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Modeling drought impact occurrence based on meteorological drought indices in Europe

James H. Stagge [a,*], Irene Kohn [b], Lena M. Tallaksen [a], Kerstin Stahl [b]

[a] Department of Geosciences, University of Oslo, Norway
[b] Institute of Hydrology, University of Freiburg, Germany

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SUMMARY

There is a vital need for research that links meteorological drought indices with drought impacts felt on the ground. Previously, this link has been estimated based on experience or defined based on very narrow impact measures. This study expands on earlier work by showing the feasibility of relating user-provided impact reports with meteorological drought indices, the Standardized Precipitation Index and the Standardized Precipitation-Evapotranspiration Index, through logistic regression, while controlling for seasonal and interannual effects. Analysis includes four impact types, spanning agriculture, energy and industry, public water supply, and freshwater ecosystem across five European countries. Statistically significant climate indices are retained as predictors using step-wise regression and used to compare the most relevant drought indices and accumulation periods across different impact types and regions. Agricultural impacts are explained by 2–12 month anomalies, though anomalies greater than 3 months are likely related to agricultural management practices. Energy and industrial impacts, typically related to hydropower and energy cooling water, respond slower (6–12 months). Public water supply and freshwater ecosystem impacts are explained by a more complex combination of short (1–3 month) and seasonal (6–12 month) anomalies. The resulting drought impact models have both good model fit (pseudo-R^2 = 0.225–0.716) and predictive ability, highlighting the feasibility of using such models to predict drought impact likelihood based on meteorological drought indices.

1. Introduction

With recent progress in participatory approaches to drought management, the common hazard-focused view of meteorological drought has been criticized and strong claims have been made for ground-truthing the numerous meteorological drought indices with respect to the drought impacts they cause (Steinemann, 2014; Kallis, 2008). This study aims to address this issue by empirically examining the linkage between meteorological drought indices and the various drought impacts they are meant to describe in a rigorous and quantitative manner. It therefore starts with the assumption that drought definitions, and hence indices to be used e.g. for risk assessment, should consider water management practices employed (Lloyd-Hughes, 2013).

Of the available meteorological drought indices (Keyantash and Dracup, 2002), the Standardized Precipitation Index (SPI, McKee et al., 1993; Guttman, 1999) and the Standardized Precipitation-Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010; Beguería et al., 2013) were selected as candidate drought indices for this study. The Standardized Precipitation Index (SPI) was selected because it is the predominant meteorological drought indices used in Europe and is recommended by the "Lincoln declaration on drought indices", which encourages Meteorological and Hydrological Services around the world to use the SPI (Hayes et al., 2011). The SPEI is a newer index, which uses a similar methodology, but includes a more comprehensive water balance, which may better quantify drought (Beguería et al., 2013). The SPI and SPEI normalize accumulated precipitation (P) and climatic water balance (P – PET), respectively, where PET represents potential evapotranspiration. The popularity of these indices is related to their simple interpretation, low data requirements satisfied by most climate data products, and their multiscalar flexibility. This multiscalar characteristic, allowing for short or long accumulated anomalies, is viewed as a major benefit, allowing the user to approximate agricultural, hydrological, and socioeconomic drought by adjusting the accumulation period of the indices (Vicente-Serrano et al., 2012; Hayes et al., 2011). However, this claim is rarely tested, with few studies identifying the most

* Corresponding author at: Department of Geosciences, University of Oslo, P.O. Box 1047 Blindern, N-0316 Oslo, Norway.
E-mail address: j.h.stagge@geo.uio.no (J.H. Stagge).

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appropriate drought index and accumulation period for different drought impact types. Without empirical evidence showing the link between drought impact occurrence and indices, drought monitoring agencies such as the European Drought Observatory (edo.jrc.europa.eu) and the US Drought Monitor (droughtmonitor.unl.edu) base their risk estimates on experience, assuming that short SPI aggregation periods explain agricultural impacts and longer SPI periods explain water resources impacts (personal communication, National Drought Mitigation Center).

Drought impacts are broadly defined as the negative environmental, economic, or social consequences of drought conditions (Knutson et al., 1998). Previous studies exploring the link between drought impacts and meteorological drought indices have primarily focused on correlating drought indices with quantitative measures of production, e.g. crop yield or hydropower generation. In Europe, such studies typically focus on agricultural impacts quantified by crop yield, particularly in southern and eastern Europe (e.g. Vicente-Serrano et al., 2006; Hlavinka et al., 2009; Rossi and Niemeyer, 2010; Tsakiris et al., 2010; Ceglar et al., 2012; Sepulcre-Canto et al., 2012). Alternatively, some studies have related meteorological drought indices with vegetation response, typically through remotely sensed measures like NDVI (Ji and Peters, 2003; Jain et al., 2010) or tree ring measurements (Vicente-Serrano et al., 2012). Low flows and hydrological drought have also been correlated with meteorological drought indices (Szalai et al., 2000; Vicente-Serrano and López-Moreno, 2005; Wong et al., 2013; Haslinger et al., 2014), though low flows are not considered drought impacts, as previously defined. Such correlation studies produce useful relationships; however, they do not focus on drought impacts alone. Using agriculture as an example, a correlation study may find a link between the 3 month SPI and wheat production. However, this link is based on the entire range of production values, including periods when harvests were successful and water was plentiful. Drought impacts represent only a small fraction of the time series, and therefore the most relevant drought index may be masked by correlations during non-drought periods.

In this study, analysis is solely based on drought impact occurrence rather than correlation and is facilitated by the European Drought Impact report Inventory (EDII, www.geo.uio.no/edc/droughtdb/), a pan-European database of drought impact reports. The EDII was developed for the purpose of cross-disciplinary drought research (Stahl et al., 2015). Its objective is to compile knowledge on the impacts of historic and recent drought events from a variety of information sources. Following the basic definitions of a drought impact by Knutson et al. (1998), which is also used by the US-Drought Impact Reporter (National Drought Mitigation Center; http://public.droughtreporter.unl.edu/), the EDII has collected reports on negative environmental, economic or social effects which have occurred due to drought conditions. Impact reports in the EDII can be based on quantitative indices, like crop production, or can include qualitative findings that would not otherwise be included in correlation analysis. This expands the scope of the study to include any agricultural consequence of drought rather than narrowly defined measures typically used in correlation analysis.

This study attempts to "move from the skies ... to the ground" (Kallis, 2008), using drought impact reports as a means to evaluate the relevance of meteorological drought indices with respect to impacts. The study approach uses logistic regression to model the extent to which drought indices can predict drought impact occurrence based on impact reports from the EDII. This builds on previous research (Blauhut et al., 2015) that examined annual drought impacts, but introduces novel methods, which include modeling impacts at the monthly scale by accounting for seasonality, incorporating interannual trends to account for sampling bias, and allowing for non-linear effects. All of these improvements better control for extraneous variables, producing a more accurate, isolated estimate of the link between drought and resulting impacts. This study tests all possible combinations of SPI and SPEI (1–24 month) separately for four general impact sectors (agriculture and livestock farming, energy and industry, public water supply, and freshwater ecosystems) and five European countries (Bulgaria, Germany, Norway, Slovenia, and the United Kingdom). The resulting drought impact models are then used to determine:

1. the most relevant drought indices and accumulation periods for each impact type and region,
2. the portion of impact likelihood explained by precipitation (SPI) or water balance (SPEI) anomalies,
3. and any consistent patterns across countries and impact types.

2. Data and methods

To determine the relevant drought indices and compare across impact types and countries, the best logistic regression model for each country and impact type is determined by stepwise regression. SPI and SPEI accumulation periods (n) of 1, 2, 3, 6, 9, 12, and 24 months are considered as potential predictor variables, as well as the joint influence of SPI-n and SPEI-n.

2.1. Drought indices (SPI/SPEI)

The Standardized Precipitation Index (SPI, McKee et al., 1993; Guttman, 1999) is calculated based on precipitation (P), while the alternative Standardized Precipitation-Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010; Beguería et al., 2013) uses the climatic water balance, measured as precipitation (P) minus potential evapotranspiration (PET). For each index, the quantities are summed over n months, termed accumulation periods and normalized to the standard normal distribution ($\mu = 0$, $\sigma = 1$) by fitting a parametric statistical distribution to the time of year during a reference period, from which non-exceedance probabilities can be calculated (McKee et al., 1993; Guttman, 1999; Lloyd-Hughes and Saunders, 2002). SPI and SPEI therefore allow for objective, relative comparisons across locations with different climatologies and highly non-normal precipitation distributions. In addition, index values are statistically interpretable, representing the number of standard deviations from typical conditions for a given location and time of year.

This study calculated SPI and SPEI for 1, 2, 3, 6, 9, 12, and 24 months, using a 30 year standard period, 1970–1999, as a reference period. Common nomenclature is used, so that SPI-6 corresponds to an SPI with a 6 month accumulation period. Index values were fitted by maximum likelihood estimation and normalized using the two parameter gamma distribution for the SPI and generalized extreme value (GEV) distribution for SPEI, following the recommendations for this dataset outlined in Stagge et al. (2015). Also, as in Stagge et al. (2015), index values are constrained to the range between -3 and 3, inclusive, to ensure reasonableness. Index values were extracted for each country using the area-weighted mean.

2.2. Climate data

The underlying climate data used to calculate the SPI and SPEI is based on the Watch Forcing Dataset (WFD) and the Watch Forcing Data ERA-Interim (WFDEI), which are gridded historical climate sets of subdaily climate data with a $0.5 \times 0.5°$ resolution, originally intended to provide comprehensive historical climate data to force global climate models (Weedon et al., 2011, 2014). Both datasets have undergone significant review and validation (Weedon et al., 2011, 2014) to ensure their historical accuracy and have been bias corrected based on Climatic Research Unit (CRU) and Global Precipitation Climatology Centre (GPCC) gauge data (Weedon et al., 2011). The two datasets differ in temporal extent, with the WFD covering the period 1/1/1958–12/31/2001 and the WFDEI spanning 1/1/1979–12/31/2012. This temporal difference is due to differences in the underlying reference data, which is the ERA-40 and ERA-Interim for the WFD and WFDEI, respectively.

Precipitation was calculated as the sum of rainfall and snowfall. Potential evapotranspiration, used only for the SPEI, was calculated using the Penman–Monteith equation with the Hargreaves–Samani modification (Hargreaves and Samani, 1985), as described in the FAO-56 for reference grass (Allen et al., 1998). This method was chosen based on SPEI sensitivity studies (Stagge et al., 2015; Beguería et al., 2013), low data requirements, and recommendations by the WMO (WMO, 2006) and the FAO-UN (Allen et al., 1998). Climate variables needed to calculate PET include daily average surface temperature (2 m), daily min/max surface temperature (2 m), and wind speed (10 m).

Combination of drought indices from the WFD and WFDEI was necessary to provide the best temporal coverage of the impact database, resulting in longer time series and therefore more confidence in the modeled relationships between drought indices and impacts. The drought indices (SPI and SPEI) were calculated for the WFD and WFDEI separately, using the WFD to fit the probability distributions because it spans the entire reference period. Once the WFD and WFDEI drought index time series were calculated, they were merged using a linear weighting scheme for the common period (1979–2001). For validation purposes, index values from the two datasets were compared during the common period and no significant differences or consistent biases were found. This is because differences due to modeling and interpolation are relatively minor compared to the interannual variability of precipitation that controls the non-exceedance percentile.

2.3. European Drought Impact report Inventory (EDII)

The EDII was designed to compile qualitative drought impact data for Europe based on a wide variety of sources (Stahl et al., 2015). Criteria for impact reports to be included in the EDII are: (i) it should be unquestionable that the observed impact is a result of drought, and (ii) it stems from a reliable information source for which citation must be provided. All report data within the EDII are referenced in time and space, classified into 15 pre-defined impact categories, and detailed by a short impact description. Drought impacts may include economic, environmental or social impacts resulting from either direct or indirect effects (e.g. Knutson et al., 1998; Wilhite et al., 2007; UN/ISDR, 2009; Logar and van den Bergh, 2013).

The EDII database is the result of a series of impact data collection campaigns, which have been conducted as part of the DROUGHT-R&SPI project (Stahl et al., 2015). Currently the EDII includes more than 2500 impact report entries for 33 countries across Europe, yet some biases in temporal and geographical coverage exist due to differences in report availability. In this study, a subset of the EDII database was used for analysis because it contained the most complete data, with the best coverage during the time period of available reanalysis climate data (1958–2012). This subset consists of five countries: Bulgaria (BG), Germany (DE), Norway (NO), Slovenia (SI), and the United Kingdom (UK) (Fig. 1), and four EDII impact categories: agriculture and livestock farming, energy and industry, public water supply, and freshwater ecosystem. Similarly, these impact categories were chosen because they had the most comprehensive information and spanned a range of drought impact processes. The resulting EDII subset includes a total of 493 impacts, of which Germany and the UK have the greatest number. Impacts in Germany are well distributed spatially, while impact reports in the UK are predominantly from the south-eastern English lowlands. Bulgaria has a high number of total impacts, but these records are concentrated in agriculture and public water supply. Norway and Slovenia have fewer total records, but are well distributed over time and hence were included in this analysis. Slovenia's impacts are solely concentrated in the agricultural sector, whereas Norway's records are spread across all impact sectors. Spatial coverage is good for Bulgaria, Slovenia, and Norway.

All EDII impact reports must contain temporal information regarding the impact start date and, if the impact is continuous, information about the end date. Temporal information is recorded at the monthly resolution or by seasons, which are converted to the monthly resolution for the purposes of this analysis by assuming the impact continued for all three months of the given season. For each country and selected impact category, a binary (presence/absence) monthly time series of impacts, Y, was generated, with $Y(t) = 0$ when no EDII impact is reported and $Y(t) = 1$ if one or more impacts were reported during a given month, t.

2.4. Logistic regression and Generalized Additive Models

This study uses logistic regression to relate the occurrence of impacts to drought indices, while employing Generalized Additive Models (GAMs) as a non-parametric alternative to linear regression. Logistic regression, also referred to as a logit model, models the relationship between a binary (e.g. presence/absence) outcome and predictor variables. Modeling a binary outcome using its raw likelihood, $p(Y)$, is statistically problematic because it is constrained between 0 and 1, while predictor variables tend to be continuous, ranging from $-\infty$ to $+\infty$. To address this, logistic regression transforms these probabilities using the log odds ratio, termed the logit transformation:

$$\text{logit}\{p(Y)\} = log\frac{p(Y)}{1 - p(Y)} \tag{1}$$

Logit transformed probabilities can then be linked to predictor variables in a method similar to simple linear regression, though when using the logit link function and maximum likelihood estimation, this class of models referred to as generalized linear models (GLMs, Nelder and Wedderburn, 1972; McCullagh and Nelder, 1989). GLMs are a broad class of models and link functions other than the logit link can be used, such as the Gaussian, Poisson, beta, or gamma distributions, though these are not described herein. GLMs are considered a parametric regression method and follow the form:

$$\text{logit }(p(Y)) = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \cdots \tag{2}$$

$$\text{logit }(p(Y)) = \beta_0 + \sum_{j=1}^{p} \beta_j x_j \tag{3}$$

An extension of GLMs, termed Generalized Additive Models (GAMs), relaxes this model form, replacing the linear terms with smoothed functions, as in the following equation:

$$\text{logit }(p) = \beta_0 + \sum_{j=1}^{p} f_j(x_j) \tag{4}$$

where the f_j are smoothing functions of the predictor variables, x_j (Hastie and Tibshirani, 1986; Hastie and Tibshirani, 1990). Because the predictors are not restricted to a linear effect, the data determines the shape of the response, allowing for features like bimodality, non-linear shapes, asymmetry, and high skewness (Yee and Mitchell, 1991). The flexibility of GAMs also allows for

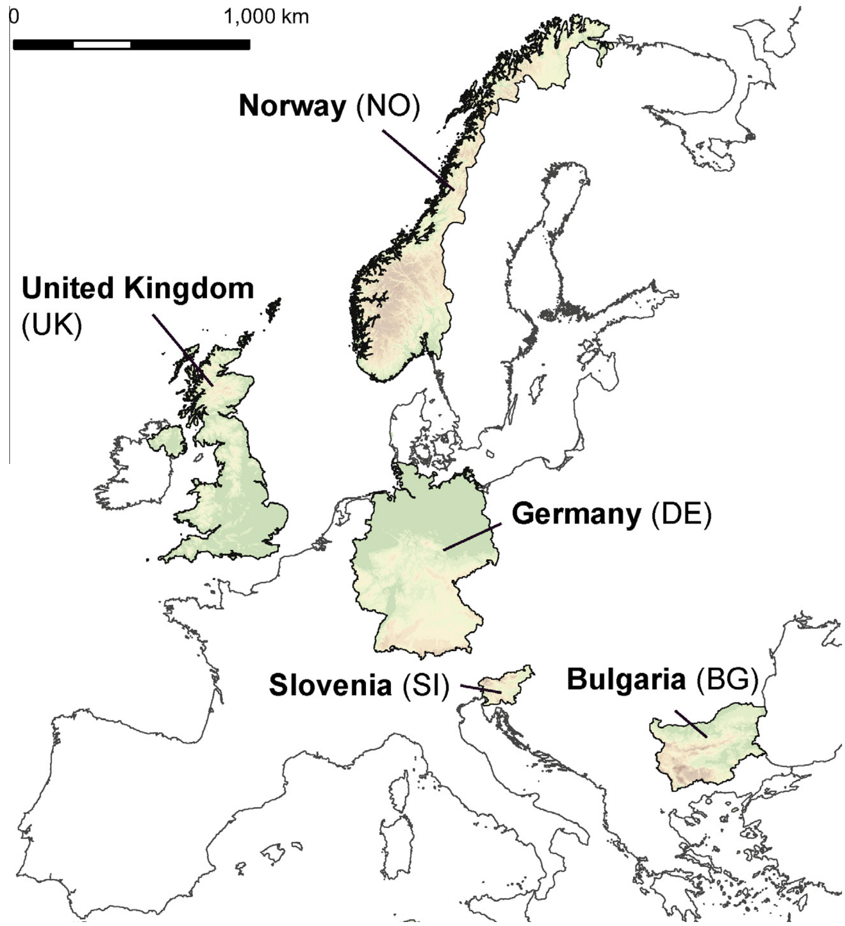

Fig. 1. Countries with drought impact models.

two-dimensional interactions of two predictors, described as $f_j(x_1, x_2)$. The resulting two-dimensional surface provides the predicted impact likelihood for all possible combinations of the two variables and is important to account for predictor pairs with high correlation, such as SPI and SPEI, that could otherwise produce an overfitted model if left as separate terms.

2.5. Model fitting

In this study, the GAM regression model is used with a logit link to regress the likelihood of a drought impact against the meteorological drought indices, f(SPI) and f(SPEI), and the interaction term f (SPI,SPEI). The interaction term accounts for the possibility that drought impacts occur due to a more complex interaction between a lack of precipitation and evapotranspiration. Model fitting was performed using the mgcv package (Wood, 2006) in *R*. Single variables were modeled using penalized regression splines, while interaction terms were modeled using thin plate regression splines (Wood, 2003). Smoothness parameters were set for each spline to avoid overfitting.

In addition to measuring the effect of drought indices on the likelihood of drought impacts, it is important to control for latent effects within the impact dataset independent of meteorological drought. These latent effects include seasonality and interannual trends over the time period (1958–2012). Controlling for these extraneous effects isolates the effect of meteorological drought and provides a more realistic estimate of its contribution to related impacts. For example, meteorological drought events (highly negative SPI/SPEI) are equally likely during the winter months because these indices measure deviations from normal conditions; however, crop impacts are only likely to be reported during the growing season in the selected countries. Therefore, monthly spline terms were included as potential variables to account for impact seasonality. In a similar manner, changes over the 54 year period were addressed using an annual spline term. The largest component of this annual trend is sampling/reporting bias due to differences in impact report availability and incomplete information. Other factors in the interannual trend may include differences in impact awareness, changes in coping capacity, economic stressors, and political impacts.

Models were fit using a forward and backward stepwise approach to retain only those variables with a significant predictive ability. The best models and predictors were selected based on the Bayesian Information Criterion (BIC) and predictor significance (p-value). Only models with statistically significant power relative to the null model were retained.

2.6. Goodness of fit

Model goodness of fit is presented using the McFadden pseudo-R^2 (McFadden, 1974) and by calculating the area under the ROC (Receiver Operating Characteristics, Mason and Graham, 2002; Wilks, 2011) curve (AUC). These measures test two important facets of logistic regression. The pseudo-R^2 provides a measure of model fit or calibration, similar to a traditional R^2, while the AUC provides a measure of model discrimination or binary predictive skill.

Traditional R^2 statistics cannot be calculated for logistic regression because it does not minimize variance, as in ordinary least squares (OLS). Instead, pseudo-R^2 can be used, which mimic the statistical properties of the OLS R^2. The McFadden (1974) pseudo-R^2 was selected because it was recommended for logistic regression among the potential pseudo-R^2 variants (Menard, 2000). It is calculated as:

$$R^2_{McF} = 1 - \frac{\ln(L_M)}{\ln(L_0)} \quad (5)$$

where ln is the natural logarithm, L_M is the estimated likelihood of the full model with predictors, and L_0 is the likelihood of a null model with no predictors, only an intercept. Despite its similarity to a traditional R^2, values of the McFadden R^2 for logistic regression are often smaller and considered satisfactory if they are between 20% and 40% (McFadden, 1974).

The AUC is used to quantify the discriminant power of impact models by describing the model's ability to correctly predict the occurrence or non-occurrence of "events" (Mason and Graham, 2002). The ROC curve is built by comparing the time series of predicted impacts to observed impacts for each threshold. For each threshold defining a predicted impact, the "hit rate" (the proportion of correctly predicted impact events) is plotted against the fraction of correctly identified non-impact months, or 1 minus the "false-alarm rate". This creates a 2-dimensional step curve, where area above the diagonal (1:1) line represents thresholds where the hit rate exceeds the false-alarm rate. A perfect model, therefore, has an AUC of 1, while a model with no predictive skill has an AUC of 0.5. The statistical significance is tested using methods outlined by Mason and Graham (2002). AUC has been shown to be a good test for distinguishing predictive skill in binary events, particularly when distinguishing between good and poor models. It has less power when distinguishing between nearly equivalent models (Marzban, 2004).

Using the ROC curve, a threshold was selected for each model that resulted in equal numbers of false positive and false negative impact predictions. In practice, such thresholds for warnings could be selected based on the needs of a community and the relative costs associated with these two types of predictive errors.

3. Results and discussion

Results from logistic regression analysis are presented for each combination of impact type and country. For each impact type, the available impact data are summarized, followed by an analysis of the relevant drought indices and a discussion of how these predictors are related to conditions within the countries. Comparisons across impact types and regions are presented in Section 4.

Table 1 presents both the number of months with impacts and the corresponding fraction (%) of the 54 year period this represents for each impact type and country. Generally, models with less than 8–10 impact report months over the 54 year period did not produce statistically significant results and were removed from analysis. Table 2 shows the goodness of fit for each model. Pseudo R^2 values range from 0.225 to 0.716, with a mean of 0.484, and AUC ranges from 0.842 to 0.992, with all models significantly better than the null model using the 1% significance level (Table 2).

3.1. Impact 1: agriculture and livestock farming

Agriculture and livestock impacts due to drought are the most consistently reported impacts across the countries of interest, with impact reports during more than 3% of months for all countries except for Norway, which was removed from analysis. The majority of impact reports are related to reduced crop yields, though the agriculture and livestock impact category can be quite diverse, including disparate impacts such as decreased milk rates or emergency livestock slaughtering.

Goodness of fit is consistent among logistic regression models for Bulgaria, Germany, and Slovenia, with pseudo-R^2 values between 0.307 and 0.395 and AUC above 0.883 (Table 2). ROC curves are significant above the 1:1 line, with high sensitivity without greatly decreasing specificity (Fig. 2). The drought impact model for the United Kingdom produced a seemingly better fit (Table 2) than the other three country models, though this is partially related to the relative scarcity of UK impact reports and clustering of UK impacts into two periods, which is addressed in greater detail below. Based on statistical significance of the ROC curve, the UK model is similar to the other countries. All agricultural impact models were highly significant using only one drought predictor combined with seasonal and interannual terms (Table 3). Table 3 shows the retained predictor variables for each model. Predictors are grouped by monthly pattern, interannual pattern, and short, medium, and long duration drought indices, corresponding to 1–3 month, 6–9 month, and 12–24 month periods, respectively. Retained predictors are shown in grey, with the name of the predictor variable, and symbols repressing the statistical significance of the variable. For this study, "SPI n/SPEI n" represents the joint influence of SPI and SPEI, modeled as a two-dimensional surface.

Table 1
Summary of drought impact reports (1958–2012) and deviance explained by the logistic regression models.

	Months with drought impacts					Months with drought impacts (%)				
	BG	DE	NO	SI	UK	BG	DE	NO	SI	UK
Agriculture	45	45	10	41	20	7.1	6.6	1.6	6.4	3.1
Energy and industry	8	16	20	3	8	1.2	2.4	3.0	0.4	1.2
Water supply	35	28	9	3	107	5.3	4.2	1.3	0.4	15.9
Freshwater ecosystems	2	23	14		54	0.3	3.4	2.1		8.0

Table 2
Model goodness of fit, showing pseudo-R^2 and area under the ROC curve (AUC).

	Pseudo R^2					AUC				
	BG	DE	NO	SI	UK	BG	DE	NO	SI	UK
Agriculture	0.307	0.395		0.325	0.705	0.883	0.909		0.903	0.991
Energy and industry		0.604	0.716		0.588		0.986	0.992		0.983
Water supply	0.225	0.349	0.538		0.402	0.842	0.898	0.962		0.890
Freshwater ecosystems		0.582	0.584		0.451		0.976	0.984		0.936

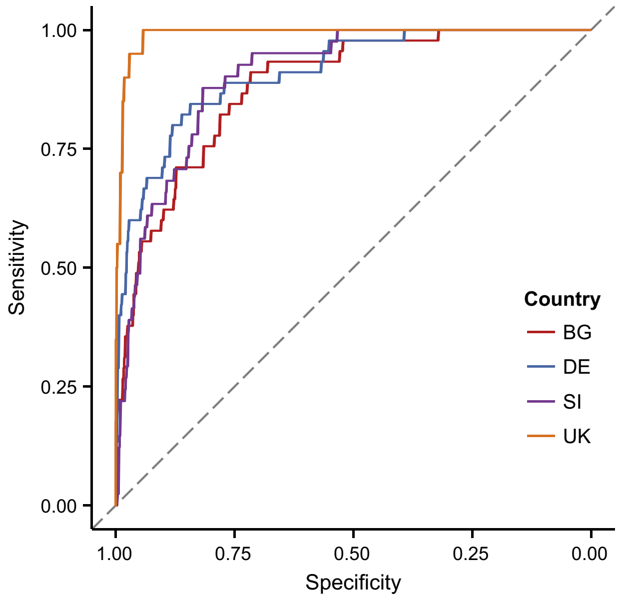

Fig. 2. ROC curve for agricultural drought impact models, with countries shown as uniquely colored curves. Sensitivity, or the fraction of correctly predicted impacts, is plotted against the specificity, or the fraction of correctly identified non-impact months. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

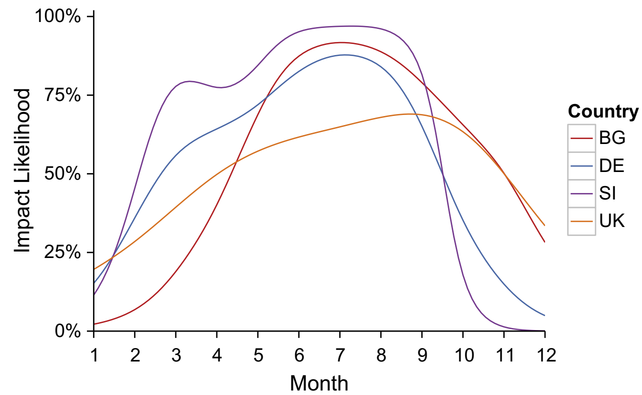

Fig. 3. Agricultural impact: seasonal component.

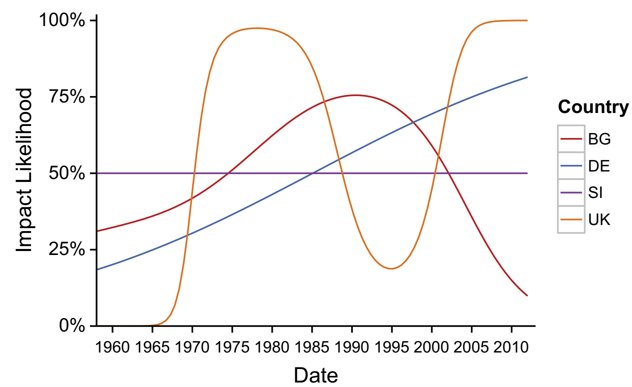

Fig. 4. Agricultural drought impacts: long term trend model component.

Seasonality is an important predictor for agricultural impacts across all four modeled countries, though it is not statistically significant for the UK (Table 3). The seasonal component, shown in Fig. 3, follows the agricultural growth period. This is reasonable, as the majority of agricultural impact reports are related to reduced crop yields, which are typically only experienced during the growing and harvest season, regardless of drought severity. This demonstrates the importance of controlling for seasonality when modeling the effect of drought on its related impacts. The interannual trend is also statistically significant for all models, except for Slovenia. The importance of incorporating this term becomes apparent by comparing the trend term for Slovenia with the remaining countries (Fig. 4). The annual trend term for Slovenia is not significant (Table 3) because impact reports for Slovenia were derived from a single, comprehensive report (AUA, 2011) that covered the entire modeled timeperiod. As such, there is no sampling bias and impact reporting effort is evenly distributed with time (Fig. 7). By comparison, UK impacts are derived from sources which mainly cover the specific drought events of 1975–1976 and 2010–2012, resulting in a significant interannual pattern which focuses on these time periods (Fig. 4). The interannual trend for Germany is also significant, but has a more consistent temporal

Table 3
Summary of drought impact models for different impact types and countries. Estimated variable significance shown as ***<0.001; ***0.001; *0.01.

Category	Predictor		BG	DE	NO	SI	UK
Agriculture	Month		***	***		***	*
	Year		***	***			***
	Indices	Short		SPEI 3***		SPI 2/SPEI 2***	
		Medium	SPEI 9**				
		Long					SPI 12/SPEI 12***
Energy and industry	Month						
	Year			***	*		*
	Indices	Short					
		Medium		SPI 9/SPEI 9***	SPEI 6**		
		Long					SPEI 12**
Water supply	Month						
	Year			*			***
	Indices	Short	SPEI 1*	SPEI 3***	SPI 1*		SPEI 3**
		Medium	SPI 6/SPEI 6***		SPI 6/SPEI 6***		SPEI 9***
		Long		SPEI 12**			SPEI 24**
Freshwater ecosystems	Month				*		
	Year			**			***
	Indices	Short		SPI 3/SPEI 3***			SPI 2/SPEI 2***
		Medium		SPEI 9**	SPI 6/SPEI 6***		
		Long					SPEI 24***

trend, with greater availability of impact reports, and thus sampling bias, nearer to the present time (Fig. 4). It should be noted that both the monthly and interannual trends do not incorporate changes in climate, as this change would be incorporated in the drought indices (e.g. a trend toward more frequent or severe drought events will be reflected in a decrease in SPI or SPEI).

Agricultural impacts in Germany and Slovenia are both related to relatively short (2–3 month) anomalies in water balance, with Germany depending on a single anomaly (SPEI3) and Slovenia depending on the interaction between SPI2 and SPEI2 (Table 3). For Germany, the index SPEI3 clearly differentiates between months with an agricultural impact (Fig. 5), which have a median SPEI3 value of −1.3, and those months without a registered impact, which follows the standard normal distribution centered around 0. Fig. 5 shows the relation between SPEI3 and impact likelihood in the center graph as a solid line with a shaded 95% confidence interval. The distribution of SPEI3 values for months with recorded impacts are shown at the top of the figure as a histogram and box plot, while the drought index values for months with no recorded impacts are shown at the bottom of the figure.

For Slovenia, the relationship between agricultural impacts and meteorological drought is instead based on the joint interaction between SPI2 and SPEI2 (Fig. 6). Joint interactions are shown by plotting the three-dimensional impact likelihood surface with respect to SPI (horizontal axis) and SPEI (vertical axis). Predicted impact likelihood is shown numerically by contours and by shading, with reds corresponding to climatic conditions with high impact likelihood and blues corresponding to conditions with low impact likelihood. The dotted 1:1 line bisects the graph, with SPEI > SPI above the line and SPEI < SPI below. Because SPI normalizes Σ(Precip) and SPEI normalizes Σ(Precip – PET) over the same period, the difference between the indices is related to PET. When SPEI is less than SPI, i.e. below the 1:1 line, PET is greater than typical, producing a drought that meteorological appears worse than if only precipitation was considered. High PET values typically correspond with higher than normal temperatures, as temperature is

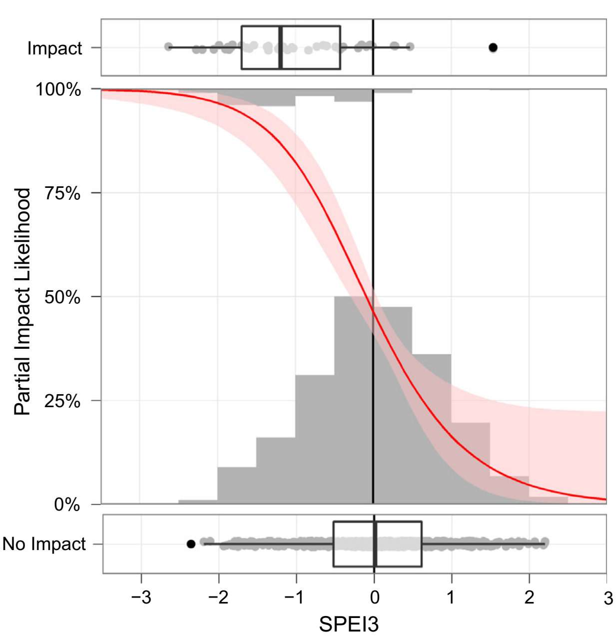

Fig. 5. Agricultural drought impacts: partial logistic regression model for Germany. Predicted impact likelihood is shown in red, while the distribution of SPEI3 is shown for impact months (top) and non-impact months (bottom). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

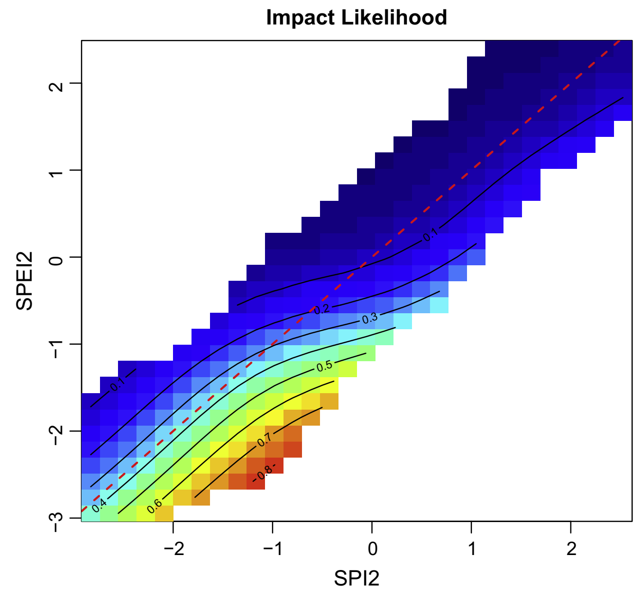

Fig. 6. Agricultural drought impacts: SPI2/SPEI2 interaction term for Slovenia. Predicted impact likelihood is shown in color, with red corresponding to high likelihood (≈100%) and blue corresponding to low likelihood (≈0%). Percent likelihood is also shown as contour labels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the most important climate variable in this PET equation (Stagge et al., 2014); however, PET may also be affected by wind speed, humidity, or solar irradiance using other methods (McVicar et al., 2012). For agricultural impacts in Slovenia (Fig. 6), the likelihood of an impact increases only when SPI2 is negative, signifying a lack of precipitation, and SPEI2 is less than SPI2, signifying abnormally high potential evapotranspiration or a temperature anomaly (heat wave). Predicted impact likelihood is calculated by applying these logit-link relationships and the predicted impacts, based on thresholds shown in grey, closely match the time series of recorded EDII impact reports (Fig. 7).

Both Germany and Slovenia have low agricultural water withdrawals (0.1% and 0.0%) relative to their Actual Renewable Water Resources (ARWR), defined as the sum of internal renewable water resources and incoming flow originating outside the country, which suggests predominantly rainfed agricultural practice without intense irrigation (Table 4, FAO, 2014). A 2–3 month drought anomaly for Germany and Slovenia is consistent with prior studies of drought impacts on rainfed crop yields in Central Europe (Hlavinka et al., 2009; Sušnik et al., 2010). As expected, agriculture is most sensitive to drought stress during the late spring and summer (Fig. 3).

By contrast, agriculture in Bulgaria and the UK is sensitive to meteorological drought accumulated over a longer (9–12 month) time period, which is assumed to be related to differences in water management practices and hydrological regimes. Both Bulgaria and the UK use a higher proportion of their annual renewable water for agriculture, with Bulgaria dedicating significantly more than any other country studied (4.7%, Table 4). Bulgaria is the most naturally water poor nation included in this analysis, yet they have a large agricultural output and extremely large dammed storage (Table 4). Bulgaria relies heavily on irrigation (Petkov and Dimitrov, 1996) and snow meltwater resources from its mountain watersheds (Knight and Staneva, 1996; Vassilev and Georgiev, 1996). The irrigation season covers the later growing season from June to September, when agricultural lowland areas experience high water deficits and natural streamflow is at its annual minimum (Petkov and Dimitrov, 1996; Hristov et al., 2004). Irrigation,

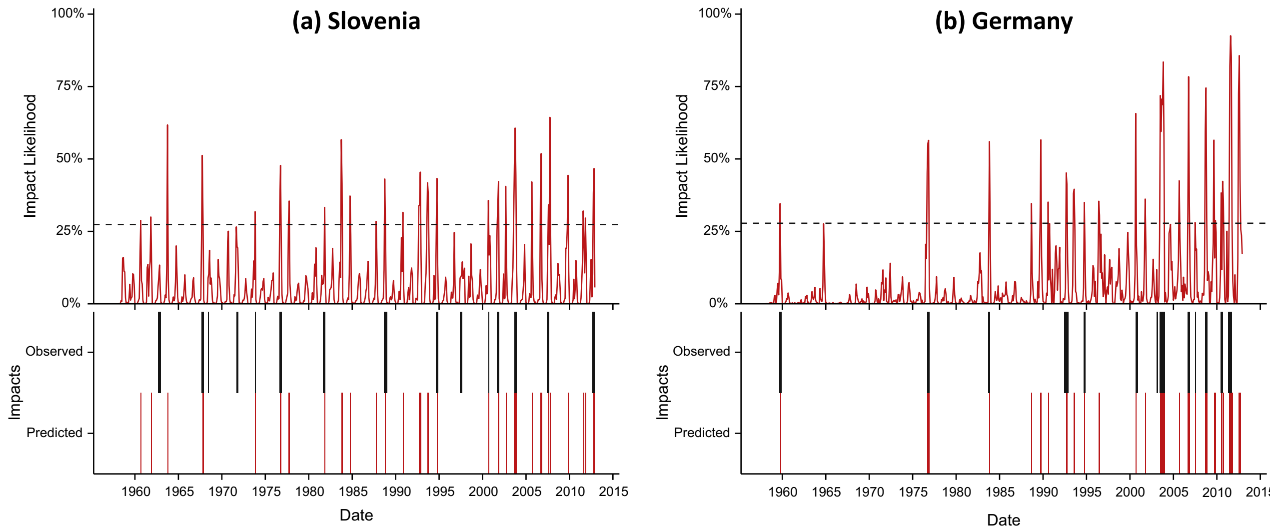

Fig. 7. Agricultural drought impacts: modeled impact likelihood timeseries for Slovenia (a) and Germany (b). The impact threshold is shown in grey and described in the Methods. Observed impacts are shown below the likelihood by grey bars and predicted impacts, based on the likelihood values above the threshold, are shown by red bars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Water resources by country. *Source:* FAO aquastat (FAO, 2014), except where noted.

Water resources	Units	BG	DE	NO	SI	UK
Average precipitation	mm/yr	608	700	1414	1162	1220
Actual Renewable Water Resources (ARWR)[a]	mm/yr	192	431	1180	1572	603
Total dam capacity	% of ARWR	30.6	2.6	8.7	0.2	3.6
Withdrawals by sector						
Agricultural	% of ARWR	4.7	0.1	0.2	0.0	0.8
Municipal	% of ARWR	4.6	3.3	0.2	0.5	5.0
Industrial	% of ARWR	19.5	17.6	0.3	2.4	2.9
Other						
Annual hydropower production[b]	kW h (million)	2952	26,106	119,729	3461	7780

[a] ARWR is the sum of internal renewable water resources and incoming flow originating outside the country.
[b] Median annual production (1990–2010), source: United Nations Statistics Division UN (2014).

dams, and snowmelt therefore buffer agricultural impacts and extend the relevant drought anomaly to 9 months (SPEI9), which includes the winter snow period in the mountains. The majority of Bulgarian agriculture referenced in the EDII is concentrated in lowland piedmont areas with high water retaining soils, which may also delay the effect of precipitation anomalies on agricultural impacts. Groundwater storage is also likely a factor in the long accumulation period (SPI12/SPEI12) for the UK. The majority of the available UK impact reports refer to irrigated potato yields and the effect of water restrictions on agriculture, particularly in the southeastern lowlands (see also DEFRA, 2013). The southeastern UK is characterized by large, highly productive chalk and limestone aquifers, which are the primary source of water for this region. These aquifers help to buffer sub-annual fluctuations, explaining the 12 month anomaly period (Kendon et al., 2013).

3.2. Impact 2: energy and industry

The energy and industrial sector produced the smallest number of impact reports, allowing for analysis across only three countries: Germany, Norway, and the UK (Table 1). The types of impacts included tend to differ among the three countries. Norway has the highest number of energy and industry impact reports (3.0% of the analyzed months) and these are predominantly related to decreased hydropower production. Impacts in Germany tend to be related to cooling water for the energy sector, with some hydropower impacts as well. The UK has very few impacts (1.2%), which tend to describe losses due to industrial water restrictions. Hydropower is a major industry in Norway, as shown by typical annual energy production (Table 4), followed by Germany and the UK. Industrial withdrawals (Table 4) should not be used to compare the relative industrial water uses of these countries, as cooling water that is immediately returned to the environment is considered a withdrawal in the FAO methodology (FAO 2014), whereas water used for hydropower is not. This explains the seemingly high industrial withdrawals in Germany relative to Norway, which has much lower withdrawals for industrial cooling water.

Models for energy and industry impacts have some of the highest pseudo R^2 and AUC values than any other impact sector, predominantly because there are fewer of these impacts recorded. However, it is important to note that Norway, with the highest number of impact reports, had the best fit of any country and impact type tested (Table 2). This is likely because Norwegian energy impacts are relatively homogenous, based almost entirely on hydropower production, whereas Germany and the UK have more varied impact reports. Energy and industry drought impacts were explained for all countries by a single medium-duration meteorological drought predictor, between 6 and 9 months (Table 3). As in the case of agricultural droughts, SPEI was a better predictor than SPI.

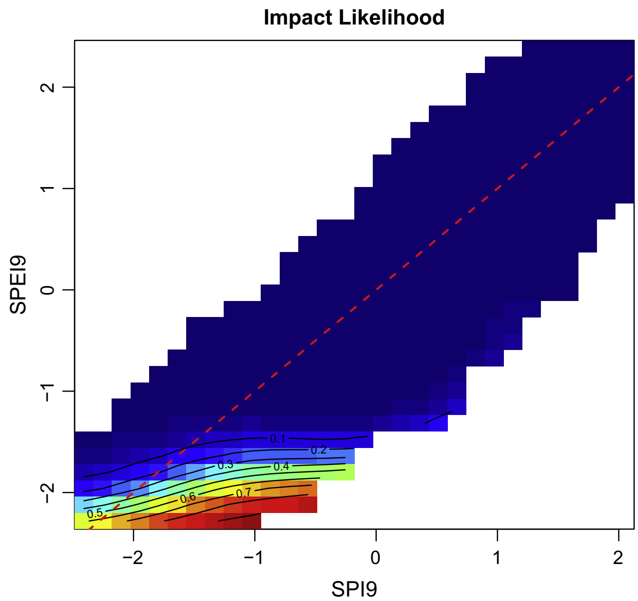

Fig. 8. Energy and Industry drought impacts: SPI9/SPEI9 interaction term for Germany. Plot follows the same conventions as Fig. 5.

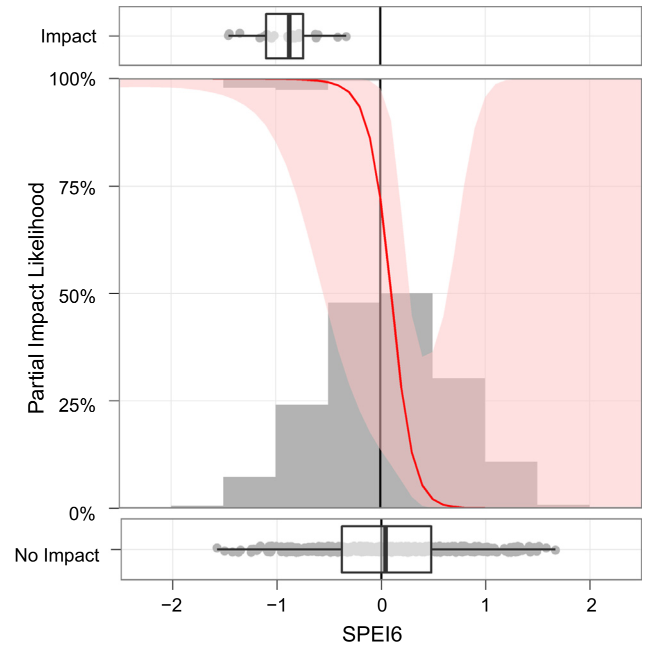

Fig. 9. Energy and Industry drought impacts: partial logistic regression model for Norway. Plot follows the same conventions as Fig. 4.

Comparing German and Norwegian impact models demonstrates the importance of impact types for determining meteorological relevant drought predictors. German energy and industry impacts are explained best by the interaction between SPI9 and SPEI9, which generally corresponds to accumulated precipitation and evapotranspiration between the winter and summer periods. The interaction term has a more narrow zone of high likelihood and sharper slopes than the agricultural impact interaction terms (Fig. 8) and shows that the likelihood of an energy or industrial drought-related impact increases for the combined condition when (1) SPI9 < 0, (2) SPEI9 < SPI9, and (3) SPEI9 < −1.5. When SPEI is much lower than SPI, evapotranspiration during the period is higher than normal, likely due to sustained higher temperatures. Because the majority of German energy and industry impact reports are related to cooling water restrictions due to high water temperatures, the interaction term models the condition when there is a combination of low water levels (SPI9 < 0) and high ambient temperatures (SPEI9 $\ll$ SPI9). This term reasonably captures both conditions leading to cooling water impacts and a typical accumulation period (9 months) for hydropower recharge in Germany, which are also included as energy and industry impacts in Germany.

This is contrasted with Norwegian energy drought impact reports, which are nearly all based on the hydropower industry, and as such, are related solely to water quantity (SPEI6, Fig. 9). SPEI6 clearly differentiates between months with energy impacts, which have a median SPEI6 of −0.87, and non-impact months, centered around an SPEI6 of 0 (Fig. 9). A relevant six month accumulation period is reasonable because Norwegian hydropower reservoirs are designed as seasonal, rather than multi-annual, reservoirs. Norwegian hydropower impact reports generally cite abnormally dry periods during the late summer and early autumn, which lead to below normal reservoir levels during the winter months, further confirming the importance of the six month anomaly.

3.3. Impact 3: public water supply

Public water supply impacts are relatively homogenous, referring to a real or perceived lack of water relative to public demand. The number of public water supply impact reports in the EDII vary to a large extent among countries, from 0.4% to 1.3% of months in Slovenia and Norway, respectively, to 15.9% of months in the United Kingdom (Table 1). The number of public water supply impacts in the UK is exceptionally high and are primarily regional outdoor water-use, or "hosepipe", bans enforced during drought periods. In Bulgaria, domestic water supply shortages have been a major problem during recent drought events, affecting substantial parts of the population, whereas in Germany and Norway, water supply problems appear to be rather rare, based on the available impact reports. Municipal water withdrawals are high in the UK and Germany due to large urban populations and are also high in Bulgaria due to a relatively low total ARWR (Table 4). There is sufficient data to generate statistically significant drought impact models for all countries except for Slovenia. Model fit is good for all countries, with pseudo-R^2 varying between 0.225 and 0.528 and AUC ranging from 0.842 to 0.890. The ROC curves are all statistically significant, though Norway's model has the lowest significance ($p = 9.2 \times 10^{-7}$) due to a smaller sample size of impact months (Table 1).

Public water supply impact predictors follow a similar pattern across all four modeled countries. Unlike agriculture and energy, public water supply impacts are generally the product of two drought predictors: a short, severe drought anomaly combined with a longer, less intense anomaly. However, the accumulation period and shape of the short and long predictors varies between countries. The countries cluster into two groups with respect to public water supply impact models. Bulgaria and Norway have a quicker response, depending on SPI1 or SPEI1 and the SPI6/SPEI6 interaction, whereas Germany and the UK have a slower response, depending on SPEI3 and either SPEI9 or SPEI24 (Table 3). This clustering and its related hydrologic response can best be explained by the relevant water source for each country: surface water in Bulgaria and Norway, and groundwater in Germany and the UK. It should be noted that while all countries use a mixture of surface and groundwater sources for public water supplies, this division refers to the predominant water source for the subset of impact reports within the EDII.

In countries with primarily surface water supply impacts (i.e. Norway and Bulgaria), these impacts are related to a one month negative anomaly of low precipitation and high evapotranspiration, in conjunction with an SPEI6 < SPI6 (Table 3). For Bulgaria, the best short predictor is the SPEI1, while for Norway, this predictor is the SPI1. It appears that short term evapotranspiration does not play a major role in water supply droughts for Norway, likely due to the relatively cool climate. The shape of the SPI1 or SPEI1 curves (Fig. 10) are similar to previous relationships, with the likelihood of drought impacts increasing with worsening drought (decreasing SPI or SPEI). However, the SPI6/SPEI6 interaction term exhibits a shape not seen in the previous impact categories. This interaction term nearly parallels the 1:1 line, with a negative offset (i.e. SPEI < SPI). This shape suggests that the likelihood of a public water supply impact increases when SPEI6 < SPI6, regardless of how dry or wet conditions are. To illustrate this point, consider the Norwegian model. The likelihood of an impact increases toward 100% equally for wet conditions (SPI6 = 1.5, SPEI6 = 1.0) or dry conditions (SPI6 = −0.5, SPEI6 = −1.0). Therefore, the important determinant for public water supply impacts an SPEI6 value 0.5 standard deviations less than the SPI6, regardless of precipitation. This unique situation suggests the importance of abnormally high 6 month PET, which in turn is related to increased temperature. The importance of six month temperature in Bulgaria and Norway may point toward the importance of warm winters, which produce less snow in these regions that depend on snowmelt to fill reservoirs. It may also describe a more direct effect of increased evaporation on surface water bodies.

By contrast, water supply in the groundwater dependent countries, Germany and the UK, reacts more slowly to meteorological drought. Water supply impacts in Germany and the UK depend on the 3 month SPEI and the 9–12 month SPEI (Table 4). In all cases, the likelihood of an impact increases with increasing drought severity. Germany and UK water supplies do not depend on an interaction term because groundwater sources are less impacted by fluctuations in temperature or evapotranspiration. The UK water supply impact model also includes a 2 year (SPEI24) drought term. This extremely long accumulation period is unique to the UK and may be related to the large storage capacity and slow hydrological response of the chalk and limestone aquifers in the southeast of England where the majority of impact reports are located. This multiyear anomaly is supported by anecdotal evidence from local UK water companies, which focus on 6–24 month rainfall anomalies in their water resources planning (DEFRA, 2013),

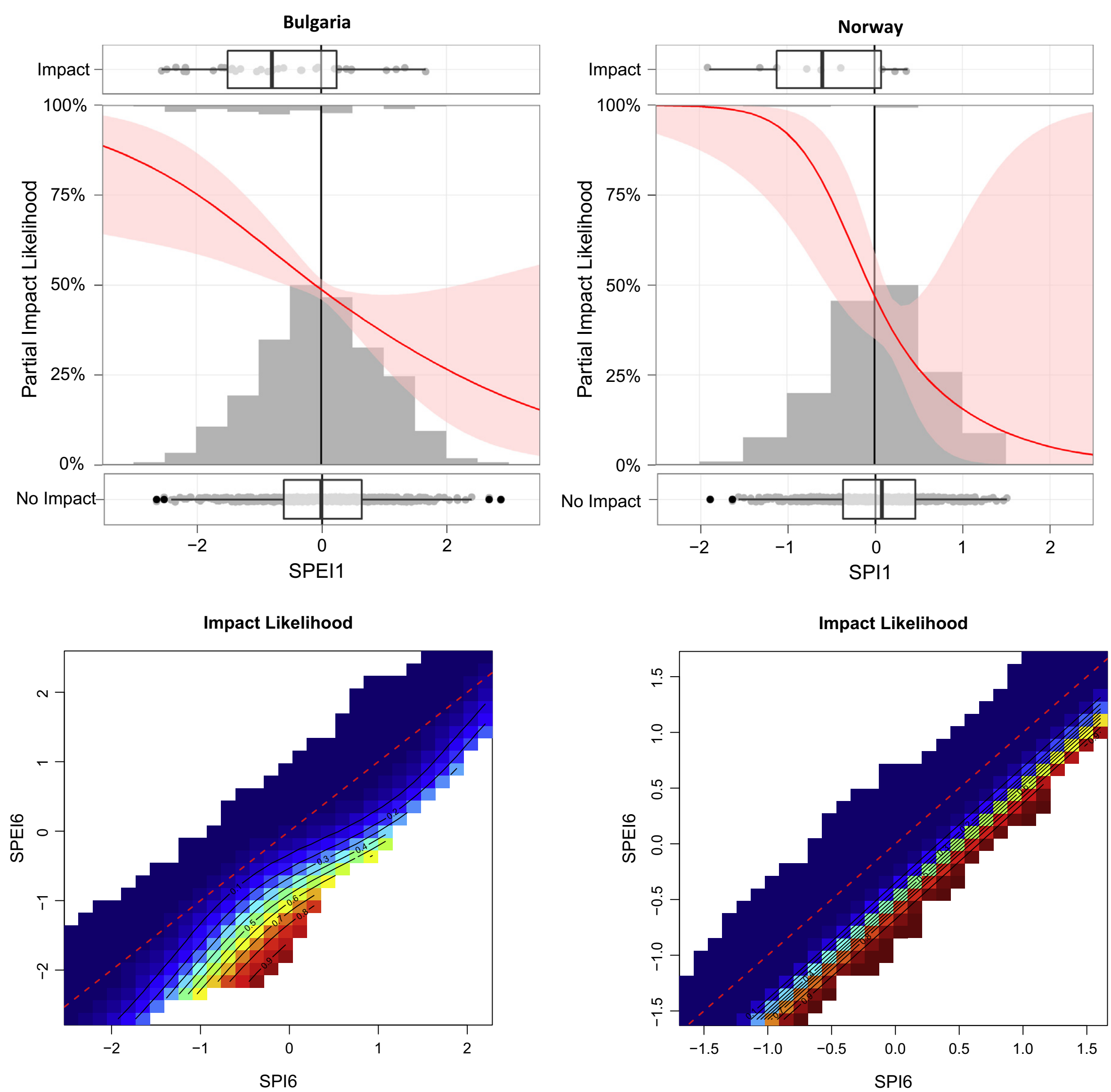

Fig. 10. Public water supply drought impacts: similarities between Bulgaria (left) and Norway (right).

studies of major UK droughts that cite the importance of multi-year drought clusters (Kendon et al., 2013), and correlations between groundwater drought in selected chalk wells and SPI8-20 (Bloomfield and Marchant, 2013). Correlation studies of groundwater levels and SPI have also cited periods from 5 to 24 months (Szalai et al., 2000; Khan et al., 2008)

3.4. Impact 4: freshwater ecosystems: habitats, plants and wildlife

Freshwater ecosystem impact reports in the EDII are typically related to the drying of surface waters, flows below critical thresholds, fish kills, and algal blooms. No such impact reports have been collected for Bulgaria or Slovenia, so analysis was limited to Germany, Norway and the UK. Model fit was quite good (pseudo-R^2 of 0.451–0.584), relative to the occurrence of freshwater ecosystem impacts (2.1–8.0%, Table 1).

Models for freshwater ecosystem impacts in Germany and the UK have similar traits, including a short (2–3 month) SPI/SPEI interaction term and a medium to long (9 and 24 month) SPEI anomaly, which is the secondary predictor. The interaction term for the UK and Germany, to a lesser extent, follows the 1:1 relationship described previously, which signals the importance of increased evapotranspiration and temperature by extension. Freshwater impacts in the UK occur when there is a multi-year lack of rainfall, followed by 2 months of excessive evapotranspiration, whereas impacts in Germany are related to a 3 month precipitation deficit and 9 months of excessive evapotranspiration or temperatures (Table 3). These predictors match the physical causes of the freshwater ecosystem impact reports, which are predominantly based on dry stream beds and critical low flows. As described previously, the regions of the UK where most impacts are noted tend to have large and slowly responding groundwater aquifers, which explains the longer accumulation time relative to Germany's impacts, which are distributed over a larger variety of watershed systems. Germany and the UK both have significant interannual terms, with a clear trend toward more impacts in recent years (Fig. 11). This is likely caused by an increasing awareness of environmental impacts and increased ecosystem monitoring efforts.

Norway's ecosystem response to meteorological drought is unique, due to a seasonal component and only a 6 month SPI6/SPEI6 interaction term (Table 3). Inclusion of a seasonal component is reasonable for Norway, which has a more pronounced winter freeze period when ecosystem impacts are unlikely. Ecosystem impacts are therefore only noted in the late spring and summer, when low precipitation and high ET losses can lead to low water levels and increases in bacterial growth and other water quality problems.

3.5. Model comparison across impact sectors and countries

Differences in predictive variables across impact categories highlight differences in the underlying hydrologic causes of the impacts. In general, agricultural and energy/industry impacts are best explained by a single drought anomaly. For agricultural droughts impacts, this can range from short, seasonal periods (2–3 months) to much longer periods (9–12 months), depending on management practices, hydrogeology, and the climatology of the region. Energy and Industry impacts have the longest accumulated period (6–12 months) among the four tested impact categories and are thus unaffected by short-term fluctuations in precipitation. This is reasonable, as reservoir storage, which affects hydropower production, and streamflow minima, which limit industrial/energy water use, are both related to longer hydrologic anomalies. Public water supply and freshwater ecosystem impacts are governed by more complex processes, depending on both short (1–3 month) components and a medium to long (6–24 month) components. Differences within the impact sectors are more heavily dependent on regional characteristics.

The only impact category with a consistent, statistically significant seasonal component is agriculture and livestock farming. Seasonal patterns were also detected for freshwater ecosystem impacts in Norway, though not in any other country, and this effect was relatively weak ($p > 0.1$) due to the low sample size of impact reports. The lack of a seasonal effect for public water supply, energy, and ecosystem impacts is surprising, as these impacts are all expected to have some degree of seasonality. The lack of significant seasonality may partially be caused by a difficulty in identifying impact timing within the EDII. Despite strict instructions dictating how to assign impact months, impacts such as hydropower losses are often reported as seasonal or annual figures, making monthly attribution difficult. In some cases, impacts were removed if no monthly impact data could be estimated, lowering the number of available impact reports (Table 1).

The relevant impact predictors also highlight important differences between the countries considered. Among the five countries, the United Kingdom responds to longer drought anomalies across nearly all impact categories, suggesting a consistently slower hydrologic response. A large part of the EDII reports in the UK refer

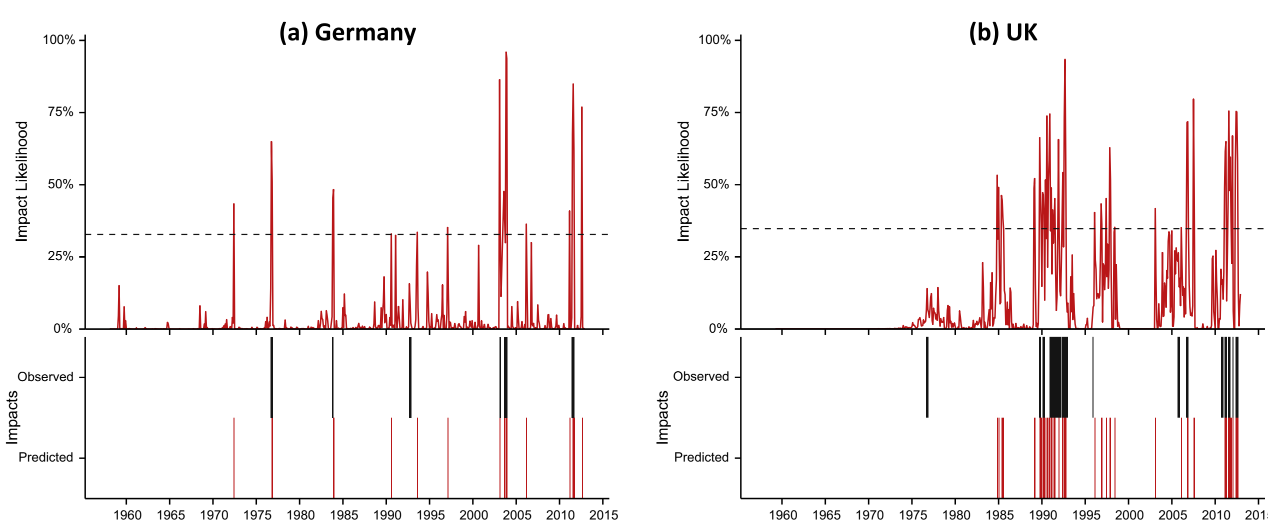

Fig. 11. Freshwater ecosystems drought impacts: fitted timeseries for Germany (a) and the UK (b). Plot follows the same conventions as Fig. 7.

to the southeast lowlands of England, which is the driest part of the UK and is characterized by groundwater-dominated watersheds that help to buffer drought response. Several regional studies of historical droughts cite the importance of multi-years droughts (successive dry winters) in conjunction with shorter, more intense drought periods in England (Cole and Marsh, 2006; Christierson et al., 2009; Parry et al., 2012), which closely matches results for the UK in this analysis. Germany has similar, though slightly quicker response to meteorological drought, likely related to a high dependence on groundwater for water supply, but a greater variety of catchment and aquifer types including smaller, more responsive sources.

The remaining countries differ from Germany and the UK, with generally quicker responses to drought anomalies, though data limitations across all impact categories prohibit a truly conclusive result. Notable common features characterizing these remaining countries (Bulgaria, Norway, and Slovenia) are mountainous topography, a significant snowmelt contribution that produces high seasonality, and a greater dependence on surface water resources. These factors combine to reduce the relevant drought accumulation period. Norway and Bulgaria show quick responses for public water supply, though Bulgarian agricultural response is relatively slow (9 month) due to an intense irrigation program. Slovenia cannot be compared across all impacts, as it is only analyzed for agricultural impacts, though it should be noted that it has the quickest response time (2 months) of all tested countries.

3.6. Methodological advances and comparison with existing knowledge

Using logistic regression and a GAM approach, this study outlines a methodology that successfully models the likelihood of a drought impact based on meteorological drought indices, using user-supplied drought impact reports. This methodology expands upon recent qualitative drought impact models by accounting for seasonality, interannual trends, and non-linear effects using techniques more commonly used in sociology and ecology (Hastie and Tibshirani, 1986; Yee and Mitchell, 1991; Guisan et al., 2002). Within these fields, researchers have developed methods to isolate the effect of predictor variables, while controlling for latent effects or biases, such as differences in sampling effort and inherent differences between subjects. This study addresses the issue of bias in the EDII's qualitative impact reports through careful model design and the use of GAM terms for seasonal and interannual patterns. Finally, the drought impact models produced are accurate, both in terms of model calibration, demonstrated by a mean pseudo-R^2 of 0.484 (0.225–0.716), and in terms of discriminant power, demonstrated by an AUC that ranges from 0.842 to 0.992, provided that most models use only one or two meteorological drought indices as predictor variables.

The ability to adjust accumulation periods to mimic different types of drought impacts has been cited as support for the SPI and the SPEI since their introduction as meteorological drought indices. This study rigorously tested this hypothesis and identified several consistent patterns among the relevant drought predictors. For all countries and impact categories except for Norwegian water supply, the SPEI was a better impact predictor than SPI because it includes potential evapotranspiration, and therefore temperature. The difference in model fit, measured by pseudo-R^2, between SPEI and SPI is often small (<10%), but the pattern is consistent across nearly all countries and impact types. This suggests that precipitation deficit is most important for predicting drought impacts, but inclusion of PET provides additional information that improves predictions. Several other studies have found that the SPEI is a better predictor of impacts, including Vicente-Serrano et al. (2012) which tested several variables (soil moisture, streamflow, tree ring width, and wheat yield) globally and Haslinger et al. (2014) which examined streamflow in Austria. Based on a correlation analysis study using corn yield, Potop (2011) concluded that the SPEI better detects agricultural droughts in Moldova than does the SPI, and stressed the importance of evapotranspiration for agriculture, as do Semenov and Shewry (2011) and Sušnik et al. (2010). The interaction term between SPI and SPEI was also a significant predictor for several drought impacts modeled in this study. This demonstrates the importance of potential evapotranspiration and confirms that impact likelihood does not react linearly with drought indices, but often has a more complex, non-linear response.

Agricultural impacts have the widest range of predictors within this subset of European countries, with drought anomalies ranging from short periods (2–3 months) to much longer (9–12 months) droughts. This range is explained primarily by agricultural management practices and soil water retention capacity, attesting to the difficulty of considering droughts in isolation from management practices that can decrease impact risk (Lloyd-Hughes, 2013). It is assumed, however, that relevant drought anomalies would be in a shorter range (of 2–3 months) without these management practices, more closely following the growing season. This broadly corresponds to correlation analysis for rain-fed farming across European countries (e.g. Hlavinka et al., 2009), for remotely sensed vegetation measures (Ji and Peters, 2003; Jain et al., 2010), and for ground-based measures of agricultural soil moisture (Szalai et al., 2000; Sims et al., 2002). The large-scale drought monitoring system for Europe, the European Drought Observer (EDO), uses this natural impact period in its composite drought indicator, which incorporates SPI at time scales of 1 and 3 months. However, as seen in this study and in correlation studies (Jain et al., 2010), external water sources, such as irrigation, aquifers, or reservoirs, can significantly buffer this relationship, extending the relevant drought period up to 12 months.

Energy and industry drought impacts tend to be triggered by medium to long (6–12 months) drought anomalies, which cause long-term hydrological deficits. This is because energy and industrial impacts in this study are primarily related to the depletion of hydropower reservoir storage or cooling water limitations due to critical stream water temperatures reached during low flow periods. Within this study, hydropower impacts (represented by Norway) tend to have a medium anomaly (6 months), while cooling water impacts (represented by the UK) tend to have longer periods (12 months). Germany, which has a mix of hydropower and cooling water impacts, is modeled best by a 9 month anomaly. Results for hydropower impacts are similar to Vicente-Serrano and López-Moreno (2005), which found the 7–10 month SPI period as the most important for a single reservoir in northeast Spain. Spanish reservoirs tend to be designed for interannual storage, while Norwegian reservoirs tend to be designed for seasonal, intra-annual storage, which may explain the slower response in Spain. Results for cooling water impacts (9–12 months) are much more similar to recommendations of long periods for simulating hydrologic drought in McKee et al. (1993), than findings in Szalai et al. (2000) and Vicente-Serrano and López-Moreno (2005), which recommend 1–6 month periods. These studies use mostly natural, headwater streams, which likely explains the rapid response, compared to this analysis which includes any river within entire countries. Public water supply and freshwater ecosystem impacts have more complex processes, depending on both a short (1–3 month) component and a longer (6–24 month) component. Differences likely reflect public water management efforts and the characteristic responses of underlying hydrological storage components.

These results inform the ongoing debate regarding the operational needs for drought monitoring by directly linking meteorological drought indices to observed drought impacts. This provides a baseline for drought monitoring, showing the best meteorological drought index for a given impact that can be combined with other available environmental data to provide drought risk forecasts for stakeholders and decision makers (Hayes et al., 2005; Botterill and Hayes, 2012; Lackstrom et al., 2013). In addition, this research supports ongoing initiatives to bring together relevant meteorological, hydrological, agricultural and socio-economic information for drought observation at the pan-European scale (Kossida et al., 2009; Horion et al., 2012). Finally, it confirms that a single accumulation period cannot explain drought impacts across regions with different climatology, geography, and management practices, reaffirming the fundamental questioning of a universal drought definition (Hayes et al., 2005; Lloyd-Hughes, 2013).

4. Conclusions

There is a vital need for research that links meteorological drought with drought impacts experienced by different sectors of society. This study addresses that need, calculating how drought impact occurrence can be explained by meteorological drought indices and testing which of these indices are relevant across different impact types and regions. This study is one of the first to test the explanatory power of meteorological drought indices on a large scale using broad, qualitative measures of drought impacts. The decision to base this study on qualitative impact reports expands the scope of impacts that can be modeled, avoiding more prescriptive quantitative measures. It fits within the "ground-up" approach of risk modeling, wherein impacts are classified based on user-reported failures rather than using summary statistics that attempt to quantify failure. Using this approach also benefits from allowing direct comparisons of very different impact types, which are otherwise difficult to compare because of differing measures and metrics.

Direct extrapolation of the results to other European countries is not possible with only five countries modeled; however, the results are sufficient to make strong hypotheses supported by the modeled data. The intensity of irrigation and the amount of groundwater relative to surface water storage appear to increase the meteorological drought duration necessary to produce agricultural impacts. Difference between groundwater-dominated and surfacewater-dominated systems affects the predictors for public water supply. Energy and industrial drought impacts is a broad category and therefore predictors of impacts are most related to the specific impacts, whether they are dominated by hydropower losses, limitations in cooling water use, or interruption of industrial operation due to water restrictions. Among the five European countries analyzed, the United Kingdom consistently had the slowest drought response, likely due to its slow responding groundwater storage, along with Germany. Norway, Bulgaria, and Slovenia tend to respond more rapidly to meteorological drought, due to differences in topography and a stronger dependence on surface water. More comprehensive conclusions can be drawn if this methodology is applied to arid or semi-arid countries.

The proposed methodology shows great promise as a predictive and analytical tool and is only limited by the availability of impact report data used as a training set. To date, there has been a huge effort to compile the 2500 unique impact reports housed within the EDII. Given the demonstrated utility of this data, it is assumed that the EDII will continue to grow in both scale and detail, increasing the potential for larger and better drought impact models. More impact reports are necessary to expand this methodology across Europe and to potentially link model differences to differences in regional characteristics. In addition, more detailed impact report data will be necessary to increase the spatial resolution of models and improve the temporal resolution.

In addition to its use as an analytical tool, identifying the most relevant impact predictors, the resulting models may also be used as a predictive tool, both for near-real time risk monitoring and long-term projections, given climate scenarios. As a real-time monitoring tool, the likelihood of various drought impacts can be estimated, given observations and predictions of climate variables such as precipitation, temperature, and wind speed. In a similar way, climate scenarios may be used as input to predict future changes in impact risk. Coordination between government, water companies, abstractors, and customers is often cited as an aspect that could be improved with better monitoring capabilities. Presenting the likelihood of specific impacts due to drought conditions, rather than presenting raw meteorological drought indices, is of great use to resource managers and policy makers and could potentially be used to control and address losses due to major drought events.

Acknowledgements

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