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Estimating drought risk across Europe from reported drought impacts, drought indices, and vulnerability factors

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Abstract. Drought is one of the most costly natural hazards in Europe. Due to its complexity, drought risk, meant as the combination of the natural hazard and societal vulnerability, is difficult to define and challenging to detect and predict, as the impacts of drought are very diverse, covering the breadth of socioeconomic and environmental systems. Pan-European maps of drought risk could inform the elaboration of guidelines and policies to address its documented severity and impact across borders. This work tests the capability of commonly applied drought indices and vulnerability factors to predict annual drought impact occurrence for different sectors and macro regions in Europe and combines information on past drought impacts, drought indices, and vulnerability factors into estimates of drought risk at the pan-European scale. This hybrid approach bridges the gap between traditional vulnerability assessment and probabilistic impact prediction in a statistical modelling framework. Multivariable logistic regression was applied to predict the likelihood of impact occurrence on an annual basis for particular impact categories and European macro regions. The results indicate sector- and macro-region-specific sensitivities of drought indices, with the Standardized Precipitation Evapotranspiration Index (SPEI) for a 12-month accumulation period as the overall best hazard predictor. Vulnerability factors have only limited ability to predict drought impacts as single predictors, with information about land use and water resources being the best vulnerability-based predictors. The application of the hybrid approach revealed strong regional and sector-specific differences in drought risk across Europe. The majority of the best predictor combinations rely on a combination of SPEI for shorter and longer accumulation periods, and a combination of information on land use and water resources. The added value of integrating regional vulnerability information with drought risk prediction could be proven. Thus, the study contributes to the overall understanding of drivers of drought impacts, appropriateness of drought indices selection for specific applications, and drought risk assessment.

1 Introduction

Drought is a natural phenomenon that can become a natural disaster if not adequately managed (Wilhite, 2000). Unlike other natural hazards, it has a creeping onset and does not have a unique definition (Lloyd-Hughes, 2014), which makes defining the beginning or end of a drought event difficult (Hayes et al., 2004; Wilhite et al., 2007). Drought is either defined by its physical characteristics, e.g. meteorological drought, soil moisture drought or hydrological drought (e.g. Wilhite and Glantz, 1985), or by its consequences on socioeconomic and environmental systems, i.e. its negative impacts (Blauhut et al., 2015a). These impacts can either be direct (e.g. reduced crop yields) or indirect (e.g. increased costs for food due to reduced crop yields) and can occur across a wide range of temporal and spatial scales. In the European Union (EU), more than 4800 unique drought impact entries have been identified in the European Drought Impact Re-

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port Inventory (EDII) across 15 different impact categories from agriculture to water quality (Stahl et al., 2016) and financial losses over the last 3 decades were estimated to over EUR 100 billion (EC, 2007).

To mitigate these impacts, until recently drought risk management at the pan-European scale has predominantly focused on coping with financial losses, mainly through calamity funds, mutual funds, and insurances (Diaz-Caneja et al., 2009). Nevertheless, today's scientific consensus points to the need to move from a reactive to a proactive risk management strategy (Wilhite et al., 2007). Rossi and Cancelliere (2012) stated that an advanced assessment of drought must include firstly, an investigation of socioeconomic and environmental impacts, secondly, multicriteria tools to mitigate these, and thirdly, a set of easily understood models and techniques for application by stakeholders and decision makers responsible for drought preparedness planning.

The risk of natural disasters in a very general sense is a combined function of hazard and vulnerability (Birkmann et al., 2013). For drought risk analysis, risk may be estimated through a combination of hazard measures and estimates of vulnerability or proxies of it. Cardona et al. (2012) observed that "vulnerability and risk assessment deal with the identification of different facets and factors of vulnerability and risk, by means of gathering and systematising data and information, in order to be able to identify and evaluate different levels of vulnerability and risk of societies – social groups and infrastructures – or coupled socioecological systems". Hence, the assessment of the vulnerability component of drought risk is based either on vulnerability factors or on past drought impacts, as these are considered to be symptoms of vulnerability (Knutson et al., 1998).

According to Knutson et al. (1998), vulnerability assessments provide a framework for identifying the root causes of drought impacts at social, economic, and environmental levels and measure a potential state, which will generate impacts if a given level of hazard occurs. Vulnerability to drought, as the predisposition to be adversely affected by a given hazard (IPCC, 2012), therefore is often assessed by the factor approach, in which a set of vulnerability factors (e.g. Swain and Swain, 2011; Jordaan, 2012; Naumann et al., 2014; Karavitis et al., 2014) contribute to an overall classification of vulnerability (e.g. information on water resources, society or technical infrastructure; González-Tánago et al., 2015). Based on their review of 46 drought-factor-based vulnerability assessments, González-Tánago et al. (2015) observed that only 57 % of the studies actually describe the process followed to select vulnerability factors. Among those, the criteria used include the consultation of previous studies and specialised literature, data availability, and expert knowledge (González-Tánago et al., 2015). The selection of vulnerability factors is guided by the focus of the study, the definition of drought applied, the study location, and data availability. Vulnerability factors are often combined and weighted by expert knowledge and stakeholder interaction to a single, overall vulnerability index (Wilhelmi and Wilhite, 1997; Adepetu and Berthe, 2007; Deems and Bruggeman, 2010). The majority of studies provide limited or no information on procedures applied to verify the derived index (González-Tánago et al., 2015). Only few studies validate their results, among them Aggett (2013), Naumann et al. (2014), and Karavitis et al. (2014).

Impact approaches to vulnerability and risk assessment, on the other hand, use information on past drought impacts as a proxy for vulnerability, assuming that a system has been vulnerable if it has been impacted. Drought risk is then considered the risk for a particular type of impact. Typically, the impact of drought is then characterised based on data of either financial or quantitative losses of agricultural production (Hlavinka et al., 2009; Rossi and Niemeyer, 2010; Tsakiris et al., 2010; Gil et al., 2011; Jayanthi et al., 2014; Quijano et al., 2014), human mortality (Dilley et al., 2005), or impacts on forestry (Vicente-Serrano et al., 2012; Muukkonen et al., 2015). Blauhut et al. (2015a) applied annual impact occurrence based on reported information in the EDII to characterise sector-specific vulnerability. Drought risk was then estimated as the probability of impact occurrence as a function of the Standardized Precipitation Evapotranspiration Index (SPEI). The function used was a fitted logistic regression model. The estimated parameters could subsequently be used to generate a first set of pan-European drought risk maps. The displayed likelihood of impact occurrence on the maps can be considered impact-category-specific drought risk for selected hazard intensities. Stagge et al. (2015b) considered variations of the logistic regression and expanded the approach to include multiple hazard predictors. Bachmair et al. (2015) applied regression tree and correlation approaches to link impact number and occurrence with a range of indices. Both studies relied on a rather high temporal resolution of reported impact occurrence, and hence considered only a few regions with particularly good data coverage.

The hazard component of drought risk is commonly derived from a statistical analysis of a single drought indicator, a single or set of drought indices, or a combined drought index (Hayes, 1998; Zargar et al., 2011). Drought indices are well researched and have been applied to characterise drought patterns across Europe in several studies (Lloyd-Hughes and Saunders, 2002; Parry et al., 2012; Stagge et al., 2013; Tallaksen and Stahl, 2014; Spinoni et al., 2015). The actual monitoring of drought in Europe is conducted at different scales: national (e.g. German Drought Monitor), transnational (e.g. Drought Management Centre for Southeastern Europe (DMCSEE), continental (e.g. European Drought Observatory, EDO), and global (e.g. SPEI Global Drought Monitor). But what is the basis for their selection as drought predictors? Bachmair et al. (2016) reviewed pertinent literature and surveyed existing monitoring systems and found that tradition as well as data availability are commonly the criteria to select the most appropriate drought index. Drought severity or warning levels are commonly categorised into arbitrarily chosen hazard index thresholds, such as those selected for the Standardized Precipitation Index (SPI) ($-1.5 < \text{SPI} < -1$: moderate drought, $-2 < \text{SPI} < -1.5$: severe drought, $\text{SPI} < -2$: extreme drought, where negative values represents less than median precipitation) (McKee et al., 1993). Defining hazard severity thresholds that relate to potential impacts on socioeconomic and natural systems, and thus the drought risk, is often left to expert judgement. However, an independent validation of the relevance of the various drought indicators for management purposes is of crucial importance (Pedro-Monzonís et al., 2015). Bachmair et al. (2016) found that although drought monitoring and early warning system providers often collect impact information, these are rarely used systematically to validate the usefulness of particular hazard indices. Such usefulness has been tested mostly in local or regional case studies based on empirical links between quantified losses such as financial or yield losses and climatic or resource (water availability) conditions (Jayanthi et al., 2014; Stone and Potgieter, 2008; Schindler et al., 2007). Stagge et al. (2015b). Bachmair et al. (2015) have assessed the link between impacts and different drought indices in selected European countries and found that the best indices vary with location and sector.

In this study, we expand the method of Blauhut et al. (2015a) into a hybrid approach, which implies the consideration of vulnerability factors into the probabilistic impact prediction. The approach builds on earlier work developed for the agricultural sector (Zhang et al., 2011; Ahmed and Elagib, 2014; Han et al., 2015; Yin et al., 2014) and a European assessment by De Stefano et al. (2015), who considered several physical and socioeconomic factors to calculate sensitivity and adaptive capacity, and used impact information collected in the EDII to estimate exposure. More specifically, the hybrid approach aims to

1. investigate the ability of commonly used drought indices and vulnerability factors to predict annual drought impact occurrence for various sectors;

2. identify the best-performing combinations of predictors to model drought risk for different sectors; and

3. map sector-specific drought risk for selected hazard severity levels across Europe.

This study addresses these aims through statistical modelling (logistic regression) of the combined effect of drought hazard, defined by drought indices, and drought vulnerability, defined by vulnerability factors, on the occurrence of historical drought impacts as extracted from the EDII. In a first step, potentially relevant drought indices and vulnerability factors were tested for their suitability as impact predictors in binary logistic models. Then, impact category and region-specific multivariable logistic models were built in a hybrid approach, combining the most relevant drought indices and

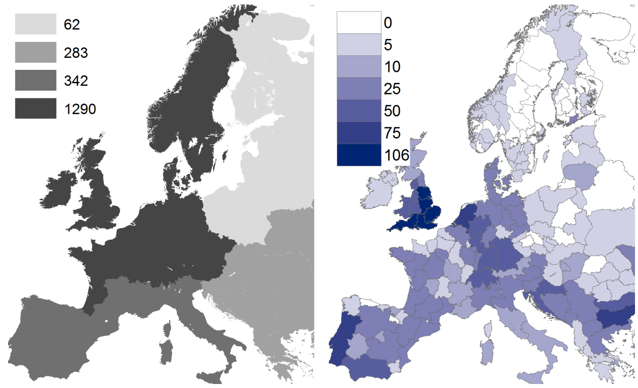

Figure 1. Number of annual aggregated NUTS-combo-scale impacts reported and archived in the European Drought Impact Report Inventory (EDII) by European macro region (left panel) and by NUTS-combo region (right panel).

vulnerability factors as predictors of drought impact likelihood using stepwise selection. The final models were then used to construct pan-European drought risk maps for specific hazard severity levels.

2 Data

2.1 Impact information

Information on drought impacts are derived from the EDII (Stahl et al., 2016; http://www.geo.uio.no/edc/droughtdb/). Since its creation in 2012, this archive has grown significantly due to extensive data collection. Documentation on the database's structure and categorisation scheme can be found on the website and in a pan-European summary assessment by Stahl et al. (2016). All reports archived in the EDII database (a) describe negative impacts of drought on society, the economy, or the environment as reported by a given information source, e.g. government report, any type of public media; (b) are spatially referenced, either to their respective NUTS (Nomenclature of Territorial Units for Statistics) region or to locations such as rivers, lakes, or coordinates; (c) are time referenced to at least the year of occurrence, preferably the season or month if given, and, when possible, assigned to a major regional drought event; and (d) are assigned to one of 15 impact categories and an associated number of subordinate impact types (105 in total). To guarantee a standard quality of entries, each entry has been reviewed by an expert (Stahl et al., 2016).

In May 2015, the EDII database contained over 4800 drought impact reports. After the transformation to NUTS-combo scale (Fig. 1, right panel), a custom combination of NUTS-level regions of similar sizes (Blauhut et al., 2015a), 2745 entries for all impact categories were retained for analysis. Figure 2 provides an overview of the distribution of these reported impacts aggregated by year

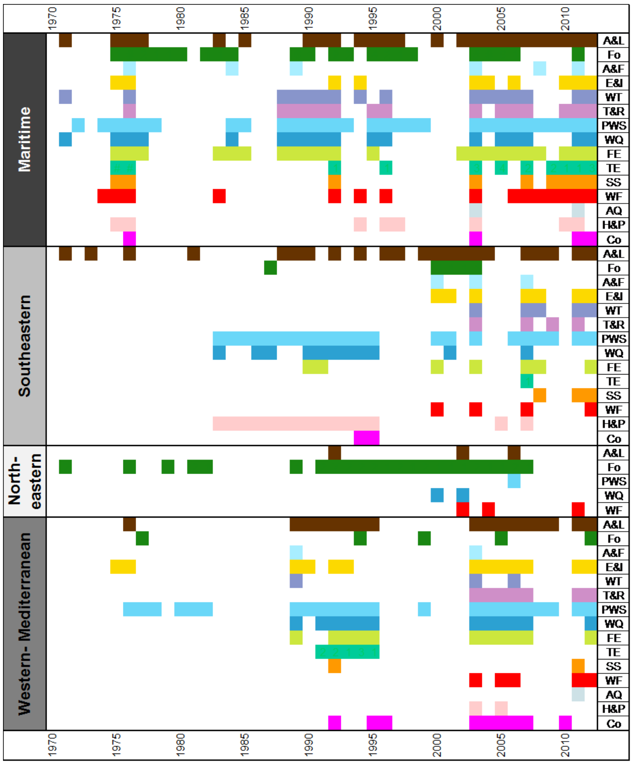

Figure 2. Annual drought impact occurrence by European macro region and impact categories. A & L: Agriculture and Livestock Farming, Fo: Forestry, A & F: Aquaculture and Fisheries, E & I: Energy and Industry, WT: Waterborne Transportation, T & R: Tourism and Recreation, PWS: Public Water Supply, WQ: Water Quality, FE: Freshwater Ecosystems, TE: Terrestrial Ecosystems, SS: Soil Systems, WF: Wildfires, H & P: Human Health and Public Safety, Co: Conflicts.

of impact occurrence and shows significant differences between European macro regions (Fig. 1, left panel). These macro regions are climatologically comparable regions defined in order to cope with larger climatic differences and data shortfalls (Blauhut et al., 2015a). The majority of impact reports are located in maritime Europe (1290) with fewer entries in the western Mediterranean (342), southeastern Europe (283), and northeastern Europe (62). The highest numbers for drought impact entries by NUTS-combo level (Fig. 1, right panel) are available for southern UK, central Europe, and the southwestern Iberian Peninsula. Northeastern Europe has the lowest number of EDII entries.

To overcome reporting biases, including regionally lacking data for a pan-European application of the EDII data set (Stahl et al., 2016), we followed Blauhut et al. (2015a) and: (a) created binary data sets (occurrence/absence of impact reports) from 1970 to 2012 for each impact category and macro region, (b) assigned multiyear drought impacts to each affected year (e.g. 1975–1976: impact occurrence in 1975 and 1976), and (c) generalised seasonal and short-term information to the year of occurrence. Figure 2 shows the timeline of annual drought impact occurrence for all reported impact categories pooled for European macro regions.

Drought impact reports stem from various sources and are assigned with a certain level of reliability, decreasing by its enumeration rank: academic work, governmental reports and documents, reports, media and webpages, and other sources (Stahl et al., 2016). The proportions of impact sources by macro regions differ significantly. In both the western Mediterranean and maritime Europe regions, academic work and governmental documents are the dominant sources of information (about two-thirds). By contrast, EDII entries for northeastern Europe are strongly dominated by academic work and the media ($\sim 90\,\%$). The majority of information sources for southeastern Europe are non-governmental reports and the media, which suggest that southeastern Europe may have the least reliable data. Explicit information is lacking that would allow assigning an uncertainty flag depending on the source. Thus, in this study all information sources were treated equally. Nevertheless, uncertainties due to the nature of the impact data need to be discussed and considered in the interpretation of any studies that are based on this or similar sources of data.

2.2 Hazard indices

Variables which describe drought hazard are numerous, and can be categorised into two main groups: indicators and indices (Heim, 2002; Zargar et al., 2011). Drought indicators directly measure a certain facet of the drought hazard, e.g. climatological conditions, vegetation health, or soil moisture by a quantitative measure. Drought indices, such as the Standardised Precipitation Index (SPI) or Soil Moisture Anomaly (ΔpF), are quantitative measures characterising drought levels by assimilating data from one or multiple drought indicators to a single numerical value (Zargar et al., 2011). Unlike these, combined drought indices, e.g. drought intensity of the US Drought Monitor (Svoboda et al., 2002) or the Combined Drought Indicator of the EDO (Sepulcre Canto et al., 2012) blend drought indicators and indices to a categorical hazard severity index. For the purpose of this study, focus is on drought indices that are commonly recommended (Stahl et al., 2015), readily available, monitored, and used operationally in Europe for drought monitoring (Table 1). For the purpose of this work, all drought indices (presented below) were first derived at the original grid scale on a monthly basis for periods with the necessary data availability. To match the spatial resolution of recorded impacts, these drought indices were aggregated to the NUTS-combo scale (Fig. 1, right panel) by taking the mean of gridded values.

Among the single indices, the most widely accepted meteorological drought index is the SPI (McKee et al., 1993). It is recommended by the WMO and is therefore applied widely in Europe for drought identification (e.g. Gregorič and Sušnik, 2010; Vogt et al., 2011; Stagge et al., 2015a). As introduced by McKee et al. (1993) "the SPI is the transforma-

Table 1. Overview of selected drought indices.

Indices	Application for drought monitoring in Europe (examples)	Data requirements	Data source used in this study	Temporal aggregation and resolution used
SPI	Drought Management Centre Southeastern Europe European Drought Reference Database Global Drought Information System JRC	Precipitation	E-OBS 9.0	Timescales of 1–6, 9, 12, 24 months; monthly; 1950–2012
SPEI	SPEI Global Drought Monitor	Precipitation evapotranspiration	E-OBS 9.0	Timescales of 1–6, 9, 12, 24 months; monthly; 1950–2012
ΔpF	German Drought Monitor (soil moisture index) European Drought Observatory	Precipitation, evapotranspiration, soil water potential, soil parameters, NDVI	National Meteo Office, Joint Research Centre	Monthly; annual average; 2001–2014
ΔfAPAR	European Drought Observatory	Fraction of the incoming solar radiation in the photosynthetically active radiation spectral region	Medium Resolution Imaging Spectrometer (MERIS), VEGETATION sensor onboard SPOT	Monthly; annual average; 2001–2014
CDI	European Drought Observatory	SPI, ΔpF, ΔfAPAR	Joint Research Centre	Monthly; annual maximum; 2001–2014

tion of the precipitation time series into a standardised normal distribution" (Lloyd-Hughes and Saunders, 2002), and is commonly used to estimate wet or dry conditions based on long-term records of monthly precipitation. SPI is computed by summing precipitation over n months, termed accumulation periods, and is typically calculated at a monthly resolution. For instance, SPI-3 for December represents the number of standard deviations from the standard normal distribution of accumulated precipitation for Oct–Dec relative to a given reference period. The SPI's strength is its low data needs and its multiscalar nature. It can be calculated for various accumulation periods and therefore can be related to different types of drought (e.g. soil moisture drought or hydrological drought) and temporal duration (e.g. summer drought to multiyear drought). Nevertheless, the SPI has limited interpretability for short accumulation periods (< 2 months) in dry regions where monthly precipitation is often near 0 (Stagge et al., 2015a). For this study we used gridded monthly aggregated precipitation from the E-OBS-9 data set and derived the SPI for accumulation periods of 1–24 months (SPI-1, SPI-2, etc.) based on the gamma distribution with a baseline for standardisation from 1970 to 2010. Subsequently, the gridded monthly SPI values were spatially aggregated by averaging all grid cells within each NUTS-combo level.

The SPEI (Vicente-Serrano et al., 2010; Stagge et al., 2015b) is an alternative drought index, which is defined as precipitation minus potential evapotranspiration. The index thus provides a more comprehensive measure of the climatic water balance while avoiding problems with zero precipitation as for the SPI. Consequently, it has been growing in popularity (Beguería et al., 2010; Lorenzo-Lacruz et al., 2010; Blauhut et al., 2015a). Here, the SPEI was calculated based on monthly aggregated E-OBS-9 data following the recommendations of Stagge et al. (2015a), which uses the Hargreaves equation (Hargreaves, 1994) to estimate potential evapotranspiration and the generalised extreme value distribution for normalisation based on data from 1970 to 2010. Finally, all gridded SPEI indices were spatially averaged to NUTS-combo level.

Besides the standardised meteorological indices, we applied the following drought indices, as used by the Joint Research Centre of the European Commission (JRC) in their EDO, a website that shows the recent and current drought situation in Europe from 2001 on. Soil moisture is known as a major driver for a variety of climate and hydrological processes and is the key indicator of agricultural drought (Kulaglic et al., 2013; Hlavinka et al., 2009; Potop, 2011). The JRC's EDO provides daily and 10-day assessments of the moisture content of the top soil layer (upper 30 cm). Soil moisture is obtained from the LISFLOOD distributed rainfall–runoff model with a grid-cell resolution of 5 km across Europe, using daily meteorological input from the JRC MARS meteorological database. Soil moisture is expressed as soil suction (pF), providing a quantitative measure of the force needed to extract water from the soil matrix. Soil moisture anomalies (ΔpF) are then calculated as the standardised deviation from the long-term average for the period 1996–2014, and are used as input for the CDI. This standardisation results in a quantification of the soil moisture deficit which is normally distributed and thus comparable to the SPI and other similar indices. For this study, the index was aggregated temporally to monthly values, and spatially to NUTS-combo level by averaging.

Direct measurement of stomatal activity (or photosynthetic activity, e.g. NDVI, VCI) (Chopra, 2006; Amoako et al., 2012) has been applied in many drought hazard analyses and has directly been used as a proxy for drought impacts (Skakun et al., 2014). The JRC derives the fraction of absorbed photosynthetically active radiation (fAPAR) from satellite measurements at approximately 1 km spatial resolution and for 10-day periods. The fAPAR is a quantitative measure of the fraction of solar energy that is absorbed by vegetation and a proxy for the status of the vegetation cover. Analogous to the SPI and soil moisture, fAPAR anomalies (ΔfAPAR) are calculated as the standardised deviation from the long-term mean (1975–2010). For this study, the index was averaged to monthly values and the NUTS-combo level. The fAPAR anomaly can be associated with plant productivity and has therefore been recommended as an agricultural drought index by the UN Global Climate Observing System (GCOS) and the FAO Global Terrestrial Observing System (GTOS). However, fAPAR measures the photosynthetic activity of the vegetation cover only, which can be due to drought but also related to factors such as pests and diseases. It is therefore important to analyse the index in conjunction with other indices in order to ensure the link to a drought situation.

The Combined Drought Indicator (CDI) (Sepulcre-Canto et al., 2012) generated by the JRC represents a logical combination of several drought indices to detect the severity of agricultural/ecosystem drought with a time step of 10 days. The method is a classification scheme that corresponds to different stages of drought propagation from the initial precipitation deficit, over a soil moisture deficit, to a water stress for the vegetation canopy. It is a logical combination of the SPI for 1- and 3-month accumulation periods, ΔpF, and ΔfAPAR with adjusted time lags. It results in four increasingly severe drought states: Watch, Warning, Alert, and Alert2, as well as two recovery states: Partial recovery and Full recovery. For the purpose of our analysis the levels of recovery were neglected. For this study, monthly and annual maxima within each NUTS-combo region were selected as further hazard indices available for the modelling.

2.3 Vulnerability factors

The most commonly used method to assess vulnerability to drought or other natural hazards is to employ a set of proxy factors or composites of them. These factors aim at capturing different issues that influence the level of vulnerability of a system to a given hazard, herein referred to as vulnerability factors. Vulnerability is often assessed through the combination of factors in the following components of vulnerability:

- Exposure is the extent to which a unit of assessment falls within the geographical range of a hazard event (Birkmann et al., 2013).
- Sensitivity is the occupance and livelihood characteristics of the system (Smit and Wandel, 2006).
- Adaptive capacity is the particular asset bundles for risk reduction (Pelling and Uitto, 2001; Gosling et al., 2009).

In Europe, the assessment of vulnerability to drought has been undertaken mostly at national or local scales. With the exception of comprehensive efforts to characterise causes, components, and factors of drought vulnerability (Flörke et al., 2011; Lung et al., 2011), De Stefano et al. (2015) was the first to map a vulnerability index at a pan-European scale. This study builds on the experience gained in that effort, which was complemented by some additional data, as explained below.

De Stefano et al. (2015) defined 16 vulnerability factors grouped into three thematic components: exposure (1), sensitivity (5), and adaptive capacity (10). The latter further subdivided into four classes. The factors were assessed through a large set of parameters produced at the NUTS-2 resolution for the 28 member states of the European Union plus Norway and Switzerland. To build the data set, De Stefano et al. (2015) extracted data from international databases, including Aquastat, the Eurobarometer, European Commission, the European Environment Agency, Eurostat, the World Bank, FAO, as well as from the literature. In order to be able to compare and combine data describing different factors, De Stefano et al. (2015) normalised the data from 0 to 1. Combined vulnerability factors and the vulnerability index itself were generated on the basis of equal weights (more details on the processes can be found in their report). For this analysis, we obtained the raw data as initially collected, their normalised values, as well as combined versions of vulnerability factors (Table 2).

For some vulnerability factors, this study completed the original data set with data available for multiple time steps. Thus, the CORINE landcover data sets for 1990, 2000, and 2006 were added to the data set. These data stem

Table 2. Factors used to assess vulnerability.

Vulnerability factor	Scale	Multiple time steps	Composed	Applied for MLRM	Data source or source combined
		Adaptive capacity			
Corruption	Country		√	√	De Stefano et al. (2015)
Drought awareness	Country		√	√	De Stefano et al. (2015)
Drought management tools	RDB		√	√	De Stefano et al. (2015)
Drought recovery capacity	Country		√	√	De Stefano et al. (2015)
Education expenditure and skilled people	NUTS-2		√	√	De Stefano et al. (2015)
Inability to finance losses	Country	√			Eurostat
Innovation capacity	NUTS-2		√	√	De Stefano et al. (2015)
Law enforcement	Country		√	√	De Stefano et al. (2015)
Law enforcement and corruption	Country		√	√	Corruption + law enforcement
Public participation	Country		√	√	De Stefano et al. (2015)
River basin management plans	Country		√	√	De Stefano et al. (2015)
Water related participation factor-EC	Country		√	√	De Stefano et al. (2015)
		Sensitivity			
A. agriculture	NC	√		√	Corine Land Cover, EEA
A. agriculture, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. artificial surfaces	NC	√		√	Corine Land Cover, EEA
A. artificial surfaces, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. forest	NC	√		√	Corine Land Cover, EEA
A. forest, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. inland water bodies	NC	√		√	Corine Land Cover, EEA
A. inland water bodies, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. lakes within region	NC	√		√	WISE large rivers and large lakes, EEA
A. non irrigated agri	NC	√		√	Corine Land Cover, EEA
A. non irrigated agri, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. NUTS-combo region	NC	√		√	Corine Land Cover, EEA
A. permanent irrigated agri	NC	√		√	Corine Land Cover, EEA
A. permanent irrigated, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. semi natural A.s	NC	√		√	Corine Land Cover, EEA
A. semi natural A.s, ratio of NC	NC	√		√	Corine Land Cover, EEA
A. wetlands	NC	√		√	Corine Land Cover, EEA
A. wetlands, ratio of NC	NC	√		√	Corine Land Cover, EEA
Agriculture under glass	Country	√			Eurostat
Aquatic ecosystem status	RBD			√	European Environment Agency (EEA). WISE WFD Database: ecological and chemical status of surface water bodies chemical and quantitative status of groundwater bodies
Arable land	Country	√			Eurostat
Biodiversity, A. protected	Country	√			Corine Land Cover, EEA
Dams + groundwater (GW) resources	Country		√	√	De Stefano et al. (2015)
Dams capacity	Country			√	FAO, AQUASTAT: geo-referenced dams database Europe (data for DK, EE, and MT was gathered in different sources)
Economic resources and equity	NUTS-2		√	√	De Stefano et al. (2015)
Economic wealth	NUTS-2			√	Eurostat
Education	Country			√	UNDP
Environmental taxes	Country	√			Eurostat

Table 2. Continued.

Vulnerability factor	Scale	Multiple time steps	Composed	Applied for MLRM	Data source or source combined
		Sensitivity			
GDP per capita by country	Country	√			Eurostat
Groundwater resources (GW)	Country			√	FAO, AQUASTAT: total Renewable water resources – Groundwater: total renewable
Human health and public safety	Country	√			Eurostat
Irrigation by country	Country	√			FAO, Aquastat
Low wage earn	Country	√			Eurostat
Major soil type	Raster: 100 m			√	European Soil Database
Population density N2	NUTS-2			√	Eurostat
Population density by country	Country	√		√	Eurostat
Population density and age	NUTS-2			√	Eurostat
Public water supply	NUTS-2	√			Eurostat
Public water supply connection	NUTS-2	√			Eurostat
Public water supply infrastructure	NUTS-2	√			Eurostat
SR agriculture	Country		√	√	De Stefano et al. (2015)
SR industry	Country		√	√	De Stefano et al. (2015)
SR services	Country		√	√	De Stefano et al. (2015)
Tourist beds by N2	NUTS-2	√			Eurostat
Tourist beds by country	Country	√			Eurostat
Water balance	Country		√	√	De Stefano et al. (2015)
Water body status	Country		√	√	De Stefano et al. (2015)
Water resources development	Country		√	√	De Stefano et al. (2015)
Water use	Country	√			Eurostat: annual freshwater abstraction
Water use	Country		√	√	Eurostat: annual freshwater abstraction
Water use agriculture	Country	√			Eurostat: annual freshwater abstraction, agriculture
Water use industry	Country	√			Eurostat: annual freshwater abstraction, industry
WR agri sector	Country		√	√	Eurostat: annual freshwater abstraction
WR industry sector	Country		√	√	Eurostat: annual freshwater abstraction, agriculture
WR services sector	Country		√	√	Eurostat: annual freshwater abstraction, industry
		Combined factors			
Sensitivity	NUTS-2		√	√	De Stefano et al. (2015)
Adaptive capacity	NUTS-2		√	√	De Stefano et al. (2015)
Vulnerability	NUTS-2		√	√	De Stefano et al. (2015)

Scale: indicates the spatial detail of information. Multiple time steps: vulnerability data have been available for different time steps or only the most recent state of the system. Composed: vulnerability factors are a composition of different data. Applied to MLRM: factor has been analysed in multivariable logistic regression models (step two) as a possible best-performing predictor for impact detection. A. = area of, SR = socioeconomic relevance, WR = water use relevance, NC = NUTS-combo region, N2 = NUTS-2 region, RBD = river basin district, MLRM = multivariable logistic regression model.

mainly from Eurostat (Eurostat, http://ec.europa.eu/eurostat/data/database) and the European Environment Agency (http://www.eea.europa.eu/data-and-maps). Data on land cover as derived from the CORINE Land Cover Datasets (http://www.eea.europa.eu/data-and-maps) were expressed as a percentage of the NUTS-combo region area. All selected vulnerability factors with their respective spatial and temporal resolution are shown in Table 2. In summary, 69 vulnerability factors were considered for analyses. Some data sets are listed multiple times, as they were created for different spatial aggregations (e.g. "Population density" for NUTS-2 or country level), for different time steps (e.g. "Water use" for single or multiple time steps), or related to different spatial scales (e.g. "Area of agriculture" to "Area of agriculture" by NUTS-combo level). Furthermore, individual components of combined vulnerability factors are analysed (e.g. "Dams capacity" and "Groundwater resources" for "Dams + groundwater resources").

For vulnerability data which did not have multiple time steps available, the most recent information for the entire period of investigation was applied. Vulnerability data with multiple time steps were assigned to the corresponding year, and preceding years up to the next time step available (e.g. available time steps were 1976, 1990 and 2003; data for 1970–1976, 1977–1990, and 1991–2012 were applied).

3 Methods

The overall approach followed a series of steps to find the best logistic regression models. Hereby one model is determined for each European macro region and impact category, using annual impact occurrence as a target variable and corresponding hazard and vulnerability observations as predictors. This is achieved by employing a regionally pooled set of target and predictor variables that includes all NUTS-combo regions that lie within the macro region. NUTS regions that did not have any reported impact or information on a given vulnerability factor were disregarded. Step 1 tested the predictors SPEI and SPI for the temporal aggregations of 1, 2, 3, 4, 5, 6, 9, 12, and 24 months and 69 vulnerability factors as individual predictors in a univariate binary logistic regression. Step 2 employed a stepwise selection process to evaluate the best-performing combination of five possible predictors in a multivariable logistic regression model. Finally, Step 3 applied the best multivariate models for selected hazard-level scenarios to create pan-European drought risk maps.

In Step 1, the ability of each single predictor (drought indices and vulnerability factors) to predict the occurrence of drought impacts on an annual basis was tested separately. Following Blauhut et al. (2015a), the likelihood of drought impact occurrence LIO is assessed using binary logistic regression models (BLMs) (Eq. 1).

$$\log\left(\frac{\mathrm{LIO_{NUTS}}}{1-\mathrm{LIO_{NUTS}}}\right) = \alpha_{\mathrm{Macro}} + \beta_{\mathrm{Macro}} \cdot P_{\mathrm{NUTS}} \tag{1}$$

The logit transformation of LIO equals the sum of the model parameter α and the product of the model parameter β_{Macro} with the selected predictor P_{NUTS} of the NUTS-combo region. All model parameters were estimated using standard regression techniques within the framework of generalised linear models (GLMs) (Harrel Jr., 2001; Venables and Ripley, 2002; Zuur et al., 2009). Hence, the LIO is a measure of the probability of drought impact occurrence from 0 to 1, depending on the selected predictor. The predictive power of each selected predictor was quantified by predictor-significance (p value for the parameter β) to estimate LIO and by the overall model performance. The latter is measured using the area under the ROC (receiver operating characteristics) curve, A_{ROC}, which quantifies the skill of probabilistic models (Mason and Graham, 2002; Wilks, 2011) in a range from 0 to 1. Significant predictors (p values < 0.05) with $A_{\mathrm{ROC}} > 0.5$ indicate that the resulting model will be superior to random guessing, but are still considered poor model performance (marked by a single star *). Significant predictors with $A_{\mathrm{ROC}} > 0.7$ are considered good model performance (**), while significant predictors with $A_{\mathrm{ROC}} > 0.9$ are considered excellent model performance (***).

In Step 2, the approach was expanded by stepwise model building to include multiple hazard indices and vulnerability predictors (hybrid approach) into one statistical model. This analysis follows Stagge et al. (2015b) and Blauhut and Stahl et al. (2015) and applies multivariable logistic regression to assess the LIO (Eq. 2).

$$\log\left(\frac{\mathrm{LIO_{NUTS}}}{1-\mathrm{LIO_{NUTS}}}\right) = \alpha_{\mathrm{Macro}} + \sum_i \left(\beta_{i,\mathrm{Macro}} \cdot H_{\mathrm{NUTS}}\right) + \sum_j \left(\beta_{j,\mathrm{Macro}} \cdot V_{\mathrm{NUTS}}\right) \tag{2}$$

Again, the left-hand side is the logit transformation of LIO, while α and β are estimated using standard regression techniques within the framework of GLMs (Harrel Jr., 2001; Venables and Ripley, 2002; Zuur et al., 2009). Multivariable logistic regression models (MLRMs) are fitted for each impact category and macro region. For each macro region and impact category, the aim was to find the best combination of one or two hazard indices (H) and up to three vulnerability factors (V). Due to the short period of available data (2001–2014) of ΔfAPAR, ΔpF, and CDI, only SPEI data of different aggregation periods were used as hazard indices for this part of analyses. The combined vulnerability factors "Sensitivity and adaptive capacity" were also neglected as they are predetermined combinations of individual factors that might also enter the model as predictors, resulting in multicollinearity.

Emphasising the effect of climatic hazard indices on drought impacts, the stepwise multivariate logistic regression began with the detection of the best single hazard index (from the univariate logistic regression model in Step 1). The best-performing hazard index was selected by predictor significance, measured by p values, and model performance measured by A_{ROC}. Then, a second hazard index was selected following two criteria: it is not correlated ($r^2 < 0.5$) with the best-performing hazard index and it significantly improves the model. Again, the best-performing predictor was assessed by predictor significance and overall model performance. Furthermore, overfitting by additional variables was penalised by the Bayesian information criterion (BIC), with smaller numbers indicating better models. Accordingly, a second hazard index is only chosen for the final MLRM if A_{ROC} increases or remains constant and BIC decreases. A maximum of two hazard indices are allowed in the final MLRM.

Furthermore then, up to three vulnerability factors are included into the model in a stepwise fashion based on the same criteria. Proceeding as in the previous step, the best-performing vulnerability factors are only considered for the final MLRM if they improve the overall model, either increasing A_{ROC} or producing equal A_{ROC}, but a lower BIC. If A_{ROC} decreases or remains constant with a poor BIC, the factor was not added to the final MLRM and further vulnerability factors were not analysed. A maximum of three vulnerability factors were included into the resultant MLRM.

In Step 3 of the study, the resultant MLRMs were applied to construct drought risk maps that show the likelihood of impact occurrence for three selected hazard levels, based on the standard deviation from normal -0.5, -1.5, and -2.5. The hazard predictors were all standardised indices representing a certain hazard severity and likely frequency of occurrence. The definition of drought severity for SPI, SPEI, ΔpF, and ΔfAPAR is inspired by the definition of McKee et al. (1993) who assigned standard deviations from normal to hazard severity levels for SPI, with a threshold of 1 corresponding to a return period of 6.3 years, classified as moderate drought, and -2 as extreme drought conditions. The final pan-European drought risk map presents the LIO by the best-performing combination of predictors for 15 impact categories and for 3 hazard levels. For countries with a lack of sufficient vulnerability data (Table S1 in the Supplement), LIO was estimated using the best hazard-only model.

4 Results

4.1 Distribution of drought impacts and impact characteristics

As shown in Fig. 2, the majority of the reported drought impacts occurred during well-known major drought events: 1975–1976 in central Europe, 1991–1995 in the Mediterranean, 2003 all over Europe (except the Mediterranean), and 2004–2007 in the western Mediterranean (Stagge et al., 2013; Stahl et al., 2016), as well as in more recent events, e.g. the drought of 2010–2012 in the United Kingdom (Kendon et al., 2013; Parry et al., 2013), the European drought of 2011 (DWD, 2011), and the 2011–2012 drought in southeastern Europe (Spinoni et al., 2015). The highest number of reports is represented by the drought events of "1975–1976 Europe", "2003 Europe", and "2010–2012 UK".

Except for northeastern Europe, almost all impact categories (except "Air Quality") have at least one annual impact recorded per macro region (Blauhut et al., 2015a). An increasing trend of impact reports with time is observed for all macro regions. Overall, maritime Europe has the highest number of impacted years in total, which is consistent with this region's higher number of overall impact reports. Generally, the number of reported impacts cluster with well-known drought events, although impacts on "Forestry" show a delay and longer duration compared to the meteorological hazard. "Waterborne Transportation", "Tourism and Recreation", "Public Water Supply", "Water Quality", and "Freshwater Ecosystems" show a similar temporal pattern of impact occurrence. Impacts on "Agriculture and Livestock Farming", Public Water Supply, and Freshwater Ecosystems are reported for almost every year. For southeastern Europe, Agriculture and Livestock Farming has the most frequent impacts. Furthermore, Public Water Supply and "Human Health and Public Safety" have a continuous presence of impacts from 1983 to 1996. From 2000 on, all impact categories have reported impacts. Northeastern Europe has only a few impact categories with drought-impacted years, but Forestry shows a long continuous time with impacts, from 1991 on. The western Mediterranean region shows a less scattered pattern. Besides a low number of impacts from the middle of the 1970s until the beginning of the 1980s for Agriculture and Livestock Farming, Forestry, "Energy and Industry", and Public Water Supply impacts occurred during the two major long-term drought events of 1989–1995 and 2003–2008.

The observed increase in the occurrence of reported impacts from 2000 onwards may have several reasons; one of the most important being an increased reporting behaviour (governmental and news) due to an increased awareness of natural hazard impacts and the possibility of easy and fast communicated information (internet). Nevertheless, we cannot exclude the fact that Europe is warming and that this warming may lead to an increase in reported drought impacts.

4.2 Suitable predictor variables for hazard and vulnerability

First, the individual predictors in binary logistic regression models, BLMs, were evaluated by impact category and macro region. Data availability allowed the identification of robust BLMs for all impact categories only for the maritime Europe region. For southeastern Europe, the impact category "Terrestrial Ecosystems", for northeastern Europe Water Quality, and for the western Mediterranean Terrestrial Ecosystems, Air Quality, and Human Health and Public Safety could not be modelled. All hazard indices performed differently across regions and impact categories. Tables S2 to S4 show the model performance for the individual hazard indices and the vulnerability factors. These detailed results are only briefly summarised here as they only represent a preliminary screening step in the model-building process.

Among the indices used within the EDO, the index ΔfAPAR generally results in robust models during the growing season, but the annual average ΔfAPAR appears not to be a suitable predictor. The ΔpF performs as the overall best predictor with mostly good models between March and November and the best overall performance of the annual average of ΔpF. The CDI resulted in only few poor to good models.

For the indices of SPEI, a longer period of hazard data was available (1970–2012) than for the EDO indices and hence overall better model fits were achieved. The best-performing indices (in terms of aggregation times) are more specific to the impact category than to the macro region and tend to span from 6- to 12-month aggregation times. SPEI-12 performs with good to excellent models for the majority of impact categories and macro regions from August to September. In comparison to the other impact categories, few robust models were identified for Forestry and Public Water Supply. In general, SPI follows the similar performance pattern as SPEI, but with consistently lower model performance and is therefore not shown in the tables. To estimate the influence of longer time series for model input, Table S5 shows model performance for SPEI applied for the shorter time period 2001–2012. Resultant model performance follows a similar but less strong performance pattern as the longer time series.

To identify patterns in the many vulnerability factor variables tested, Table S4 groups the individual vulnerability factors by the vulnerability components of adaptive capacity and sensitivity. In general, none of these obtained an excellent model performance. Factors related to "Sensitivity" that characterise land use and are based on multiple time steps, such as "Area of Agriculture", "Area of Forest", "Area of Semi-natural Areas", and "Percentage of Area of Agriculture" proved to be significant in many cases. In addition, robust model predictors for all macro regions include "Dams and Groundwater Resources" and "Water related Participation EC" for Agriculture and Livestock Farming or "Social relevance for services sector" for Energy and Industry. For the remaining vulnerability factors, no clear patterns were detectable. Only few robust models could be identified. Predictive skill for vulnerability factors such as "GDP by country", "Public Water Supply connection by NUTS-2" or "Biodiversity, Areas protected" was not found. The combined vulnerability factors resulted in few macro region and impact category robust models. Impact occurrence for the categories "Aquacultures and Fisheries", "Soil Systems", "Wildfires" and Air Quality were generally difficult to model by vulnerability factors.

In summary, the drought hazard indices SPEI and SPI alone were better suited than the rather static vulnerability factors alone to estimate the likelihood of annual drought impact occurrence, and will therefore be treated as more important for the identification of the best-performing MLRMs (Step 2, ref. Sect. 3).

4.3 Estimating the best-performing combinations of hazard indices and vulnerability factors to assess the likelihood of impact occurrence

Out of the final 44 best-performing MLRMs, 18 models used the maximum of three vulnerability predictors, 14 models used two, 9 models only one, and 3 models did not use any vulnerability predictor at all. For the majority of MLRMs, two hazard predictors are used, whereas four models found that one hazard index alone was sufficient to obtain the optimum model performance.

Table 3 shows the MLRM performance for the best-performing hazard indices and the improvement for the final models that include vulnerability factors. In general, integrating vulnerability factors to the MLRMs improved the model performance, except for models of the impact categories Soil Systems and Wildfires for southeastern Europe and Forestry for the western Mediterranean region. The improvement in model performance differed by region and impact category, whereas an increase of A_{ROC} and a decrease of BIC reflect model performance improvement. ΔROC (improvement of A_{ROC} with vulnerability factor predictors) ranges from 0 to 0.32 with an average increase of 0.08, whereas ΔBIC range between 9 and −347 with an average value of −65.

Figure 3 summarises the selected hazard predictors and vulnerability factor predictors for all models. Among the drought hazard indices, 34 short-, 32 mid-, and 18 long-term SPEI predictors were selected for the best model performance (with short-, mid-, and long-term periods corresponding to 1–3, 4–9, and 12–24 month accumulation). The majority of MLRMs with two selected hazard indices are combinations of SPEIs with one longer and one shorter accumulation period. Generally, the most frequent SPEI predictors cover the summer months from May to August with accumulation intervals between 1 and 6 months.

For all regions, about 40 % of the selected vulnerability factors describe land surface characteristics related to agricultural and semi-natural land cover. Among the vulnerability factors, only 16 % of those selected are associated with Adaptive Capacity components. For the western Mediterranean, all selected vulnerability factors, apart from "Drought Management Tools", describe Sensitivity.

4.4 Mapping drought risk

For each impact category, a robust MLRM was identified for at least one macro region. Figures 4–6 show the results of applying these robust models for risk mapping, i.e. mapping the likelihood of drought impact occurrence (LIO) for 15 sectors (columns) and 3 hazard severity levels (rows), in total 35 drought risk maps. Overall, the maps illustrate that with increasing hazard severity (from top to lower row) the spatial patterns of LIO begin to diverge for each impact category, macro region, and NUTS-combo regions. LIOs start with rather low values at low severity levels and increase as the hazard intensifies, whereas the characteristics of drought risk differ with impact category and macro region. In general, southeastern Europe and northern Europe (Iceland, Norway, Finland) are under low drought risk in comparison to the other European regions, whereas parts of maritime Europe and the western Mediterranean show increasing drought risk with hazard conditions for the majority of impact categories.

The largest differences in drought risk are present under severe hazard conditions. Agriculture and Livestock Farming results in highest LIO in southern Sweden, the Netherlands, Portugal, Spain, and southern Italy, whereas Forestry is more likely to be affected in Sweden, southern Finland, central Europe and Hungary, Slovenia, and Romania. In contrast to these rather spatially consistent risk patterns, Aquaculture and Fisheries shows rather dispersed regions with increased LIOs: in Spain (Andalucía and La Rioja), southern France (Provence–Alpes–Côte d'Azur and Languedoc–Roussillon), northeast Italy, and southern Austria. The risk for impacts in the category Energy and Industry is high for the majority of maritime Europe and the western Mediterranean, with hotspots in Portugal, Croatia, southeastern Germany (Bavaria), and central France (the Centre region). For impacts in the category Waterborne transportation, high LIO was found for Croatia and eastern Hungary (high risk), central Europe, and southern UK. Impacts on Tourism and Recreation under the most severe hazard conditions are very likely for the majority of maritime Europe and the western Mediterranean, with highest LIOs for Portugal, southern Italy, the Netherlands, Scotland, and central and northern Sweden, whereas southeastern Europe is not at risk for any hazard level. Impacts on Public Water Supply appear not to be present for the majority of southeastern Europe, and are less likely for central European regions, but show high LIOs for the Mediterranean, Bulgaria, Slovakia, Denmark, and the UK. For the impact category of Water Quality these pattern change with higher drought risk for central Europe. Hot spots of drought risk for this impact category are identified for the majority of the western Mediterranean, Bulgaria, northern central Europe, and England. Northeastern Europe and the majority of southeastern Europe are not at risk. High risk estimates for Freshwater Ecosystems are rather spatially extensive and present for the majority of the Iberian Peninsula, England, and northern central Europe. Impacts on Terrestrial Ecosystems, which could only be modelled for maritime Europe, display high risk for England, the Benelux countries, Switzerland, Bavaria, and southern Austria under the most severe hazard conditions. Drought risk for the impact category of Soil Systems is limited to the Netherlands (high risk) and the region of Paris (Île de France), England, Belgium, and some French NUTS-combo regions (low risk). Impacts related to Wildfires are very likely for the majority of the western Mediterranean, Lithuania, and northern Finland. Air Quality is the only impact category with almost no risk of drought impacts for all hazard severity levels. In contrast, under the most severe hazard conditions, impacts on Human

Table 3. MLRM performance of models with hazard predictors only and performance improvement (Δ) with added vulnerability factors.

IC	Maritime Europe						Southeastern Europe						Northeastern Europe						Western Mediterranean					
	Hazard			Vulnerability			Hazard			Vulnerability			Hazard			Vulnerability			Hazard			Vulnerability		
	n	A_{ROC}	BIC	n	ΔA_{ROC}	ΔBIC	n	A_{ROC}	BIC	n	ΔA_{ROC}	ΔBIC	n	A_{ROC}	BIC	n	ΔA_{ROC}	ΔBIC	n	A_{ROC}	BIC	n	ΔA_{ROC}	ΔBIC
A & L	2	0.80	749	2	0.07	−95	2	0.86	378	3	0.04	−196	2	0.02	68	2	0.02	−5	2	0.79	318	3	0.10	−52
Fo	2	0.83	477	2	0.10	−110	2	0.82	109	2	0.08	−30	2	0.32	287	3	0.32	−110	1	0.75	50	0		
A & F	1	0.96	86	1	0.01	−2	2	0.98	47	1	0.01	−6							2	0.97	37	2	0.02	9
E & I	2	0.91	257	3	0.04	−25	2	0.86	237	2	0.10	−167							2	0.82	178	2	0.06	−23
WT	2	0.82	456	2	0.09	−50	2	0.87	114	3	0.11	−46							1	0.98	45	2	0.02	−9
T & R	2	0.85	331	3	0.09	−45	2	0.75	92	2	0.21	−34							2	0.89	116	1	0.05	−16
PWS	2	0.76	1125	3	0.16	−347	2	0.75	511	3	0.19	−298							2	0.84	266	3	0.07	−29
WQ	2	0.83	606	3	0.08	−115	2	0.78	178	2	0.20	−86							2	0.83	182	3	0.12	−57
FE	2	0.77	845	3	0.14	−207	2	0.93	119	1	0.05	−60	2	0.01	37	1	0.01	0	2	0.83	238	3	0.09	−40
TE	2	0.85	311	3	0.10	−83																		
SS	2	0.79	302	3	0.11	−31	2	0.95	64	0									2	1.00	30	1	0.00	−6
WF	2	0.86	445	1	0.02	−25	2	0.93	134	0			2	0.04	58	3	0.04	9	2	0.90	101	3	0.08	−12
AQ	2	0.95	67	1	0.02	2																		
H & P	2	0.94	287	2	0.02	−20	2	0.72	293	2	0.27	−198												
Co	1	0.99	60	2	0.01	−16	1	0.93	65	1	0.05	−20							2	0.88	127	3	0.10	−31

IC: impact category; n: number of indices or vulnerability factors applied; ΔA_{ROC}: difference of A_{ROC} of MLRM with vulnerability factors to MLRM without vulnerability factors; ΔBIC: difference of BIC of MLRM with vulnerability factors to MLRM without vulnerability factors (negative values indicate performance increase); A & L: Agriculture and Livestock Farming, Fo: Forestry, A & F: Aquaculture and Fisheries, E & I: Energy and Industry, WT: Waterborne Transportation, T & R: Tourism and Recreation, PWS: Public Water Supply, WQ: Water Quality, FE: Freshwater Ecosystems, TE: Terrestrial Ecosystems, SS: Soil Systems, WF: Wildfires, AQ: Air Quality, H & P: Human Health and Public Safety, Co: Conflicts.

	Impact	Hazard		Vulnerability		
	category	**Predictor 1**	**Predictor 2**	**Predictor 3**	**Predictor 4**	**Predictor 5**
Maritime	A&L	SPEI-06 Jun	SPEI-01 Jun	Groundwater resources	A. inland water bodies, ratio of NC	
	Fo	SPEI-04 Jun	SPEI-24 Nov	Population density and age	Water balance	
	A&F	SPEI-09 Oct		Dams + GW resources		
	E&I	SPEI-06 Jul	SPEI-01 Jun	A. agriculture	Innovation capacity	A. perm irrigated agri, ratio of NC
	WT	SPEI-05 May	SPEI-24 Dec	Groundwater resources	Wate body status	
	T&R	SPEI-04 Apr	SPEI-24 Nov	Groundwater resources	A. inland water bodies, ratio of NC	A. artificial surfaces
	PWS	SPEI-24 Dec	SPEI-04 Jun	Water use	A. agriculture, ratio of NC	Aquatic ecosystem status
	WQ	SPEI-09 Aug	SPEI-02 Dec	Dams & GW resources, norm.	A. agriculture, ratio of NC	SR services
	FE	SPEI-06 Jun	SPEI-12 Feb	Groundwater resources	A. agriculture, ratio of NC	SR industry
	TE	SPEI-09 Aug	SPEI-01 Feb	GW resources, norm.	WR industry	A. forest
	SS	SPEI-06 Jun	SPEI-02 Jan	Drought management tools	A. inland water bodies, ratio of NC	SR services, norm.
	WF	SPEI-05 Aug	SPEI-04 Oct	Drought awareness		
	AQ	SPEI-03 Apr	SPEI-04 Nov	Drought recovery capacity		
	H&P	SPEI-03 Apr	SPEI-12 Dec	Groundwater resources	Water resources development	
	Co	SPEI-04 Jun		Drought recovery capacity	Economic wealth	
Southeastern	A&L	SPEI-06 Aug	SPEI-01 Dec	Population density N2	Drought awareness	A. artificial surfaces, ratio of NC
	Fo	SPEI-05 Oct	SPEI-01 Feb	A. NUTS-combo region	Dams capacity	
	A&F	SPEI-04 Jul	SPEI-24 Mar	Water use Indus		
	E&I	SPEI-06 Aug	SPEI-06 Dec	WR services	A. artificial surfaces, ratio of NC	
	WT	SPEI-06 Sep	SPEI-01 Nov	Public participation	A. agriculture, ratio of NC	A. seminatural areas
	T&R	SPEI-06 Sep	SPEI-24 Jun	Population density and age	A. artificial surfaces, ratio of NC	
	PWS	SPEI-24 Dec	SPEI-03 Sep	Drought awareness	Wate body status	A. seminatural areas, ratio of NC
	WQ	SPEI-24 Mar	SPEI-03 Sep	Aquatic ecosystem status	A. of lakes within region	
	FE	SPEI-02 Jul	SPEI-01 Dec	Drought awareness		
	SS	SPEI-04 Nov	SPEI-01 Aug			
	WF	SPEI-12 Aug	SPEI-01 Feb			
	H&P	SPEI-06 Jan	SPEI-03 Oct	Aquatic ecosystem status	A. forest, ratio of NC	
	Co	SPEI-24 May	SPEI-03 Jan	Drought awareness		
North eastern	A&L	SPEI-03 Jul	SPEI-02 Nov	A. agriculture, ratio of NC	Drought management tools	
	Fo	SPEI-03 Sep	SPEI-06 Jun	A. wetlands, ratio of NC	Population density NC	A. inland water bodies, ratio of NC
	WQ	SPEI-01 May	SPEI-02 Mar	Water use		
	WF	SPEI-01 Apr	SPEI-01 Nov	Drought recovery capacity	SR industry	Groundwater resources
Western-Mediterranean	A&L	SPEI-01 Jan	SPEI-12 Dec	A. agriculture	WR services	Drought management tools
	Fo	SPEI-04 Apr				
	A&F	SPEI-05 Sep	SPEI-04 Mar	A. wetlands, ratio of NC	A. lakes witin region	
	E&I	SPEI-01 Jan	SPEI-03 May	A. inland water bodies	Water exploitation index	
	WT	SPEI-02 Jul		Population density and age	Water use	
	T&R	SPEI-09 Aug	SPEI-01 Dec	Aquatic ecosystem status		
	PWS	SPEI-06 May	SPEI-01 Dec	Aquatic ecosystem status	Socioeconomic relevance agri	A. seminatural areas
	WQ	SPEI-05 May	SPEI-02 Dec	A. seminatural areas	Aquatic ecosystem status	A. lakes within region
	FE	SPEI-06 May	SPEI-01 May	A. seminatural areas	A. not irrigted agri, ratio of NC	A. agriculture, ratio of NC
	SS	SPEI-05 Oct	SPEI-24 Sep	Population density and age		
	WF	SPEI-05 Jun	SPEI-01 Dec	Aquatic ecosystem status	A. artificial surfaces	A. wetlands, ratio of NC
	Co	SPEI-05 May	SPEI-06 Dec	A. seminatural areas	SR agriculture	Population density and age
		Short-	Medium-	Long- temporal aggregation	Sensitivity	Adaptive capacity

Figure 3. Selected of the best-performing predictors, yellow: SPEI with short temporal accumulation, light yellow to brown: SPEI with increasing temporal aggregation (short, medium, and long temporal accumulation), red: vulnerability factors associated with sensitivity, blue: vulnerability factors associated with adaptive capacity, A. = Area of, GW = Groundwater, norm. = normalised, NC = NUTS-combo region, N2 = NUTS-2 region, SR = Socioeconomic relevance, WR = Water use relevance.

Health and Public Safety are at high risk for Bulgaria, Czech Republic, Switzerland, the Netherlands and Sweden and increased risk for the remaining maritime regions. The risk of "Conflicts" under extreme dry conditions is either very high (majority of the western Mediterranean and Germany, Switzerland, the Netherlands, and the southeast UK) or not a risk at all.

5 Discussion

5.1 Hazard indices and vulnerability factors' individual predictive potential

The systematic test of a series of hazard indices and vulnerability factors individually allowed a first order assessment of their potential to predict impact occurrence. Despite their short period of data availability, soil moisture anomalies from the JRC's EDO proved to have high potential as an index for drought impact prediction in all impact categories. Concurring e.g. with Skakun et al. (2014), fAPAR proved its usage as a drought index for vegetation-process-related impact categories, for the growing season particularly. Thus, of the use of a fAPAR-based seasonal index in further studies appears promising. The combined index CDI, however, was not found to be a good predictor of impact occurrence in our study. Given that its individual contributing indices (ΔfAPAR and ΔpF) performed generally well, and the fact that the CDI had been tested successfully against quantitative impacts in the agricultural sector by Sepulcre-Canto et al. (2012), suggest that further studies should explore possible reasons for this poor performance, e.g. through further sector-specific data stratification.

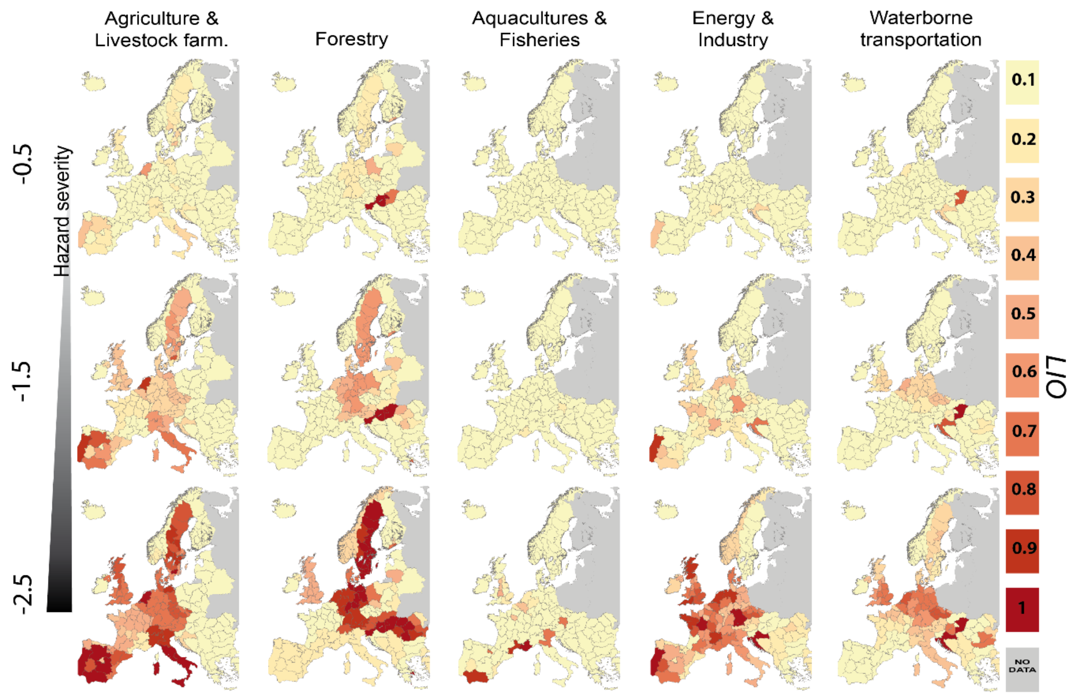

Figure 4. Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Agriculture and Livestock Farming, Forestry, Aquaculture and Fisheries, Energy and Industry, and Waterborne transportation (columns) for three hazard levels of SPEI with −0.5: near normal, −1.5: severely dry, and −2.5: extremely dry (rows).

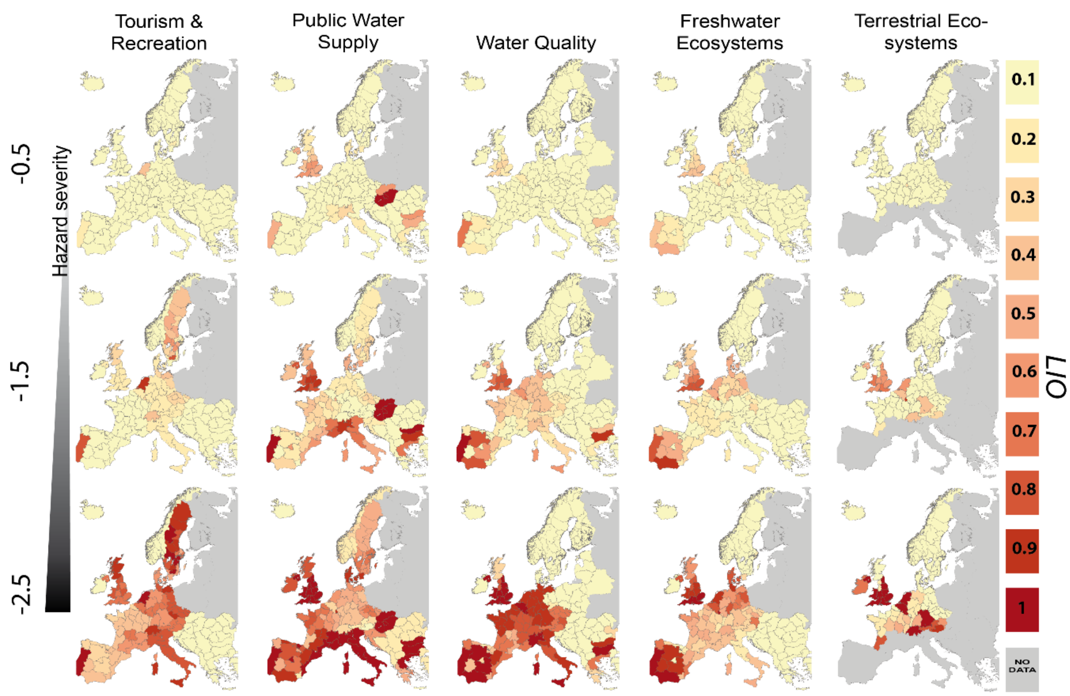

Figure 5. Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Tourism and Recreation, Public Water Supply, Water Quality, Freshwater Ecosystems, and Terrestrial Ecosystems (columns) for three hazard levels of SPEI with −0.5: near normal, −1.5: severely dry, and −2.5: extremely dry (rows).

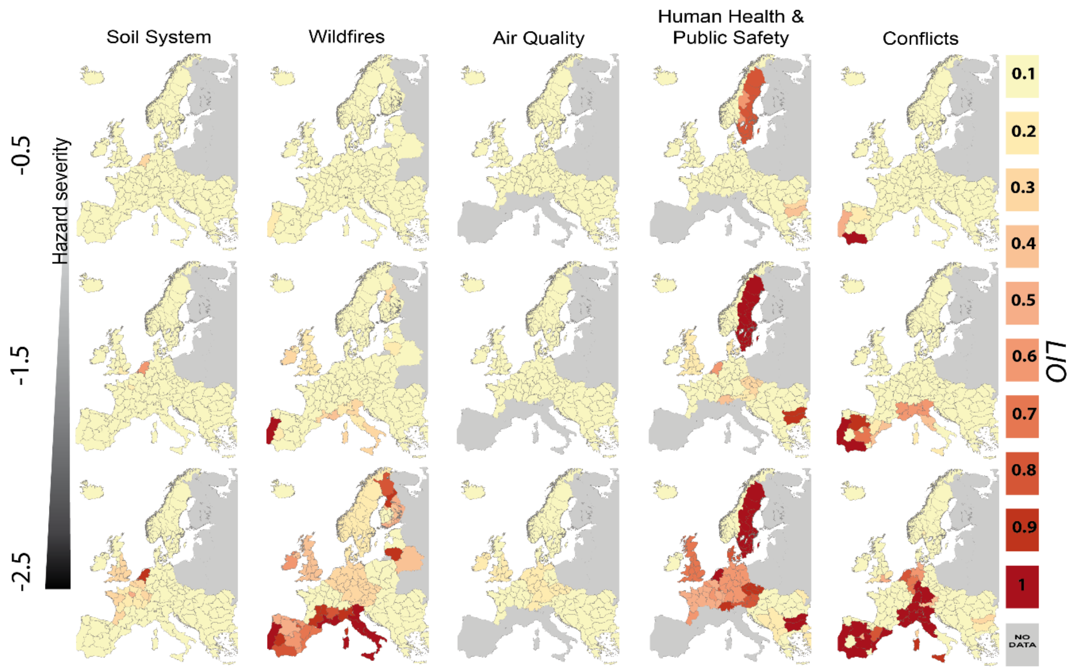

Figure 6. Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Soil System, Wildfires, Air Quality, Human Health and Public Safety, and Conflicts; (columns) for three hazard levels of SPEI with −0.5: near normal, −1.5: severely dry, and −2.5: extremely dry (rows).

Generally, the tests showed that the hazard impact linkage will benefit from longer time series and thus a wider range of drought conditions. Furthermore, it was found that the overall better performance of SPI and SPEI to JRC hazard indices was not due to the differences in time series length. SPEI shows an overall better model performance than SPI for all accumulation times and impact categories. This is in agreement with the studies of Lorenzo-Lacruz et al. (2010) and López-Moreno et al. (2013), who found the SPEI to be better correlated than the SPI with environmental impacts. The overall best-performing (across all impact categories and macro regions) temporal accumulation was 12 months, which is as expected, since the target variables are impact occurrences on an annual basis. The best performance was found for SPEI-12 of September and December. SPEI-12 of December measures the same calendar year used for aggregating annual impact information. Alternatively, the SPEI-12 of September measures water balance during a water year, defined by the US Geological Survey as 1 October–30 September, which captures the growing season along with the entire preceding winter. Thus, both indices can be recommended for analyses at an annual scale.

The tested vulnerability factors alone revealed generally limited skills to predict impact occurrence, with exceptions of land surface cover types or information on regional water uses/storages. This is somehow at odds with the fact that the most commonly used vulnerability factors in vulnerability assessments are related to "Economic and financial resources" and to technical, technological, and infrastructural aspects (González-Tánago et al., 2015). As few of the factors varied in time, the models reflect mostly spatial differences of impact occurrence among the pooled NUTS-combo regions rather than temporal differences. Although data to characterise vulnerability in Europe are numerous, there are important gaps that implied constraints in our analysis and predictor selection. Much of the data are available only at country level or are not available in a centralised data repository. For instance, De Stefano et al. (2015) observe that there are no European-wide data of water use efficiency, or data about alternative water sources such as desalination, reused water, or rainwater harvesting, especially in those locations where these sources are important, such as the islands or tourist areas on the Mediterranean coast. We found that vulnerability factor normalisation practices did not improve the predictive potential model performance and composed vulnerability factors were not better than individual ones. For an application like in our study, this can be interpreted as meaning that prior standardisation, composition, and weighting of vulnerability factors appears unnecessary.

5.2 Building hybrid models with hazard indices and vulnerability factors

The stepwise procedure employed to find predictor combinations for the multivariable models may have excluded possible similar or even better combinations. However, a full permutation of all possible combinations was computationally too expensive for this study. Nevertheless, it was possible to identify suitable models for most cases and the multi-variable selection process further elucidated joint important controls on drought risk. The majority of SPEIs selected for final model application were combinations of SPEI with different accumulation times, often short and long periods. The stepwise procedure showed that hazard indices with temporal accumulations from 3 to 12 months generally performed best, depending on the region and impact. These results confirmed previous case studies on the best combinations, e.g. by Stagge et al. (2015b), and common practice using combined drought monitoring indices, such as the US Drought Monitor (Svoboda et al., 2002). The majority of MLRMs also performed better by adding at least one vulnerability factor, suggesting that these can improve the predictability of annual drought impact occurrence. The vulnerability factors selected are dominated by factors associated with the vulnerability component of Sensitivity. This could be explained by the fact that adaptive capacity evolves much faster than sensitivity and the values of "Adaptive Capacity" factors used in the models refer to present conditions while impacts span over a 50-year time period. Thus, the poor performance of Adaptive Capacity indicators as predictors of impact could be due to the mismatch between the adaptive capacity that existed when impact occurred in the past and the one used in our models rather than their lack of relevance in absolute terms.

The predictor selection was likely influenced by some of the particular biases and characteristics of the underlying databases. The EDII's impact categories broadly pool impact types of similar topics. Reported impact types within a category can be very different and reported impact types can differ between countries (Stahl et al., 2015). Using Agriculture and Livestock Farming impacts as an example, the large range of SPEIs selected for the final models (with regard to temporal accumulation and month) can be due to several reasons. These may include differences in impacts in irrigated vs. rain-fed agriculture. Whereas impacts on rain-fed agriculture are often described best by meteorological drought (short accumulation periods), irrigated agriculture strongly depends on lagged hydrological drought (Pedro-Monzonís et al., 2015). Characteristics of location and cultivation may also play a role. Depending on the climatic and orographic conditions of a NUTS-combo region, impact-category-specific characteristics differ (e.g. growing season, dormancy, development). Hence, the most relevant SPEI for each region may differ in accumulation time and month selected. This corresponds e.g. to Lei et al. (2011) and Potopová et al. (2015) who detected different optimal accumulation times of SPEI for maize productivity for northern China and Czech Republic. A reason for the selection of more unexpected combination of SPEI (e.g. SPEI-6 of August was selected together with SPEI-1 in December for Agriculture and Livestock Farming in southeastern Europe) might be due to the criterion of variable independence employed.

For wildfires, Gudmundsson et al. (2014) suggested SPI with lead times not longer than 2 months to indicate major effects of wildfires in southern Europe, contradicting the longer accumulation times selected in this study. However, Gudmundsson et al. (2014) used the comprehensive European Fire Database, whereas the EDII only contains wildfire reports that were directly attributed to drought. On the other hand, our variable selections match the results of Catry et al. (2010) who estimated that the majority (51 %) of all wildfires occur during the summer months.

Hydrological drought takes the longest time to respond to drought conditions. Accordingly, impact categories for which surface and groundwater availability is important and often linked to water quality (e.g. higher water temperatures due to low flow) (Aquaculture and Freshwater Fisheries, Energy and Industry, Waterborne Transportation, Water Quality, Freshwater Ecosystems), are best predicted by longer accumulation times ($\geq$ SPEI-9). Impacts on Public Water Supply are generally poorly predicted by SPEI. The best performances are obtained for long accumulation times (SPEI-24) indicating that impacts on water resources rely on the storage characteristics (natural or artificial) and thus depend on a variety of conditions that cannot be characterised by SPEI on the larger scale. Other impact categories show weaker patterns, but in general show better results for predictions in summer.

This seasonal focus points to a related data challenge. The temporal resolution of reported impacts, which often only refer to an entire season, year, or multiyear drought, does not allow an identification of the onset, duration, and ending of a given drought impact. The annual timescale employed here is a compromise between a sufficient high number of reported impacts and spatial coverage. Stagge et al. (2015b) showed that seasonal models can be constrained better, but sufficient seasonal information on impacts was not available for all regions or countries across Europe. Furthermore, in order to overcome data availability issues, Europe was divided into four European macro regions to pool impact information, some of which may not reflect regions with similar drought impacts and as such influence the model performance obtained (Blauhut et al., 2015a).

The selection of vulnerability factors for the final MLRMs in this study is also driven by the model fits and thus based on empirical relation rather than on commonly applied epistemic selection procedures (Gonzáles Tánago et al., 2015). In several cases, MLRM performance differed only marginally between different factors included in the models. Due to the limitation of only selecting the best-performing and model-performance-increasing vulnerability factors, further important factors that might have an influence on regional vulnerability may thus not have been included. Whereas there is considerable variability in the impact-category-specific or macro regional factors selected, some general trends can be noted.

More than one-third of applied factors quantitatively characterise regional land use, and almost half of the selected factors characterise the water resources. This is in accordance with Gonzáles Tánago et al. (2015) who summarised that drought vulnerability analyses have often applied information on water resources and land use information. Nevertheless, according to Gonzáles Tánago et al. (2015), the most commonly applied information in drought vulnerability assessment is related to economic and financial resources and technical infrastructure, but these priorities are not reflected in our findings where e.g. "Economic Wealth", "Public Water Supply Connection" or "Drought Recovery Capacity" were of minor importance or not selected at all in the model building process. Nevertheless, the results call for a review of the relevance of vulnerability factors in wider ranges of drought cases and for progress with regard to thematic content, data generation, and transformation from qualitative to quantitative data and their rationalisation.

5.3 Regional patterns of modelled sectorial drought risk across Europe

Statistical models to predict drought impact occurrence remain a relatively new approach that has proved successful within targeted country-scale studies (e.g. Bachmair et al., 2015; Stagge et al., 2015b). As with any data-driven approach, the presented risk modelling relies on the quality and availability of its underlying data. Since its establishment, the EDII database has been constantly growing and now contains data across Europe, covering the majority of major past drought events (Stagge et al., 2013). The database used here was also considerably larger than that used in the previous pan-European risk modelling study by Blauhut et al. (2015a). This increased database, as well as addition of vulnerability factors, led to some differences in the resulting risk maps. Nevertheless, the updated EDII database still has certain biases and characteristics (Stahl et al., 2016) that may affect the results of the risk models and maps this study presents. One bias in the impact data is a decreasing data availability from west to east and poor data availability in northern Europe. Additionally, using binary information of annual impact occurrence is less sensitive to these reporting biases than e.g. the number of reports or impacts as discussed by Bachmair et al. (2015). Overall, uncertainties of the risk models are likely higher in regions with lower report availability as well as with lower availability of vulnerability data as in this study for the macro region of southeastern Europe.

Agriculture and Livestock Farming is the best-covered impact report data category across Europe and thus an issue at pan-European scale (Kossida et al., 2012; Stahl et al., 2016). In accordance with reports of the European Commission (EC, 2007, 2008), the derived risk maps for Agriculture and Livestock Farming show high drought risk for most of the western Mediterranean regions, covering water scarce regions as detected by Strosser et al. (2012). Moderate to high drought risk for maritime Europe confirms pattern previously identified by Blauhut et al. (2015a) based on hazard predictors only. A relatively low risk such as for most of France, may reflect the added vulnerability predictor, particular agricultural land use as well as drought management (e.g. compensation) tools. The relatively high risk for Sweden in the Nordic countries may reflect that agriculture is a much larger sector in Sweden than in the neighbouring countries (Eurostat database: "Agricultural production", 2015). The relatively low drought risk for Agriculture and Livestock Farming in southeastern Europe may result from the aforementioned lack of data. Stahl et al. (2015) actually found the impact category in the region to be relatively important among all impact categories. Regional pooling for this study may also have affected these results and should be further tested in future studies.

The pattern of drought risk for Energy and Industry identified by Blauhut et al. (2015a) were confirmed by this study. Regions with a high dependency on water resources for energy production, such as Slovenia or Bavaria, are at higher risk of impacts in this category. As an example, Slovenia's total energy production is based on $\sim 55\,\%$ hydropower sources and $\sim 45\,\%$ by thermal power plants (HEP, 2009) and Bavaria (and also France) has several nuclear powerplants. Quite contrarily, Norway is at low risk for severe hazard conditions even though about 98 % of its energy production is by hydropower (Christensen et al., 2013). A relative index should be able to pick up deviations from normal inducing impacts on hydropower production. Rather there must be some other reasons (e.g. regional averaging of the indices, pooling of impact information to macro regions). Future work will require higher temporally and spatially resolved impact information such as daily power production to solve this issue. Nevertheless, drought indices quantifying the absolute state of water reservoirs or sources could improve predictions for this impact category.

The pattern of risk of impacts on Public Water Supply differs somewhat from the results of Blauhut et al. (2015a) who presented medium risk for extreme conditions (SPEI-$12=-3$) all over Europe. For regions with high water stress (Mediterranean) (EEA, 2009), impacts on Public Water Supply are more likely, as well as in regions where water storage capacity is limited (UK). Estimates for southeastern Europe are likely to be impaired due to data availability and regional pooling.

Water Quality aggregates very different impact causes within one impact category, ranging from water quality deterioration (e.g. algal bloom) to salt water intrusion, bathing water quality, and economic losses. Risk patterns show high LIOs for the majority of the maritime region (excluding Scandinavia), the western Mediterranean, Bulgaria, and northern Greece. This is in accordance with drought risk as estimated by Blauhut et al. (2015a). In maritime Europe, relatively high risk areas reflect areas with poor ecological status of European waters and lakes for maritime Europe (EEA, 2012), even though this was not a selected predictor in the models (as for the other regions). In their study on drivers of vulnerability, Blauhut et al. (2015b) raised an additional point of uncertainty to consider for this category: an increase of reported impacts due to an increased ecological monitoring and increased public and scientific recognition. The UK has the densest surface water monitoring network in Europe and the longest history of ecological status care (Royal Geographical Society (with IBG), 2012). Hence, a higher number of reported impacts even under less severe drought is likely. A high risk for southern England, northern central Europe, and the Iberian Peninsula is also detected for the impact category of Freshwater Ecosystems. For maritime Europe, the regional pattern also resembles that of diffuse agricultural emissions of nitrogen to freshwater (EEA, 2010), and for the Mediterranean it resembles that of highly irrigated regions (EEA, 2014). These relations indicate a strong influence of agriculture on Freshwater Ecosystems, which could be taken into account in future impact-data-based risk assessments.

Analysing the risk of Wildfires at the pan-European scale has particular challenges. According to the European Forest Fire Information System, over 95 % of forest fires are human-induced (San-Miguel and Camia, 2009; Ganteaume et al., 2013). The EDII data only contain reports that have attributed fires to drought (Stahl et al., 2015). Hence, patterns of high risk as derived for the Mediterranean, the Baltics, and Finland do not fully agree e.g. with the findings of Gudmundsson et al. (2014). However, a comparison to the forest fire hazard map by the ESPON, which is based on a combination of numbers of observed fires and biogeographic regions (EEA, 2012), and to the fire density map by Catry et al. (2010), shows high similarities for the western Mediterranean, maritime, and northeastern Europe with only a few national exceptions. For southeastern Europe, a high number of fires has been reported, but this is not reflected in the drought risk maps.

For the impact category of Waterborne Transportation a specifically high drought risk was modelled mainly for NUTS regions with rivers of high international importance for transportation, such as the large rivers draining into the North and Baltic seas and the Danube (Eurostat, 2015).

Impacts on Tourism and Recreation can occur all over Europe and throughout the year, whereas drought risk maps indicate comparably low risk for Spain, France, and southeastern Europe. However, this category incorporates a very wide range of impacts and for more informative characteristics, a more detailed analyses of impact types or subjects, e.g. light outdoor activities, freshwater, tourism, and winter sports as used by Amelung and Moreno (2009) may be required.

Conflicts caused by drought are reported over all of Europe and affect a wide range of interest groups such as farmers, fishers, golfers, or citizens. However, the risk for these resource conflicts is elevated in southern Europe's water scarce regions, regions with high proportion of irrigation in agriculture, and regions with a high water exploitation index (EEA, 2016).

The presented hazard severity levels are based on an arbitrary choice inspired by McKee et al. (1993) and cannot be used as fixed threshold. In accordance with Blauhut et al. (2015a) and Stagge et al. (2015b), it should be highlighted that drought risk is sensitive to impact category and location, and develops very differently with increasing hazard severity (deviation from normal). Thus, common overall severity thresholds are not recommendable.

6 Conclusion

This study tested commonly used drought hazard indices and vulnerability factors for the empirical modelling of drought risk in terms of likelihood of impact occurrence and applied these models to map sector-specific drought risk across Europe. Building on prior applications of the statistical modelling of drought impact occurrence (Blauhut et al., 2015a; Stagge et al., 2015b; Bachmair et al., 2015), an important expansion of this study was the inclusion of vulnerability factors as predictors into the models in addition to only the hazard indices previously used. Furthermore, the use of the updated EDII database allowed a pan-European application to the risk modelling and assessment of a wider range of drought impact categories than previously possible. As with all empirical modelling, the application demonstrated the benefits of the availability of high-quality data. Representative records on past drought impacts as well as a good coverage of vulnerability factors are crucial to obtain meaningful models. In regions where data are scarce, modelling may be biased due to the limited information available. Hazard indices were confirmed to be impact-sector-sensitive and should thus be selected carefully to enable the characterisation of different drought causing impacts. Here the distinction was mainly made through using different accumulation times of SPEI. However, hydrological drought indices based on streamflow, groundwater, reservoir levels, etc. may also improve the drought impact models.

Generally, the addition of vulnerability factors improved the performance of the empirical drought risk models and for many impact categories, it added plausible spatial details to the drought risk. Since only vulnerability, and not hazard, can be reduced through active measures, a modelling exercise as presented here can shed light into possible opportunities for risk reduction. The collection of relevant data at a high resolution and at regular interval is key to advance the refinement of the assessment and the use of such maps for drought management. Present impact categories pool a wide range of impact types and further studies may want to evaluate the use of more specific impact types. Further, to overcome impact data scarcity, pooling of regions into larger macro regions based on an existing classification was necessary. A more specific classification could improve future applications. As also shown in smaller-scale companion studies, generally, the smaller the region, the higher is the chance for appropriate impact detection and the better the impact-hazard relation can be quantified. Nevertheless, the larger, regional level applied in this study provide an important scale to explain regional differences of drought risk on a continental scale. Additionally, it provides ideas for further improvements towards a quantitative drought risk assessment with the potential to be adapted to larger scale or refined to focus on specific aspects of drought risk for the region in question.

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References

Adepetu, A. and Berthe, A.: Vulnerability of Rural Sahelian Households to Drought: Options for Adaptation, A Final Report Submitted to Assessments of Impacts and Adaptations to Climate Change (AIACC), Project No. AF 92, The International START Secretariat, Washington, USA, 2007.

Aggett, G.: A Multi-sector Drought Vulnerability Assessment for the State of Colorado, Vol. 15, EGU General Assembly Conference Abstracts, Vienna, Austria, p. 13395, 2013.

Ahmed, N. and Elagib, N. A.: Development and application of a drought risk index for food crop yield in Eastern Sahel, Ecol. Indic., 43, 114–125, doi:10.1016/j.ecolind.2014.02.033, 2014.

Amelung, B. and Moreno, A.: Impacts of climate change in tourism in Europe, PESETA-Tourism study, JRC Scientific and Technical Reports, JRC, Seville, doi:10.2791/3418, 2009.

Amoako, P. Y. O., Asamoah, K. A., Mantey, P. P., Ametefe, V. W., Addabor, V. O., and Agbleze, K.: Flood and Drought Risk Mapping in Ghana, Five African Adaptation Program Pilot Districts, Final Report, Forestry Consulting Unit, Kumasi, Japan, 2012.

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

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

Beguería, S., Vicente-Serrano, S. M., and Angulo-Martínez, M.: A Multiscalar Global Drought Dataset: The SPEIbase: A New Gridded Product for the Analysis of Drought Variability and Impacts, B. Am. Meteorol. Soc., 91, 1351–1356, doi:10.1175/2010bams2988.1, 2010.

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., and Welle, T.: Framing vulnerability, risk and societal responses: the MOVE framework, Nat. Hazards, 67, 193–211, doi:10.1007/s11069-013-0558-5, 2013.

Blauhut, V. and Stahl, K.: Mapping drought risk in Europe, Drought R & SPI, Technical Report no. 27, http://www.eu-drought.org/technicalreports, last access: 1 July 2015.

Blauhut, V., Gudmundsson, L., and Stahl, K.: Towards pan-European drought risk maps?: quantifying the link between drought indices and reported drought impacts, Environ. Res. Lett., 10, 14008, doi:10.1088/1748-9326/10/1/014008, 2015a.

Blauhut, V., Stahl, K., and Kohn, I.: The dynamics of vulnerability to drought from an impact perspective, in: Drought: Research and Science-Policy Interfacing, edited by: Andreu, J., Solera, A., Paredes-Arquiola, J., Haro-Monteagudo, D., and van Lanen, H. A. J., CRC Press, London, 349–354, doi:10.1201/b18077-56, 2015b.

Cardona, O. D., Ordaz, M. G., Reinoso, E., Yamín, L. E., and Barbat, A.: CAPRA – comprehensive approach to probabilistic risk assessment: international initiative for risk management effectiveness, in: Proceedings of the 15th world conference of earthquake engineering, Lisbon, Portugal, 24–28, 2012.

Catry, F. X., Rego, F. C., Silva, J. S., Moreira, F., Camia, A., Ricotta, C., and Conedera, M.: Fire Starts and Human Activities, in: Towards Integrated Fire Management – Outcomes of the European Project Fire Paradox, edited by: Silva, J. S., Rego, F., Fernandes, P., and Rigolot, E., European Forest Institute, Porvo, Finland, 9–22, 2010.

Chopra, P.: Drought Risk Assessment Using Remote Sensing and GIS: A Case Study of Gujarat, ME thesis, Indian Institute of Remote Sensing, Dehradun & International Institute for Geo-information & Earth Observation, Enschede, the Netherlands, 2006.

Christensen, T. H., Ascarza, A., and Throndsen, W.: Country-specific factors for the development of household smart grid solutions. Comparison of the electricity systems, energy policies and smart grid R & D and demonstration projects in Spain, Norway and Denmark, ERA-Net Smart Grids project, "Integrating households in the smart grid", Copenhagen, Denmark, 2013.

Deems, H. and Bruggeman, A.: Vulnerability Index, The Cyprus Institute, https://www.cyi.ac.cy/system/files/DeemsBruggeman_Vulnerability_Index_handout_Jun2010.pdf (last access: 1 July 2015), 2010.

De Stefano, L., González-Tánago, I., Ballesteros, M., Urquijo, J., Blauhut, V., James, H., and Stahl, K.: Methodological approach considering different factors influencing vulnerability – pan-European scale, Drought R & SPI, Technical Report no. 26, http://www.eu-drought.org/technicalreports, last access: 1 July 2015.

Diaz-Caneja, M. B., Conte, C. G., Pinilla, F. J. G., Stroblmair, J., Catenaro, R., and Dittmann, C.: Risk Management and Agricultural Insurance Schemes in Europe, EUR-OP, Luxembourg, 2009.

Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., and Arnold, M.: Natural Disaster Hotspots – A Global Risk Analysis, Vol. 5, World Bank Publication, Washington, USA, 2005.

DWD: Drought conditions in Europe 2011, report, Issued by WMO RA VI Pilot RCC on Climate Monitoring, Lead Centre DWD, http://www.wmo.int/pages/mediacentre/news/drought_en.html (last access: 1 December 2015) 2011.

EC: Water Scarcity and Droughts, In-Depth-Assessment, Second Interim Report, Brussels, http://ec.europa.eu/environment/water/quantity/pdf/comm_droughts/2nd_int_report.pdf (last access: 1 July 2015) 2007.

EC: Drought Management Plan Report – Including Agricultural, Drought Indicators and Climate Change Aspects, Water Scarcity and Droughts Expert Network, Luxembourg, 2008.

EEA: Water resources across Europe: confronting water scarcity and drought, EEA Report No. 2/2009, Luxembourg, 2009.

EEA: The European environment – state and outlook 2010, Assessment of global megatrends, EEA, Luxembourg, 2010.

EEA: Water resources in Europe in the context of vulnerability, EEA Report No. 11/2012, European Environmental Agency (EEA), Copenhagen, 2012.

EEA: Water-2012-pressures_ Map_4.2, http://www.eea.europa.eu/data-and-maps/figures/proportion-of-classified-water-bodies/fig5-2-water-2012-pressures_map_4.eps (last access: 1 July 2015), 2014.

European Environmental Agency: Water exploitation index plus for river basin districts, http://www.eea.europa.eu/data-and-maps/figures/water-exploitation-index-based-on-1, last access: 11 July 2016.

Eurostat: Navigable inland waterways by carrying capacity of vessels, http://ec.europa.eu/eurostat/web/products-datasets/-/iww_if_infrastr, last access: 15 August 2015.

Flörke, M., Wimmer, F., Laaser, C., Vidaurre, R., Tröltzsch, J., Dworak, T., Stein, U., Marinova, N., Jaspers, F., Ludwig, F., Swart, R., Giupponi, C., Bosello, F., and Mysiak, J.: Final Report for the project Climate Adaptation – modelling water scenarios and sectoral impacts (ClimWatAdapt), Center for Environmental Systems Research (CESR), Kassel, Germany, 2011.

Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., and Lampin, C.: A review of the main driving factors of forest fire ignition over Europe, Environ. Manage., 51, 651–662, doi:10.1007/s00267-012-9961-z, 2013.

Gil, M., Garrido, A., and Gómez-Ramos, A.: Economic analysis of drought risk: An application for irrigated agriculture in Spain, Agr. Water Manage., 98, 823–833, doi:10.1016/j.agwat.2010.12.008, 2011.

González-Tánago, I., Urquijo, J., Blauhut, V., Villarroya, F., and De Stefano, L.: Learning from experience: a systematic review of assessments of vulnerability to drought, Nat. Hazards, 80, 951–973, doi:10.1007/s11069-015-2006-1, 2015.

Gosling, S., Lowe, J., McGregor, G., Pelling, M., and Malamud, B.: Associations between elevated atmospheric temperature and human mortality: a critical review of the literature, Climatic Change, 92, 299–341, doi:10.1007/s10584-008-9441-x, 2009.

Gregorič, G. and Sušnik, A.: Drought Management Centre for South Eastern Europe, in: Global Environmental Change: Challenges to Science and Society in Southeastern Europe, Springer Netherlands, Sofia, Bulgaria, 237–242, 2010.

Gudmundsson, L., Rego, F. C., and Seneviratne, S. I.: Predicting above normal wildfire activity in southern Europe as a function of meteorological drought, Environ. Res. Lett., 9, 084008, doi:10.1088/1748-9326/9/8/084008, 2014.

Han, L., Zhang, Q., Ma, P., Jia, J., and Wang, J.: The spatial distribution characteristics of a comprehensive drought risk index in southwestern China and underlying causes, Theor. Appl. Climatol., 124, 517–528, doi:10.1007/s00704-015-1432-z, 2015.

Hargreaves, G.: Defining and Using Reference Evapotranspiration, J. Irrig. Drain. Eng., 120, 1132–1139, 1994.

Harrell Jr., F. E.: Multivariable modeling strategies, in: Regression Modeling Strategies, Springer, New York, USA, 53–85, 2001.

Hayes, M.: Drought Indices, National Drought Mitigation Center, University of Nebraska-Lincoln, Lincoln, NE, 1998.

Hayes, M. J., Wilhelmi, O. V., and Knutson, C. L.: Reducing Drought Risk: Bridging Theory and Practice, Nat. Hazards Rev., 5, 106–113, 2004.

Heim, R. R.: A Review of Twentieth- Century Drought Indices Used in the United States, Am. Meteorol. Soc., 83.8, 1149–1165, 2002.

HEP: Annual Report 2009, HEP group, http://www.hep.hr/hep/en/publications/Annual/2009Annual.pdf (last access: 1 December 2015), 2009.

Hlavinka, P., Trnka, M., Semeradova, D., Dubrovský, M., Žalud, Z., and Možný, M.: Effect of drought on yield variability of key crops in Czech Republic, Agr. Forest Meteorol., 149, 431–442, 2009.

IPCC: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, edited by: Field, C. B., Barros, V., Stocker, T. F., and Dahe, Q., Cambridge University Press, Cambridge, 2012.

Jayanthi, H., Husak, G. J., Funk, C., Magadzire, T., Adoum, A., and Verdin, J. P.: A probabilistic approach to assess agricultural drought risk to maize in southern Africa and millet in Western Sahel using satellite estimated rainfall, Int. J. Disaster Risk Reduc., 10, 1–34, doi:10.1016/j.ijdrr.2014.04.002, 2014.

Jordaan, A. J.: Drought risk reduction in the Northern Cape, South Africa, PhD thesis, University of the Free State Bloemfontein, Bloemfontein, 2012.

Karavitis, C. A., Tsesmelis, D. E., Fassouli, V., Vasilakou, C. G., Oikonomou, D., Gregori, G., Grigg, N. S., and Vlachos, E. C.: Linking drought characteristics to impacts on a spatial and temporal scale, Water Policy, 16, 1–26, doi:10.2166/wp.2014.205, 2014.

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

Knutson, C. L., Hayes, M. J., and Phillips, T.: How to Reduce Drought Risk, Western Drought Coordination Council, Preparedness and Mitigation Working Group, National Drought Mitigation Center, Lincoln, Nebraska, 1998.

Kossida, M., Kakava, A., Tekidou, A., Iglesias, A., and Mimikou, M.: Vulnerability to Water Scarcity and Drought in Europe, European Topic Centre on inland, Coastal and Marine Waters (ETC/ICM), Prague, 2012.

Kulaglic, A., Berk, B., and Bagis, S.: Spatiotemporal Soil Moisture Estimation for Agricultural Drought Risk Management, in: Agro-Geoinformatics, 2013 Second International Conference on IEEE, edited by: Ministry of Food, Agriculture and Livestock and Istanbul Technical University, Istanbul, 76–81, 2013.

Lei, Y., Wang, J., and Luo, L.: Drought risk assessment of China's mid-season paddy, Int. J. Disaster Risk Sci., 2, 32–40, doi:10.1007/s13753-011-0009-4, 2011.

Lloyd-Hughes, B.: The impracticality of a universal drought definition, Theor. Appl. Climatol., 117, 607–611, doi:10.1007/s00704-013-1025-7, 2014.

Lloyd-Hughes, B. and Saunders, M. A.: A drought climatology for Europe, Int. J. Climatol., 22, 1571–1592, doi:10.1002/joc.846, 2002.

López-Moreno, J. I., Vicente-Serrano, S. M., Zabalza, J., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C., and Morán-Tejeda, E.: Hydrological response to climate variability at different time scales: A study in the Ebro basin, J. Hydrol., 477, 175–188, doi:10.1016/j.jhydrol.2012.11.028, 2013.

Lorenzo-Lacruz, J., Vicente-Serrano, S. M., López-Moreno, J. I., Beguería, S., García-Ruiz, J. and Cuadrat, J. M.: The impact of droughts and water management on various hydrological systems in the headwaters of the Tagus River (central Spain), J. Hydrol., 386, 13–26, doi:10.1016/j.jhydrol.2010.01.001, 2010.

Lung, T., Lavalle, C., Hiederer, R., and Bouwer, L. M.: Report on potential impact of climatic change on regional development and infrastructure (RESPONSES project deliverable D6.3), 7th Framework Programme RESPONSES project, European responses to climate change: deep emissions reductions and mainstreaming of mitigation and adaptation, Amsterdam, the Netherlands, 2011.

Mason, S. J. and Graham, N. E.: Areas beneath the relative operating characteristics (ROC) and relative operating levels (ROL) curves: Statistical significance and interpretation, Q. J. Roy. Meteorol. Soc., 128, 2145–2166, 2002.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, in: Proceedings of the 8th Conference on Applied Climatology, vol. 17, American Meteorological Society, Boston, MA, USA, 179–183, 1993.

Muukkonen, P., Nevalainen, S., and Lindgren, M.: Spatial occurrence of drought-associated damages in Finnish boreal forests?: results from forest condition monitoring and GIS analysis, Boreal Environ. Res., 20, 172–180, 2015.

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., and Vogt, J.: Exploring drought vulnerability in Africa: an indicator based analysis to be used in early warning systems, Hydrol. Earth Syst. Sci., 18, 1591–1604, doi:10.5194/hess-18-1591-2014, 2014.

Parry, S., Hannaford, J., Lloyd-Hughes, B, Prudhomme, C.: Multiyear droughts in Europe: analysis of development and causes, Hydrol. Res., 43, 689–706, 2012.

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

Pedro-Monzonís, M., Solera, A., Ferrer, J., Estrela, T., and Paredes-Arquiola, J.: A review of water scarcity and drought indexes in water resources planning and management, J. Hydrol., 527, 482–493, 2015.

Pelling, M. and Uitto, J. I.: Small island developing states: natural disaster vulnerability and global change, Global Environ. Change Pt. B, 3, 49–62, 2001.

Potop, V.: Evolution of drought severity and its impact on corn in the Republic of Moldova, Theor. Appl. Climatol., 105, 1–15, doi:10.1007/s00704-011-0403-2, 2011.

Potopová, V., Štěpánek, P., Možný, M., Türkott, L., and Soukup, J.: Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic, Agr. Forest Meteorol., 202, 26–38, 2015.

Quijano, J. A., Jaimes, M. A., Torres, M. A., Reinoso, E., Castellanos, L., Escamilla, J., and Ordaz, M.: Event-based approach for probabilistic agricultural drought risk assessment under rainfed conditions, J. Int. Soc. Prev. Mitig. Nat. Hazards, 76, 1297–1318, doi:10.1007/s11069-014-1550-4, 2014.

Rossi, G. and Cancelliere, A.: Managing drought risk in water supply systems in Europe: a review, Int. J. Water Resour. Dev., 29, 272–289, doi:10.1080/07900627.2012.713848, 2012.

Rossi, S. and Niemeyer S.: Monitoring droughts and impacts on the agricultural production: Examples from Spain, in: Economics of drought and drought preparedness in a climate change context, Options Méditerranéennes Série A, Séminaires Méditerranéens; no. 95, edited by: López-Francos, A., CIHEAM/FAO/ICARDA/GDAR/CEIGRAM/MARM, Zaragoza, Spain, 35–40, 2010.

Royal Geographical Society (with IBG): Water policy in the UK: The challenges, RGS-IBG Policy Briefing, http://eprints.lancs.ac.uk/56158/1/RGS_IBG_Policy_Document_Water_7_32pp.pdf (last access: July 2016), 2012.

San-Miguel, J. and Camia, A.: Forest fires at a glance: facts, figures and trends in the EU, in Living with Wildfires: what science can tell us, A contribution to the Science-Policy dialogue, EFI Discussion Paper 15, European Forest Institute, Joensuu, Finland, 2009.

Schindler, U., Steidl, J., Müller, L., Eulenstein, F., and Thiere, J.: Drought risk to agricultural land in Northeast and Central Germany, J. Plant Nutr. Soil Sci., 170, 357–362, doi:10.1002/jpln.200622045, 2007.

Sepulcre-Canto, G., Horion, S., Singleton, A., Carrao, H., and Vogt, J.: Development of a Combined Drought Indicator to detect agricultural drought in Europe, Nat. Hazards Earth Syst. Sci., 12, 3519–3531, doi:10.5194/nhess-12-3519-2012, 2012.

Skakun, S., Kussul, N., Kussul, O., and Shelestov, A.: Quantitative estimation of drought risk in Ukraine using satellite data, in: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Quebec, Canada, 5091–5094, 2014.

Smit, B. and Wandel, J.: Adaptation, adaptive capacity and vulnerability, Global Environ. Change, 16, 282–292, doi:10.1016/j.gloenvcha.2006.03.008, 2006.

Spinoni, J., Naumann, G., Vogt, J., and Barbosa, P.: European drought climatologies and trends based on a multi-indicator approach, Global Planet. Change, 127, 50–57, doi:10.1016/j.gloplacha.2015.01.012, 2015.

Stagge, J. H., Tallaksen, L. M., Kohn, I., Stahl, K., and Van Loon, A. F.: European drought reference (EDR) database: design and online implementation, Drought R & SPI, Technical Report no. 12, http://www.eu-drought.org/technicalreports (last access: 1 December 2015), 2013.

Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., and Stahl, K.: Candidate Distributions for Climatological Drought Indices (SPI and SPEI), Int. J. Climatol., 35, 4027–4040, doi:10.1002/joc.4267, 2015a.

Stagge, J. H., Kohn, I., Tallaksen, L. M., and Stahl, K.: Modeling drought impact occurrence based on climatological drought indices for four European countries, J. Hydrol., 530, 37–50, doi:10.1016/j.jhydrol.2015.09.039, 2015b.

Stahl, K., Stagge, J. H., Bachmair, S., Blauhut, V., Rego, F. C., Stefano, D., Dias, S., Gudmundsson, L., Gunst, L., Kohn, I., Van Lanen, H. A. J., Reguera, U., and Tallaksen, L. M.: Recommendations for indicators for monitoring and early-warning considering different sensitivities: Pan-European scale, Drought R & SPI, Technical Report no. 28, http://www.eu-drought.org/technicalreport, last access: 1 December 2015.

Stahl, K., Kohn, I., Blauhut, V., Urquijo, J., De Stefano, L., Acácio, V., Dias, S., Stagge, J. H., Tallaksen, L. M., Kampragou, E., Van Loon, A. F., Barker, L. J., Melsen, L. A., Bifulco, C., Musolino, D., de Carli, A., Massarutto, A., Assimacopoulos, D., and Van Lanen, H. A. J.: Impacts of European drought events: insights from an international database of text-based reports, Nat. Hazards Earth Syst. Sci., 16, 801–819, doi:10.5194/nhess-16-801-2016, 2016.

Stone, R. C. and Potgieter, A.: Drought Risk and vulnerability in rainfed agriculture- Example of a case study from Australia, Options Mediterr. A, 80, 29–40, 2008.

Strosser, P., Dworak, T., Garzon Delvaux, P. A., Berglund, M., Schmidt, G., Mysiak, J., Kossida, M., Iacovides, I., and Ashton, V.: Final Report Gap Analysis of the Water Scarcity and Droughts Policy in the EU European Commission, European Commission, 2012.

Svoboda, M., Lecomte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., and Stephens, S.: Drought Monitor, B. Am. Meteorol. Soc., 83, 1181–1190, 2002.

Swain, M. and Swain, M.: Vulnerability to Agricultural Drought in Western Orissa: A Case Study of Representative Blocks, Agr. Econ. Res. Rev., 24, 47–56, 2011.

Tallaksen, L. M. and Stahl, K.: Spatial and temporal patterns of large-scale droughts in Europe: model dispersion and performance, Geophys. Res. Lett., 41, 429–434, 2014.

Tsakiris, G., Vangelis, H., and Tigkas, D.: Drought impacts on yield potential in rainfed agriculture, Options Méditerranéennes. Séries A, Mediterr. Semin., 197, 191–197, 2010.

Venables, W. N. and Ripley, B.: Modern Applied Statistics with S, Springer, Berlin, 2002.

Vicente-Serrano, S. M., Beguería, S. and López-Moreno, J. I.: A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index, J. Climate, 23, 1696–1718, doi:10.1175/2009jcli2909.1, 2010.

Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J. J., López-Moreno, J. I., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., and Sanchez-Lorenzo, A.: Performance of Drought Indices for Ecological, Agricultural, and Hydrological Applications, Earth Interact., 16, 1–27, doi:10.1175/2012ei000434.1, 2012.

Vogt, J., Barbosa, P., Hofer, B., Magni, D., Jager, A. D., Singleton, A., and Horion, S.: Developing a European drought observatory for monitoring, assessing and forecasting droughts across the European continent, AGU Fall Meeting Abstracts, vol. 1, p. 07, 2011.

Wilhelmi, O. V and Wilhite, D. A.: Assessing Vulnerability to Agricultural Drought: A Nebraska Case Study, Nat. Hazards, 25, 37–58, 1997.

Wilhite, D. A.: Droughts as a natural hazard: concepts and definitions, in: Drought, a Global Assessment, vol. 1, Routledge, London, 3–18, 2000.

Wilhite, D. A. and Glantz, M. H.: Understanding: the Drought Phenomenon: The Role of Definitions, Water Int., 10, 111–120, doi:10.1080/02508068508686328, 1985.

Wilhite, D. A., Svoboda, M. D., and Hayes, M. J.: Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness, Water Resour. Manage., 21, 763–774, doi:10.1007/s11269-006-9076-5, 2007.

Wilks, D. S.: Statistical methods in the atmospheric sciences, 2nd Edn., International Geophysics Series, Vol. 100, 2011.

Yin, Y., Zhang, X., Lin, D., Yu, H., Wang, J., and Shi, P.: GEPIC-V-R model: A GIS-based tool for regional crop drought risk assessment, Agr. Water Manage., 144, 107–119, doi:10.1016/j.agwat.2014.05.017, 2014.

Zargar, A., Sadiq, R., Naser, B., and Khan, F. I.: A review of drought indices, Environ. Rev., 19, 333–349, doi:10.1139/a11-013, 2011.

Zhang, D., Wang, G., and Zhou, H.: Assessment on agricultural drought risk based on variable fuzzy sets model, Chinese Geogr. Sci., 21, 167–175, doi:10.1007/s11769-011-0456-2, 2011.

Zuur, E., Walker, N., Saveliev, A., and Smith, G.: Mixed effects models and extensions in ecology with R Statistics for Biology and Health, Springer, New York, 2009.