. The relationship between SPEI and PSMD

The SPI and SPEI calculation depend on long-term mean values in the region being considered, so that a value of 0 represents approximately average conditions for that region. Consequently, the same value for SPEI may represent very different degrees of water stress in different regions, given the large spatial differences in climate across the UK. To explore this, a comparison was made between SPEI and potential soil moisture deficit (PSMD), which is indicative of the water stress experienced by crops.

For consistency with the impacts model, SPEI calculated over six months ($SPEI_6$) and maximum PSMD over the same period ($PSMD_{max6}$) were examined. In order to have sufficient results to perform a statistical comparison, the months with $SPEI_6$ in the range $[-2, 0]$ (drier than average, but not extremely dry) were selected and the mean value of $PSMD_{max6}$ for these months was compared between regions by analysis of variance and post-hoc analysis using Tukey's Honest Significant Difference (Tukey, 1949) to adjust for the effect of multiple comparisons.

3. Results and discussion

3.1. Selection of variables and smoothing functions

Models of the recorded drought impacts were first fitted to each of the drought indices with no other variables, using a single model for the UK and also separate models for each region. NUTS1 regions UKC (north-east England), UKD (north-west England), UKI (London), UKL (Wales) and UKN (Northern Ireland), which are generally wet or highly urbanised regions, were found to contain too few reported impacts to estimate the models reliably (see Table 1). Table 2 shows the results of using SPI and SPEI over different periods for the complete UK dataset; the results for the regions were similar. SPEI for a six-month period ($SPEI_6$) gave the best performance, and so it was used for all the subsequent analyses.

This contrasts with Bachmair et al. (2016), who found that SPI and SPEI were very similar in terms of the strength of correlation in the UK. More recently, Bachmair et al. (2018) found that the meteorological indicators best linked to agricultural drought were SPI2 or SPI3 in most

Table 2
Fit statistics for generalised linear models containing the drought indices only fitted to the complete UK data set.

Drought index	Adjusted R^2	Deviance explained	AUC	AIC
SPI_1	0.0099	0.0086	0.551	3341
SPI_3	0.0700	0.0586	0.620	3173
SPI_6	0.1017	0.0894	0.648	3069
SPI_12	0.0259	0.0240	0.588	3290
SPI_18	0.0369	0.0341	0.606	3255
SPI_24	0.0164	0.0154	0.577	3318
SPEI_1	0.0268	0.0220	0.580	3296
SPEI_3	0.1011	0.0829	0.656	3091
SPEI_6	0.1188	0.1043	0.669	3019
SPEI_12	0.0429	0.0405	0.610	3234
SPEI_18	0.0496	0.0492	0.619	3205
SPEI_24	0.0269	0.0270	0.591	3279

Table 3
Fit statistics for models based on $SPEI_6$ with additional variables when fitted to the UK data set (s() indicates smoothing applied to a variable).

Model terms	Adjusted R^2	Deviance explained	AUC	AIC
SPEI6	0.119	0.104	0.669	3019
SPEI6 + s(Month)	0.269	0.236	0.757	2590
SPEI6 + Year	0.185	0.167	0.709	2811
SPEI6 + s(Month) + Year	0.333	0.306	0.796	2358
s(SPEI6)	0.119	0.108	0.669	3010
s(SPEI6) + s(Month)	0.270	0.240	0.758	2582
s(SPEI6) + Year	0.187	0.171	0.712	2800
s(SPEI6) + s(Month) + Year	0.336	0.310	0.796	2348

of southern England (UKK and UKJ), and mostly SPI12 for North-Eastern England (UKE and UKF). For the rest of the UK, the drought indicator best correlated to agricultural impact was more variable. Of SPI, SPEI and PDSI, Haro-Monteagudo et al. (2017) found that SPEI3 was best suited for identifying drought conditions for both irrigated and rainfed crops. The differences are probably due to a very different way of quantifying agricultural impact. Bachmair et al. (2018) based their analysis on remotely sensed vegetation health indicators, using them as proxy for crop yield, and Haro-Monteagudo et al. (2017) used simulated yields from a biophysical potato model, whereas this study used a comprehensive database of reported impacts, which included many other agricultural impacts not measurable by considering the vegetation health alone or a single crop type.

The GAM fitted slightly better with smoothing than without, as would be expected, since it contains additional parameters (Table 3). However, plotting the response for estimated probability of impact against $SPEI_6$ showed severe overfitting in many cases: rather than being monotone, the curve had numerous local minima and maxima. Reducing the basis dimension of the smoothing reduced overfitting, but did not prevent it, except at the minimum value, where the fit was no better than the linear model. The use of a smoothing function for $SPEI_6$ was therefore rejected and was not used in the subsequent analysis.

The inclusion of the month without smoothing was not considered, because a linear term would not be able to model a seasonal effect. Including the month with smoothing improved the model fit and resulted in a clear seasonal response, with a peak in the summer. Conversely, the effect of a linear term for the year was examined to model potential long-term trends. The combined model using $SPEI_6$ (linear), month (smoothed) and year (linear) fitted better than the models containing one or two of these terms on all the criteria (Table 3). The linear parameters for all the NUTS1 regions are shown in Table 4. All three variables and the constant term were significant with $p < .01$ for all regions, except for the $SPEI_6$ term for Scotland, which was significant with $p < .05$.

The coefficient of $SPEI_6$ was always negative, representing a greater estimated probability of impacts at lower values of the drought index, as expected. The coefficient of year was positive, indicating an increasing trend in estimated drought impact probability for the same value of $SPEI_6$.

3.2. Responses to month and year

The response to the month term, illustrated by fixing $SPEI_6$ and year (Fig. 2), had a seasonal pattern for all regions, with a maximum in summer (July or August), and a minimum in winter. It was not possible to include continuity constraints between January and December, but the values in these months were generally similar. Stagge et al. (2015) also observed that seasonality had an important effect in the four countries they modelled, although in their data set it was not significant for the UK.

The model thus suggests that the probability of reported impacts of drought is higher in summer than winter for the same value of $SPEI_6$; several factors may contribute to this. In the UK, most arable crops and many other crops are harvested around July and August, which typically have the highest temperatures, so this period is often when drought effects are manifest and likely to be reported, even if the cause was lack of water earlier in the growing season. The six-month period used to calculate the $SPEI_6$ for July and August covers most of the main growing season for the majority of crops, so water stress in this period would have a strong effect on yield at harvest, and also on the quality of crops such as potatoes. It is also more likely that there will be low river levels, resulting in irrigation restrictions in some dry regions (principally the east and south-east) during this period (Salmoral et al., In press).

Drought in the spring and summer could also have an impact on grass-based livestock, by reducing the available grass for grazing and the yield of forage for conservation. Poor cereal yields would also increase feed prices for intensive livestock producers, which would become evident around the harvest period.

The year term had a positive coefficient, showing an upward trend over time (Table 4 and Fig. S.1 in the online supplementary material), which is slightly surprising. There is no obvious biophysical reason why the same value of $SPEI_6$ should have a greater effect in 2012 than 1975, but the effect was substantial (Fig. S.1), especially in the South East. Two possible explanations are a change in the actual or perceived vulnerability of farm enterprises to drought or a change in reporting practice. A change in vulnerability might have resulted from the trends towards intensification, particularly larger farms with lower labour inputs. This may have reduced the crop diversity within farms or the capacity to respond to drought pressures. It may also have arisen from increasing sectoral and regional concerns regarding the effects of strengthening environmental legislation (e.g. the European Water Framework Directive), ongoing reform of the abstraction licencing system in England and increasing competition for water resources, particularly in the South East. However, (Rey et al., 2017) found that farms in Eastern England utilising irrigation considered themselves to be becoming more resilient to drought, through farm-level adaptations and drought planning, collective actions at catchment level, and improved

Table 4
Coefficients of linear terms and fit statistics for the best model ($SPEI_6$ + smoothed(month) + year) fitted to the whole UK and to the regions.

Region[a]	Coefficients			Adjusted R^2	Deviance explained	AUC	AIC
	Intercept	$SPEI_6$	Year				
UK	−154	−1.022	0.0759	0.333	0.306	0.796	2358
UKE: Yorkshire and the Humber	−135	−1.287	0.0658	0.264	0.320	0.849	156
UKF: East Midlands	−172	−0.707	0.0856	0.345	0.331	0.835	260
UKG: West Midlands	−152	−1.662	0.0744	0.414	0.389	0.833	157
UKH: East of England	−189	−1.368	0.0943	0.444	0.472	0.853	273
UKJ: South East	−244	−0.839	0.1215	0.467	0.430	0.854	242
UKK: South West	−229	−1.275	0.1137	0.503	0.467	0.862	233
UKM: Scotland	−168	−0.697	0.0832	0.229	0.255	0.807	178

[a] UKC, UKD, UKI, UKL and UKN are omitted due to lack of sufficient impact records.

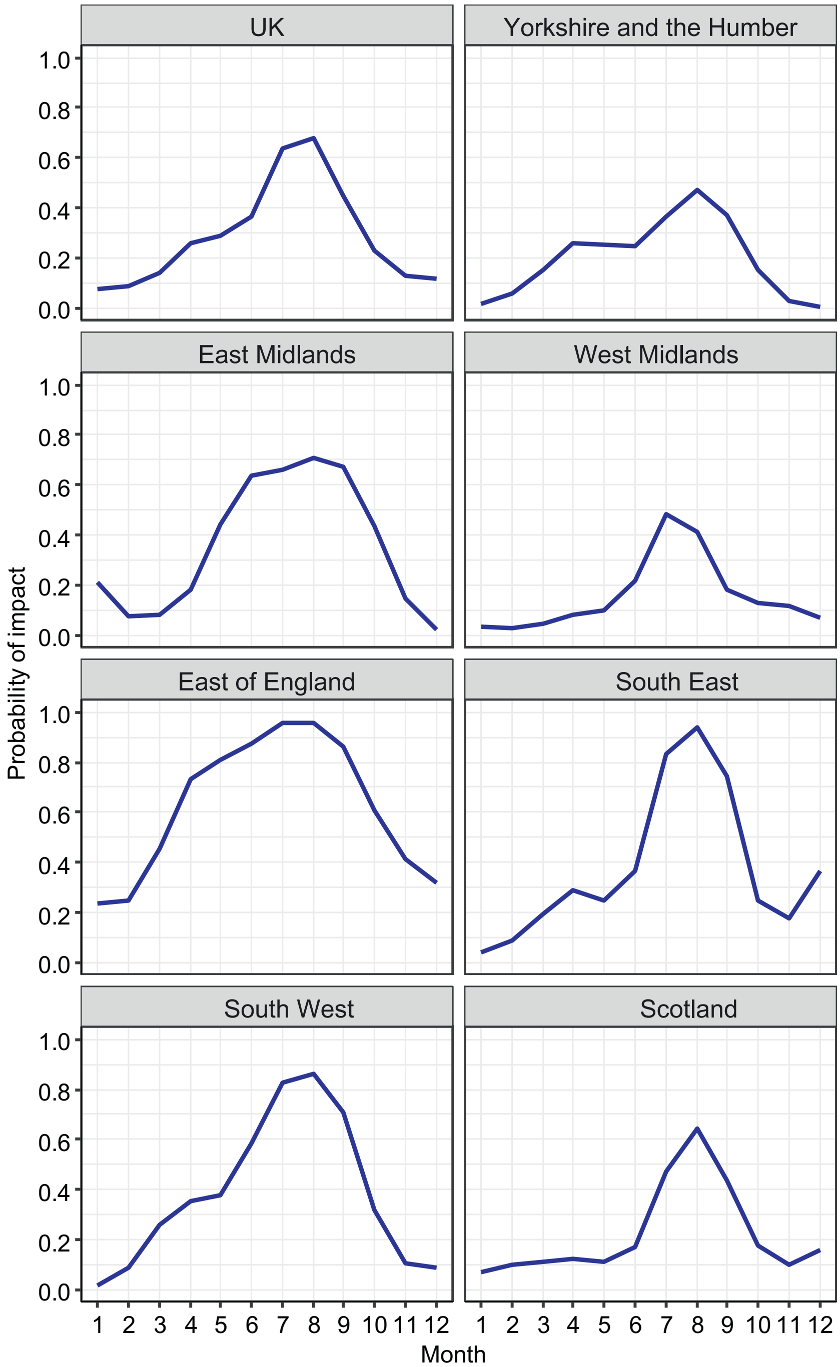

Fig. 2. Estimated probability of drought impacts vs month for $SPEI_6 = -1$ and year 1996.

working relationships with the regulator. It therefore seems more likely that the results reflect a change in awareness and reporting of drought impacts.

3.3. Regional responses

The variation in the response to $SPEI_6$ differed between regions. This can be seen in the model fitted to $SPEI_6$ alone (Fig. 3) and the full model with the year and month fixed (Fig. 4). The response was normally a reversed S-shape, though in some regions it was truncated at one or both ends for the range of $SPEI_6$ values considered. The regions differed in both the slope of the steepest part of the curve (the point of inflection) and the value of $SPEI_6$ where it occurred. Two possible components of the regional effect are the relationship of $SPEI_6$ to other measures of the water stress actually experienced by crops and the differences in types of agriculture between regions.

The comparison between the regions appeared to show that drought impacts were likely to be reported in the East and South East at higher values of $SPEI_6$ than in the other regions. However, as the SPEI depends on the long-term mean values for a region, the soil water conditions for the same SPEI may differ between regions.

$PSMD_{max6}$ was derived from regional meteorological data as an indicator of the water stress experienced by crops, whilst avoiding assumptions regarding regionally-averaged crop development, rooting depth and soil properties. Fig. S.3 in the online supplementary material shows $PSMD_{max6}$ plotted against $SPEI_6$ for all the regions of the UK. It is clear that much higher values of $PSMD_{max6}$ are common in southern and eastern regions than in Scotland, Wales and northern England, and

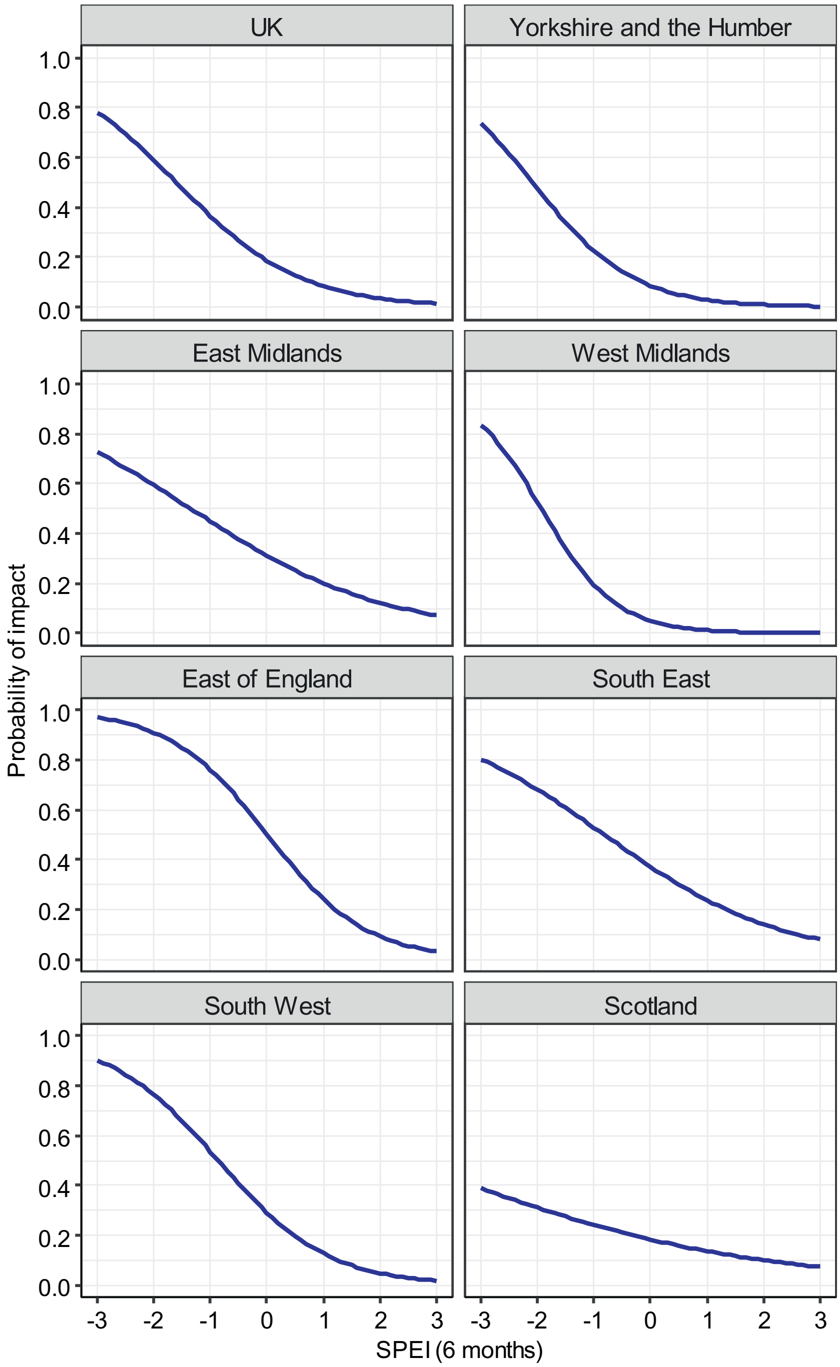

Fig. 3. Estimated probability of drought impacts vs $SPEI_6$ from model fitted to $SPEI_6$ only.

that the same $SPEI_6$ in the south and east corresponds to drier soil conditions. Furthermore, even at negative values of $SPEI_6$, the soil conditions in Wales and Scotland can be maintained close to field capacity, so an agricultural drought is unlikely.

The $PSMD_{max6}$ values corresponding to $SPEI_6$ in the range $[-2,0]$ (drier than average) were compared between regions using analysis of variance. The effect of region was found to be highly significant ($p < .001$). Using Tukey's HSD to test the differences between pairs of regions showed that many of the apparent differences were significant with $p < .05$ (Fig. 5). It is possible to divide the regions into four groups, all of whose members differ significantly from regions in the other groups. The 'very dry' region (group f in the boxplot) is the East of England; the 'dry' regions are South East and East Midlands (group e); the 'medium' regions (groups c and d) are North East, Yorkshire and Humberside, West Midlands and South West; and the 'wet' regions (groups a and b) are North West, Wales and Scotland. A similar trend is seen in the number of reported drought impacts.

The highest drought vulnerability was found in the East of England and the South East (Fig. 4). These were in the 'very dry' and 'dry' groups above, and they are the two UK regions with the highest competition for water resources and greatest water scarcity (Knox et al., 2018; Rio et al., 2018). The response curve for the East of England was S-shaped, but slightly truncated on the right, in the range considered, with a steep slope, and the point of inflection was between -1 and -2. As a result, the estimated probability of reported impact was over 0.8 at $SPEI_6 \cong 0$, so even average or moderately dry conditions by this measure resulted in a high risk of reported impacts. Over 80% of the agricultural land in this region is in arable production, including drought-sensitive crops,

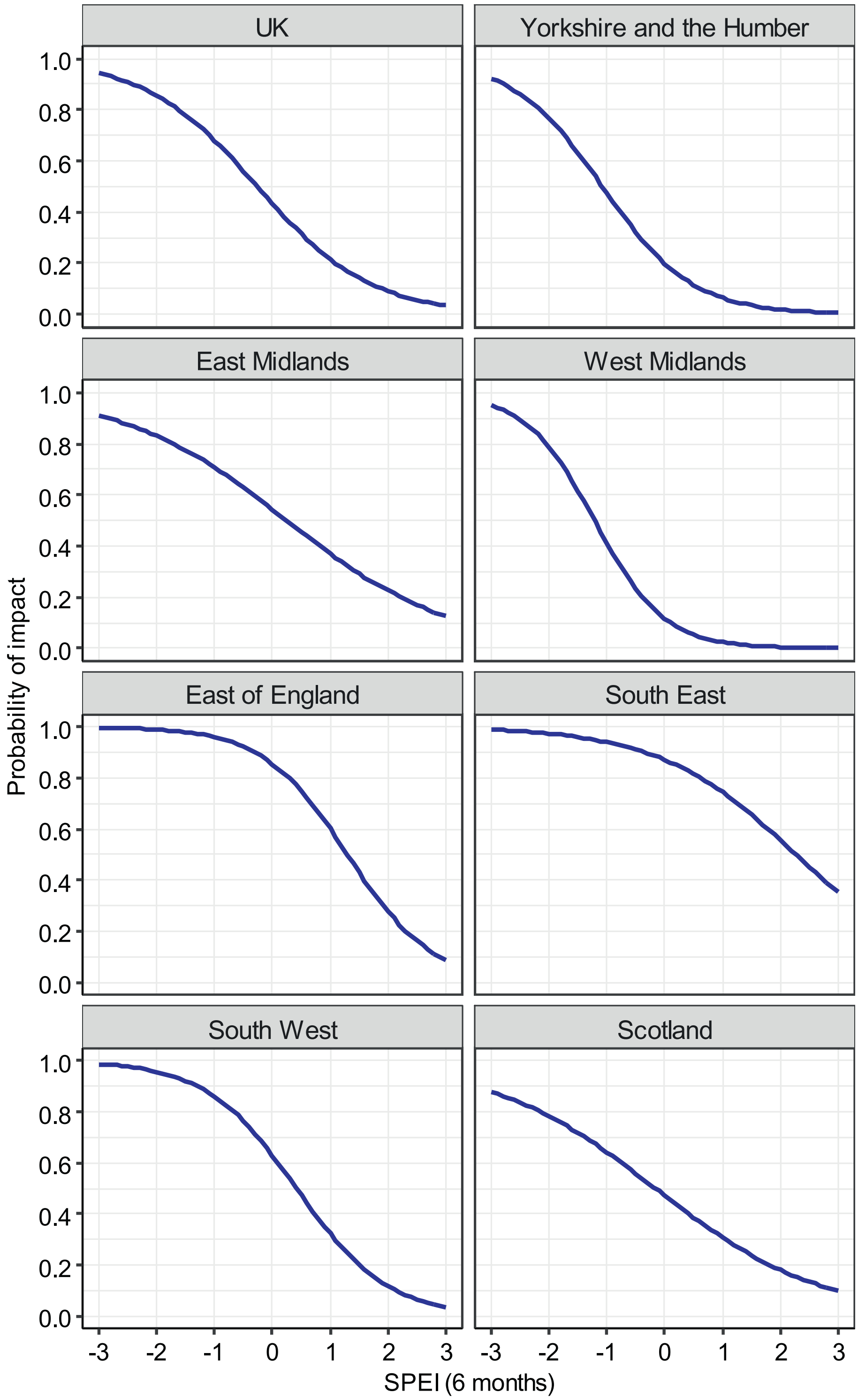

Fig. 4. Estimated probability of drought impacts vs $SPEI_6$ from model fitted to $SPEI_6$, month and year, for month 8 and year 1996.

such as potatoes and sugar beet. Irrigation is more common in this region than the other regions of the UK, and it is notable that it had the highest probability of impacts throughout the year (Fig. 2) for a fixed value of $SPEI_6$. This may reflect the fact that concerns for a summer drought will start during the winter recharge period, whereas a moderately dry winter is less likely to be problematic for rain-fed agriculture.

The South East also showed a less steep slope, but the point of inflection occurred at $SPEI_6 \cong 2.5$, so the lower tail of the S-shape fell outside the range of $SPEI_6$ considered: at 3 the estimated probability of reported impact was > 0.3 and at 0 it was 0.9, so there was a high chance of reported impacts across most of the range of $SPEI_6$. Agriculture in this region is mixed: about 50% of the land is arable, and several livestock-based farming systems are present; however it also includes top fruit (apples, pears etc.) and salad vegetables, which occupy small areas but are high-value drought-sensitive crops (Salmoral et al., In press).

Two regions – East Midlands and Scotland – had comparatively

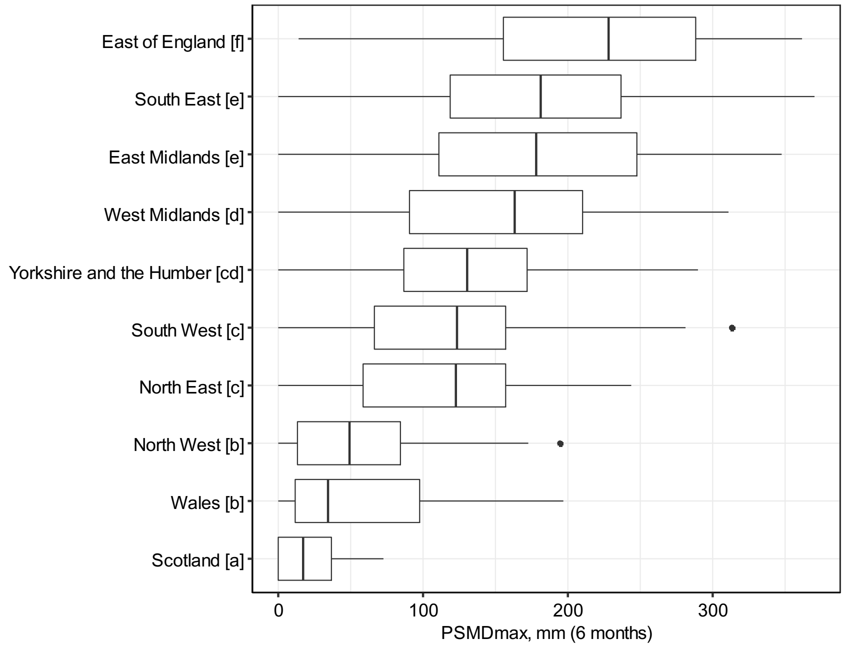

Fig. 5. Boxplot of $PSMD_{max6}$ for records with $SPEI_6$ in the range $[-2,0]$ by regions. Regions including the same letter in brackets are not significantly different (at $p < .05$). For example, Yorkshire and the Humber does not differ significantly from West Midlands, South West or North East.

shallow slopes with the point of inflection at $SPEI_6 \cong 0$, resulting in an almost linear response across the range of values for $SPEI_6$, representing progressively increased chance of reported impact with drought severity. The estimated probability of reported impact at $SPEI_6 = 0$ was about 0.5 for both regions, and an estimated probability of 0.8 occurred at $SPEI \cong -2$, so a severe drought was necessary for there to be a high estimated probability of reported impacts. This similarity shows that the relationship with PSMD is not the complete explanation for the regional variations: the East Midlands was in the 'dry' group, whereas Scotland was the wettest region.

Scotland is also much larger than any other region and more geographically diverse, ranging from the drier southern lowlands, with arable farming and soft fruits, to low-intensity grazing in upland areas (Fig. S.2 in the online supplementary material). The large proportion of high-rainfall, grazed uplands may explain the relatively low sensitivity to drought. In contrast, agriculture in the East Midlands is predominantly arable farming (65% of the area), with the most of the remaining agricultural land used for livestock and mixed farming. The reason for the similarity of response in these areas is not entirely clear.

West Midlands and Yorkshire and the Humber, both in the 'medium' group, had similar responses: fairly steep slopes with the point of inflection occurring at $SPEI_6 \cong -1$. The steeper slope showed greater sensitivity to $SPEI_6$ around the point of inflection, but the value where it occurred meant that the estimated probability of reported impact was quite low over most of its range. For both regions the estimated probability of reported impact at $SPEI_6 \cong 0$ was < 0.2, and an estimated probability of 0.8 occurred at $SPEI_6 \cong -2$. These regions are thus vulnerable only to severe droughts (as measured by $SPEI_6$). Both regions have substantial combined areas of grazed livestock and mixed farming (65% and 50% respectively).

The South West, which was also in the 'medium' group showed a response intermediate between these two and the 'dry' or 'very dry' regions. The point of inflection was slightly > 0, resulting in somewhat greater vulnerability to drought than the other 'medium' regions. The estimated probability of reported impact at $SPEI_6 \cong 0$ was about 0.6, and an estimated probability of 0.8 occurred at $SPEI \cong -0.7$, so a less severe drought than the other 'medium' regions had the same risk of impact. This region had the third highest number of reported impacts (Fig. 1). There is relatively little arable farming (27%) and this region has the highest proportion of land used for cattle (40%). The reason for the relatively high drought sensitivity is not completely clear from the data, although it might relate to the need to conserve forage for the winter for cattle, especially dairy cows. Some of the reported impacts in the database also relate to heat stress effects on cattle during summer drought periods.

These results show that SPEI cannot be interpreted reliably at a national scale in a country with as much regional variation in climate and agricultural practice as the UK. The same value of SPEI in different locations corresponds to widely different growing conditions, as indicated here by $PSMD_{max}$, but this does not explain all of the observed differences in the reported impacts. Therefore, if SPEI is to be used as an indicator of agricultural drought, it must be calibrated on a regional (or smaller) scale.

3.4. Non-drought years

The agricultural impacts data focused on years where there were known to be regional droughts in the UK, but contained results for complete years, not just the drought periods, and for all regions in these years whether affected or not. In order to test whether the selection of drought years biased the results, additional data was collected from the same sources for the years 2007–2009, and the model was refitted for all the regions.

The fit of the model was slightly worse with the additional data: the two R^2 measures decreased by 1–11%, AUC decreased by 0–4% and AIC increased by 6–22%. There was a small systematic decrease in the influence of the year: the coefficient decreased by 6–19% depending on the region and the magnitude of the intercept decreased by the same amount. The change in the coefficient of $SPEI_6$ was mixed, ranging from a 15% decrease in magnitude to a 27% increase, with most changes being $< 10\%$, tending to reduce the range of differences between the regions. The effects on the response curves were very slight.

There is thus some evidence that the response to the year may be partly due to the years selected, and that the difference between the regions are most evident in the drought years. This is not unexpected, as the number of reported impacts in the non-drought years was relatively low in all regions and was mainly associated with drought-related discussions that did not relate to contemporary hydro-meteorological

Table 5
Values of $SPEI_6$ corresponding to specific probabilities of reported drought impacts for August in 2012.

Region	Probability of impacts			
	0.25	0.5	0.75	0.9
UKE	0.6	−0.3	−1.1	−2.0
UKF	> 3.0	2.2	0.6	−0.9
UKG	0.2	−0.5	−1.2	−1.8
UKH	> 3.0	2.4	1.6	0.8
UKJ	> 3.0	> 3.0	> 3.0	2.0
UKK	2.7	1.8	1.0	0.1
UKM	> 3.0	1.7	0.2	−1.4

conditions.

3.5. Implications for drought monitoring and early warning

The results show that $SPEI_6$ combined with year and month at regional level may be able to predict, albeit imperfectly, the probability of drought impacts. Clearly, within-season planning would require a forecast value of $SPEI_6$, which could be derived from a combination of recent past observations and short-term or medium-term weather forecasts, ideally using an ensemble of forecasts to model the variability. For example, in the spring, weather observations for the past three months could be combined with a three-month forecast to estimate the probability of drought impacts in the summer.

As an example of the type of estimates that could be derived, Table 5 gives estimates of the values of $SPEI_6$ with the month set to August and the year set to 2012 (the last year used in fitting the model) at which the probability of impacts reached 0.25, 0.5, 0.75 and 0.9. In several regions, the threshold value of $SPEI_6$ for some levels of probability exceeded 3.0, the maximum value in the model. Thus the model predicts a substantial risk of drought impacts in August within these regions in the later years of the period studied even in years that are relatively wet for those regions, as also seen in Fig. S.1 in the online supplementary material.

4. Conclusions

Because of its slow onset and lengthy duration, the impacts of a drought are difficult to quantify or predict. There is still no full understanding of the relationship between drought severity and the associated impacts on different sectors. This paper aims to help fill this gap by exploring the national and regional relationship between drought indicators and reported agricultural impacts in the UK for the period 1975–2012, using a more comprehensive dataset than previous studies.

From these results, of the indices examined, $SPEI_6$ is the best predictor of drought impacts on agriculture in UK regions. However, the results demonstrate that the relationship between drought indicators and reported drought impacts are complex and vary between regions, reflecting differences in agricultural drought sensitivity, agro-meteorology, and the relative regional concerns surrounding regulatory and legal reform, water scarcity and sectoral water competition.

As a result, it is misleading to use a national value of $SPEI_6$, or one aggregated over a large heterogeneous area, because there are substantial differences in the relationship between $SPEI_6$ and the number of reported drought impacts between the regions. Therefore, in any climatically and agriculturally diverse country, it is likely to be necessary to derive relationship for smaller spatial units.

The comparison of PSMD and SPEI shows that the value of SPEI alone is potentially a poor indicator of soil conditions related to an agricultural drought unless the regional variations are also taken into account. For example, negative values of SPEI during the winter are a poor indicator of drought for rain-fed agriculture, especially in wetter areas, because soils may still reach field capacity.

Improving the predictive ability of indicators will require more systematic recording of drought impacts and the derivation of indices that are designed around the conditions that result in agricultural droughts. These will need to differentiate between the regional effects on different types of agriculture, such as irrigated crops, rain-fed crops and grazing livestock. However, given the drought sensitivity of agriculture, the integration of regional predictions within drought monitoring and forecasting would help to reduce the large on-farm economic damage of drought and increase the sector's resilience to future drought.

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The meteorological datasets supporting this study are openly available from https://doi.org/10.5285/8baf805d-39ce-4dac-b224-c926ada353b7 (CHESS-PE), https://doi.org/10.5285/33604ea0-c238-4488-813d-0ad9ab7c51ca (CEH-GEAR) and https://doi.org/10.5285/17b9c4f7-1c30-4b6f-b2fe-f7780159939c (historic gridded PET – used for Northern Ireland).

The Agricultural Drought Inventory data used in this article and supporting information are openly available from http://reshare.ukdataservice.ac.uk/853167/

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2019.02.015.

References

Bachmair, S., Kohn, I., Stahl, K., 2015. Exploring the link between drought indicators and impacts. Nat. Hazards Earth Syst. Sci. 15, 1381–1397. https://doi.org/10.5194/nhess-15-1381-2015.

Bachmair, S., Svensson, C., Hannaford, J., Barker, L.J., Stahl, K., 2016. A quantitative analysis to objectively appraise drought indicators and model drought impacts. Hydrol. Earth Syst. Sci. 20, 2589–2609. https://doi.org/10.5194/hess-20-2589-2016.

Bachmair, S., Svensson, C., Prosdocimi, I., Hannaford, J., Stahl, K., 2017. Developing drought impact functions for drought risk management. Nat. Hazards Earth Syst. Sci. 17, 1947–1960. https://doi.org/10.5194/nhess-17-1947-2017.

Bachmair, S., Tanguy, M., Hannaford, J., Stahl, K., 2018. How well do meteorological indicators represent agricultural and forest drought across Europe? Environ. Res. Lett. 13, 034042. https://doi.org/10.1088/1748-9326/aaafda.

Blauhut, V., Gudmundsson, L., Stahl, K., 2015. Towards pan-European drought risk maps: quantifying the link between drought indices and reported drought impacts. Environ. Res. Lett. 10, 014008. https://doi.org/10.1088/1748-9326/10/1/014008.

Bradley, A.P., 1997. The use of the area under the ROC curve in the evaluation of machine learning algorithms. Pattern Recognit. 30, 1145–1159. https://doi.org/10.1016/S0031-3203(96)00142-2.

Byun, H.-R., Wilhite, D.A., 1999. Objective quantification of drought severity and duration. J. Clim. 12, 2747–2756. https://doi.org/10.1175/1520-0442(1999)012<2747:OQODSA>2.0.CO;2.

Dalezios, N.R., Dunkel, Z., Eslamian, S., 2016a. Meteorological drought indices: definitions. In: Eslamian, S., Eslamian, F.A. (Eds.), Handbook of Drought and Water Scarcity. Principles of Drought and Water Scarcity, vol. 1. CRC Press, New York, pp. 24–44.

Dalezios, N.R., Gobion, A., Tarquis Alfonso, A.M., Eslamian, S., 2016b. Agricultural drought indices: combining crop, climate, and soil factors. In: Eslamian, S., Eslamian, F.A. (Eds.), Handbook of Drought and Water Scarcity. Principles of Drought and Water Scarcity, vol. 1. CRC Press, New York, pp. 73–90.

European Commission, 2007a. Drought Management Plan Report: Including Agricultural, Drought Indicators and Climate Change Aspects. European Commission, Water Scarcity and Drought Expert Network, Luxemburg.

European Commission, 2007b. Mediterranean Water Scarcity and Drought Report. Technical Report on Water Scarcity and Drought Management in the Mediterranean and the Water Framework Directive. Mediterranean Water Scarcity & Drought Working Group. Technical Report -009-2007.

FAO, 2008. Climate change and disaster risk management. Technical Background Document from the Expert Consultation held on 28–29 February 2008, Rome. Food and Agriculture Organization of the United Nations.

Giddens, A., 2011. The Politics of Climate Change, 2nd ed. Polity, Cambridge.
Gunst, L., Rego, F.M.C.C., Dias, S.M.A., Bifulco, C., Stagge, J.H., Rocha, M.S., Van Lanen, H.A.J., 2015. Impact of Meteorological drought on crop yield on pan-European scale, 1979-2009. In: Technical Report No. 36, Fostering European Drought Research and Science-Policy Interfacing Project. Wageningen University, The Netherlands, Instituto Superior de Agronomia, Portugal, University of Oslo, Norway.
Haro-Monteagudo, D., Daccache, A., Knox, J., 2017. Exploring the utility of drought indicators to assess climate risks to agricultural productivity in a humid climate. Hydrol. Res. 49, 539–551. https://doi.org/10.2166/nh.2017.010.
Hastie, T., Tibshirani, R., 1986. Generalized additive models. Stat. Sci. 1, 297–310. https://doi.org/10.1214/ss/1177013604.
Hosmer, D.W., Lemeshow, S., 2013. Applied Logistic Regression, 2nd ed. Wiley-Interscience Publication, New York.
IPCC, 2014. Climate Change 2014. Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.
Keller, V.D.J., Tanguy, M., Prosdocimi, I., Terry, J.A., Hitt, O., Cole, S.J., Fry, M., Morris, D.G., Dixon, H., 2015. CEH-GEAR: 1 km resolution daily and monthly areal rainfall estimates for the UK for hydrological and other applications. Earth Syst. Sci. Data 7, 143–155. https://doi.org/10.5194/essd-7-143-2015.
Knox, J.W., Weatherhead, E.K., Bradley, R.I., 1997. Mapping the total volumetric irrigation water requirements in England and Wales. Agric. Water Manag. 33, 1–18. https://doi.org/10.1016/S0378-3774(96)01285-1.
Knox, J.W., Haro-Monteagudo, D., Hess, T.M., Morris, J., 2018. Identifying trade-offs and reconciling competing demands for water: integrating agriculture into a robust decision-making framework. Earth's Future 6, 1457–1470. https://doi.org/10.1002/2017EF000741.
Lange, B., Holman, I., Bloomfield, J.P., 2017. A framework for a joint hydro-meteorological-social analysis of drought. Sci. Total Environ. 578, 297–306. https://doi.org/10.1016/j.scitotenv.2016.10.145.
McFadden, D.L., 1973. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Wiley, New York.
McKee, T.B., Doesken, N.J., Kleist, J., 1993. The Relationship of Drought Frequency and Duration to Time Scales. in Eighth Conference on Applied Climatology, 17–22 January 1993, Anaheim, California.
Meyer, S.J., Hubbard, K.G., Wilhite, D.A., 1993. A crop-specific drought index for corn: I. Model development and validation. Agron. J. 85, 388. https://doi.org/10.2134/agronj1993.00021962008500020040x.
Palmer, W.C., 1965. Meteorological Drought (U.S. Research Paper No. 45). US Weather Bureau, Washington, DC.
Palmer, W.C., 1968. Keeping track of crop moisture conditions, Nationwide: the new crop moisture index. Weatherwise 21, 156–161. https://doi.org/10.1080/00431672.1968.9932814.
Parry, S., Wilby, R.L., Prudhomme, C., Wood, P.J., 2016. A systematic assessment of drought termination in the United Kingdom. Hydrol. Earth Syst. Sci. 20, 4265–4281. https://doi.org/10.5194/hess-20-4265-2016.
Pedro-Monzonís, M., Solera, A., Ferrer, J., Estrela, T., Paredes-Arquiola, J., 2015. A review of water scarcity and drought indexes in water resources planning and management. J. Hydrol. 527, 482–493. https://doi.org/10.1016/j.jhydrol.2015.05.003.
Potopová, V., Štěpánek, P., Možný, M., Türkott, L., Soukup, J., 2015. Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. Agric. For. Meteorol. 202, 26–38. https://doi.org/10.1016/j.agrformet.2014.11.022.
R Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Rey, D., Holman, I.P., Daccache, A., Morris, J., Weatherhead, E.K., Knox, J.W., 2016. Modelling and mapping the economic value of supplemental irrigation in a humid climate. Agric. Water Manag. 173, 13–22. https://doi.org/10.1016/j.agwat.2016.04.017.
Rey, D., Holman, I.P., Knox, J.W., 2017. Developing drought resilience in irrigated agriculture in the face of increasing water scarcity. Reg. Environ. Chang. 17, 1527–1540. https://doi.org/10.1007/s10113-017-1116-6.
Rio, M., Rey, D., Prudhomme, C., Holman, I.P., 2018. Evaluation of changing surface water abstraction reliability for supplemental irrigation under climate change. Agric. Water Manag. 206, 200–208. https://doi.org/10.1016/j.agwat.2018.05.005.
Robinson, E.L., Blyth, E., Clark, D.B., Comyn-Platt, E., Finch, J., Rudd, A.C., 2016. Climate Hydrology and Ecology Research Support System Potential Evapotranspiration Dataset for Great Britain (1961–2015) [CHESS-PE]. https://doi.org/10.5285/8baf805d-39ce-4dac-b224-c926ada353b7.
Robinson, E.L., Blyth, E.M., Clark, D.B., Finch, J., Rudd, A.C., 2017. Trends in atmospheric evaporative demand in Great Britain using high-resolution meteorological data. Hydrol. Earth Syst. Sci. 21, 1189–1224. https://doi.org/10.5194/hess-21-1189-2017.
Rodríguez Díaz, J.A., Weatherhead, E.K., Knox, J.W., Camacho, E., 2007. Climate change impacts on irrigation water requirements in the Guadalquivir river basin in Spain. Reg. Environ. Chang. 7, 149–159. https://doi.org/10.1007/s10113-007-0035-3.
Salmoral, G., Rey, D., de Morgan, P., Rudd, A.C., Holman, I.P., 2019. A probabilistic risk assessment of the national economic impacts of regulatory drought management on irrigated agriculture. Earth's Future. https://doi.org/10.1029/2018EF001092. (in press).
Sing, T., Sander, O., Beerenwinkel, N., Lengauer, T., 2005. ROCR: visualizing classifier performance in R. Bioinformatics 21, 3940–3941.
Stagge, J.H., Kohn, I., Tallaksen, L.M., Stahl, K., 2015. Modeling drought impact occurrence based on meteorological drought indices in Europe. J. Hydrol. 530, 37–50. https://doi.org/10.1016/j.jhydrol.2015.09.039.
Svoboda, M.D., Fuchs, B.A. (Eds.), 2016. Handbook of Drought Indicators and Indices, Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines Series 2. World Meteorological Organization and Global Water Partnership, Geneva.
Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., Stephens, S., 2002. The drought monitor. Bull. Amer. Meteor. Soc. 83, 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181.
Tanguy, M., Hannaford, J., Barker, L., Svensson, C., Kral, F., Fry, M., 2015a. Gridded Standardized Precipitation Index (SPI) Using Gamma Distribution with Standard Period 1961–2010 for Great Britain [SPIgamma61–10]. https://doi.org/10.5285/94c9eaa3-a178-4de4-8905-dbfab03b69a0.
Tanguy, M., Hannaford, J., Barker, L., Svensson, C., Kral, F., Fry, M., 2015b. Gridded Standardized Precipitation-Evapotranspiration Index (SPEI) Using Generalised Logistic Distribution with Standard Period 1961–2010 for Great Britain [SPEIgenlog61–10]. https://doi.org/10.5285/d201a2af-568e-4195-bf02-961fb6954c72.
Tanguy, M., Dixon, H., Prosdocimi, I., Morris, D.G., Keller, V.D.J., 2016. Gridded Estimates of Daily and Monthly Areal Rainfall for the United Kingdom (1890–2015) [CEH-GEAR]. https://doi.org/10.5285/33604ea0-c238-4488-813d-0ad9ab7c51ca.
Tanguy, M., Prudhomme, C., Smith, K., Hannaford, J., 2018. Historic Gridded Potential Evapotranspiration (PET) Based on Temperature-Based Equation McGuinness-Bordne Calibrated for the UK (1891–2015). https://doi.org/10.5285/17b9c4f7-1c30-4b6f-b2fe-f7780159939c.
Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8, 127–150. https://doi.org/10.1016/0034-4257(79)90013-0.
Tukey, J.W., 1949. Comparing individual means in the analysis of variance. Biometrics 5, 99–114. https://doi.org/10.2307/3001913.
Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2009. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J. Clim. 23, 1696–1718. https://doi.org/10.1175/2009JCLI2909.1.
Vicente-Serrano, S.M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J.J., López-Moreno, J.I., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., Sanchez-Lorenzo, A., 2012. Performance of drought indices for ecological, agricultural, and hydrological applications. Earth Interact. 16, 1–27. https://doi.org/10.1175/2012EI000434.1.
Wilhite, D.A., 2007. Preparedness and coping strategies for agricultural drought risk management: recent Progress and trends. In: Sivakumar, M.V.K., Motha, R.P. (Eds.), Managing Weather and Climate Risks in Agriculture. Springer, Berlin, Heidelberg, pp. 21–38. https://doi.org/10.1007/978-3-540-72746-0_2.
Wilhite, D.A., Sivakumar, M.V.K., Pulwarty, R., 2014. Managing drought risk in a changing climate: the role of national drought policy. Weather Clim. Extrem. 3, 4–13. https://doi.org/10.1016/j.wace.2014.01.002.
Wood, S.N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. J. R. Stat. Soc. B 73, 3–36.
Zargar, A., Sadiq, R., Naser, B., Khan, F.I., 2011. A review of drought indices. Environ. Rev. 19, 333–349. https://doi.org/10.1139/a11-013.