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 (1) 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 (2) 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. (1) The results indicate sector- and macro region specific sensitivities of drought indices, with the Standardised Precipitation Evapotranspiration Index (SPEI) for a twelve month accumulation period as the overall best hazard predictor. Vulnerability factors have only limited ability to predict drought impacts as single predictor, with information about landuse and water resources being the best

vulnerability-based predictors. (2) The application of the "hybrid approach" revealed strong regional and sector specific differences in drought risk across Europe. The majority of best predictor combinations rely on a combination of SPEI for shorter and longer accumulation periods, and a combination of information on landuse 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, current practice of drought indices selection for specific application, 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 Glanz 1985); or by its consequences on socio-economic and environmental systems, i.e. its negative impacts (Blauhut et. al 2015a). These impacts can either be direct (e.g. reduced yields) or indirect (e.g. increased costs for food due to reduced 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 Report Inventory (EDII) across fifteen different impact categories from agriculture to water quality (Stahl et al. 2016) and financial losses over the last three decades were estimated to over 100 billion Euros (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 Calamities Funds, Mutual Funds and Insurances (Diaz-Caneija, 2009). Nevertheless, today's scientific consensus points to the need to move from a re-active to a pro-active risk management strategy (Wilhite et al. 2007). Rossi and Cancelliere (2012) stated that an advanced assessment of drought must include firstly, an investigation of socio-economic and environmental impacts, secondly, multi criteria 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 socio-ecological 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. 2013, Karavitis et al. 2014) contribute to an overall classification of vulnerability. Based on their review of 46 drought factor-based vulnerability assessments, Gonzalez-Tanago 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 (Gonzalez-Tanago 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 (Gonzales Tanago et al., 2015). Only few studies validate their results, among them, Aggett (2012), Naumann et al. (2013), 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 Standardised Precipitation and Evapotranspiration Index. 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. (2015a) 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 2000, 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 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 South-eastern 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. (2015b) 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 arbitrary chosen hazard index thresholds such as those selected for the Standardized Precipitation Index SPI (-1.5<SPI<-1: moderate drought, -2<SPI<-1.5: severe drought, 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 socio-economic 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 resources (water availability) conditions (Jayanthi et al.2014, Stone and Potgieter 2008; Schindler et al. 2007). Stagge et al. (2015b) and Bachmair et al. (2015a) 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 an European assessment by De Stefano et al. (2015), who considered several physical and socio-economic 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,

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

This study addresses these aims through statistical modeling (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 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 European Drought Impact Report Inventory, 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 (Figure 1, right), 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 of impact occurrence and shows significant differences between European macro regions. 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 Western-Mediterranean (342), Southeastern Europe (283) and Northeastern Europe (62). The highest numbers for drought impact entries by NUTS-combo level (Figure 1, left) are available for southern UK, Central Europe and the south- western 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-dataset (Stahl et al., 2016), we followed Blauhut et al. (2015a) and: a) created binary datasets (occurrence/ absence of impact reports) from 1970-2012 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 2/3). By contrast, EDII-entries for Northeastern Europe are strongly dominated by academic work and the media (~ 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 study 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 Jr 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 European Drought Observatory (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 (Figure 1, right panel) by taking the mean of gridded values.

Among the single indices, the most widely accepted meteorological drought index is the Standardized Precipitation Index (SPI, McKee et al., 1993). It is recommended by the WMO and is therefore applied widely in Europe for drought identification (e.g. Gregorič, G., and Sušnik, A., 2010; Vogt et al., 2011; Stagge et al., 2015a). As introduced by McKee et al. (1993) "the SPI is the transformation 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 multi-year drought). Nevertheless, the SPI has limited interpretability for short accumulation periods (<2 months) in dry regions where monthly precipitation is often near zero (Stagge et al. 2015a). For this study we used gridded monthly aggregated precipitation from the E-OBS-9 dataset 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 1970-2010. Subsequently, the gridded monthly SPI values were spatially aggregated by averaging all grid cells within each NUTS-combo level.

The Standardised Precipitation Evapotranspiration Index (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 1970-2010. 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 European Drought Observatory (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 to 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. 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 months accumulation periods, ΔpF, and ΔfAPAR with adjusted time lags. It results in four increasingly severe drought states: “Watch”, “Warning”, ”Alert”,”Alert2” , as well as two recovery states: ”Partial recovery”, “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: the extent to which a unit of assessment falls within the geographical range of a hazard event (Birkmann et al. 2013)
- Sensitivity: the occupance and livelihood characteristics of the system (Smit and Wandel 2006)
- Adaptive capacity: particular asset bundles for risk reduction (Pelling 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 dataset, 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 dataset with data for multiple time steps were available. Thus, the CORINE Landcover datasets for 1990, 2000, and 2006 were added to the dataset. These data stem mainly from Eurostat (Statistical office of the European Communities, 1990) 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) was expressed as 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 datasets are listed multiple times, as they were created for different spatial aggregations (e.g. 'Population density' for NUTS-2 or country level), for different timesteps (e.g. 'Water use' for single or multiple timesteps), 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').

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

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, Steps 2-5 employed a stepwise selection process to evaluate the best performing combination of five possible predictors in a multivariable logistic regression model. Finally, Step 6 applied the best multivariate models for selected hazard level scenarios to create pan-European drought risk maps.

First, 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) (Equation 1)

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

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 (GLM) (Harrel 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 $A_{ROC} > 0.5$ 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_{ROC} >0.7 are considered 'good' model performance ('**'), while significant predictors with A_{ROC} >0.9 are considered 'excellent' model performance ('***').

Second, the approach was expanded by stepwise model building to include 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 *(Equation 2)*.

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

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 Generalised Linear Models (Harrel 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 pre-determined combinations of individual factors that might also enter the model as predictors, resulting in multicollinearity.

In Step 1, 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}. In Step 2, 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.

Steps 3-5 then add additional predictors from the pool of vulnerability factors. Up to three vulnerability factors are included in a stepwise fashion based on the same criteria. Proceeding as in Step 2, 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.

Lastly, 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, -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, ΔfAPAR is inspired by the definition of McKee(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 best performing combination of predictors for fifteen impact categories and for three hazard levels. For countries with a lack of sufficient vulnerability data (Table S1), LIO was estimated using the best hazard-only model.

4 Results

4.1 Distribution of drought impacts and impact characteristics

The majority of the reported drought impacts occurred during well-known major drought events: 1975-1976 in Central Europe, 1991-95 in the Mediterranean, 2003 in 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 2010-12 in the United Kingdom (Kendon et al. 2013; Parry et al. 2013), the European drought of 2011 (DWD 2011), and the 2011-12 drought in Southeastern Europe (Spinoni et al. 2015). The highest number of reports is represented by the drought events of: '1975-76 Europe', '2003 Europe' and '2010-12 United Kingdom'.

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 one 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 European Drought Observatory, 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 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 6-12 month aggregation time. 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 follow similar performance pattern, but less strong, as for 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 landuse and are based on multiple timesteps, 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 best performing MLRMs (Step 2, ref. section 3).

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

Out of the final 44 best-performing multivariable logistic regression models, MLRM, , 18 models used the maximum of three vulnerability predictors, 14models use two, nine models only one, and three 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 'Forests' 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 to -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 best model performance (with short-, mid-, and long-term corresponding to 1-3, 4-9, and 12-24 month accumulation periods). 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 three times five sectors (figures and columns) and three 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, 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); North-East Italy, 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 hot spots in Portugal, Croatia, Southeastern Germany (Bavaria) and Central France (Centre). 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 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 Western-Mediterranean and Germany, Switzerland, Netherlands and South East 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 Shakun et al. (2014), fAPAR proved its usage as 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-Cantó et al.

(2012), suggest that further studies should explore possible reasons for this poor performance, e.g. through further sector specific data stratification.

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 twelve 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 U.S. Geological Survey as Oct 1-Sep 30, 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-Tanago 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 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 multivariable 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 three to twelve months generally performed best, depending on the region and impact. These results confirmed previous case studies on 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 versus rain-fed agriculture. Whereas impacts on rainfed 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 Potopováa 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 two month 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 ground water 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 (≥SPEI-9). Impacts on 'Public Water Supply' are generally poorly predicted by SPEI. 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 pattern, 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 multi-year drought, does not allow an identification of the onset, duration and ending of a given drought impact. The annual time scale 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 a such influence the model performance obtained (Blauhut et al. 2015a).

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., 2015a; 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 North. 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. 2015a. 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 2007a, 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 ~55% hydropower sources and ~45 % by thermal power plants (HEP 2009) and Bavaria (and also France) has several nuclear powerplants. Quite contrary, 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 (Batterbee et al. 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 contains reports that have been 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 Sea 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 and 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, 2015).

The presented hazard severity levels are based on an arbitrary choice inspired by McKee (1998) and cannot be used as fixed threshold. In accordance with Blauhut et al. (2015a) and Stagge (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., 2015a), 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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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 South Eastern 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 Evapo-transpiration	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 Center	monthly ; annual maximum; 2001-2014

Table 1 Factors used to assess vulnerability

Vulnerability factor	Scale	Multiple timesteps	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 & skilled people	NUTS-2		✓	✓	De Stefano et al. (2015)
Innability 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. permant 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
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: 100m			✓	European Soil Database
Population density N2	NUTS-2			✓	Eurostat
Population density by country	Country	✓		✓	Eurostat
Population density & 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 timesteps: vulnerability data has been available for different timesteps or only the most recent state of the system. Composed: vulnerability factors is a composition of different data as. Applied to MLRM: Factor has been analysed in multivariable logistic regression models (Step two) as possible best performing predictor for impact detection. A= Area of, SR= socioeconomic relevance, WR = water use relevance, A= adaptive capacity, S= sensitivity, NC= NUTS-combo region, N2= NUTS-2 region, RBD= river basin district, MLRM= multivariable logistic regression model

Table 2, MLRM performance of models with hazard predictors only and performance improvement (Δ) with added vulnerability factors

	Maritime Europe						**Southeastern Europe**						**Northeastern Europe**						**Western-Mediterranen**					
	Hazard			Vulnerability			Hazard			Vulnerability			Hazard			Vulnerability			Hazard			Vulnerability		
IC	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 = 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, H&P: Human Health and Public Safety, Co: Conflicts.

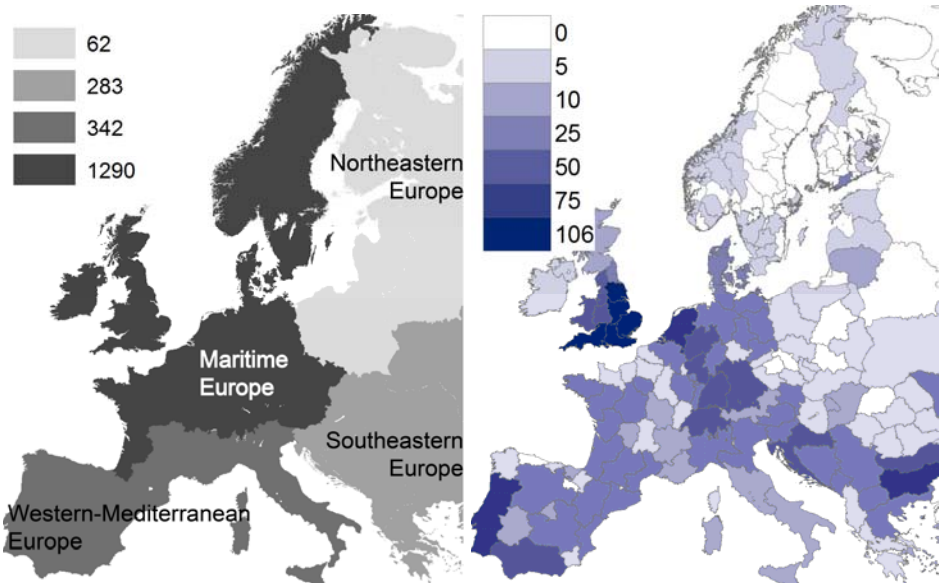

Figure 1: Number of annual aggregated NUTS-combo scale impacts reported and archived in the European Drought Impact report Inventory (EDII) by European macro region (left panel) and by NUTS-combo region (right panel)

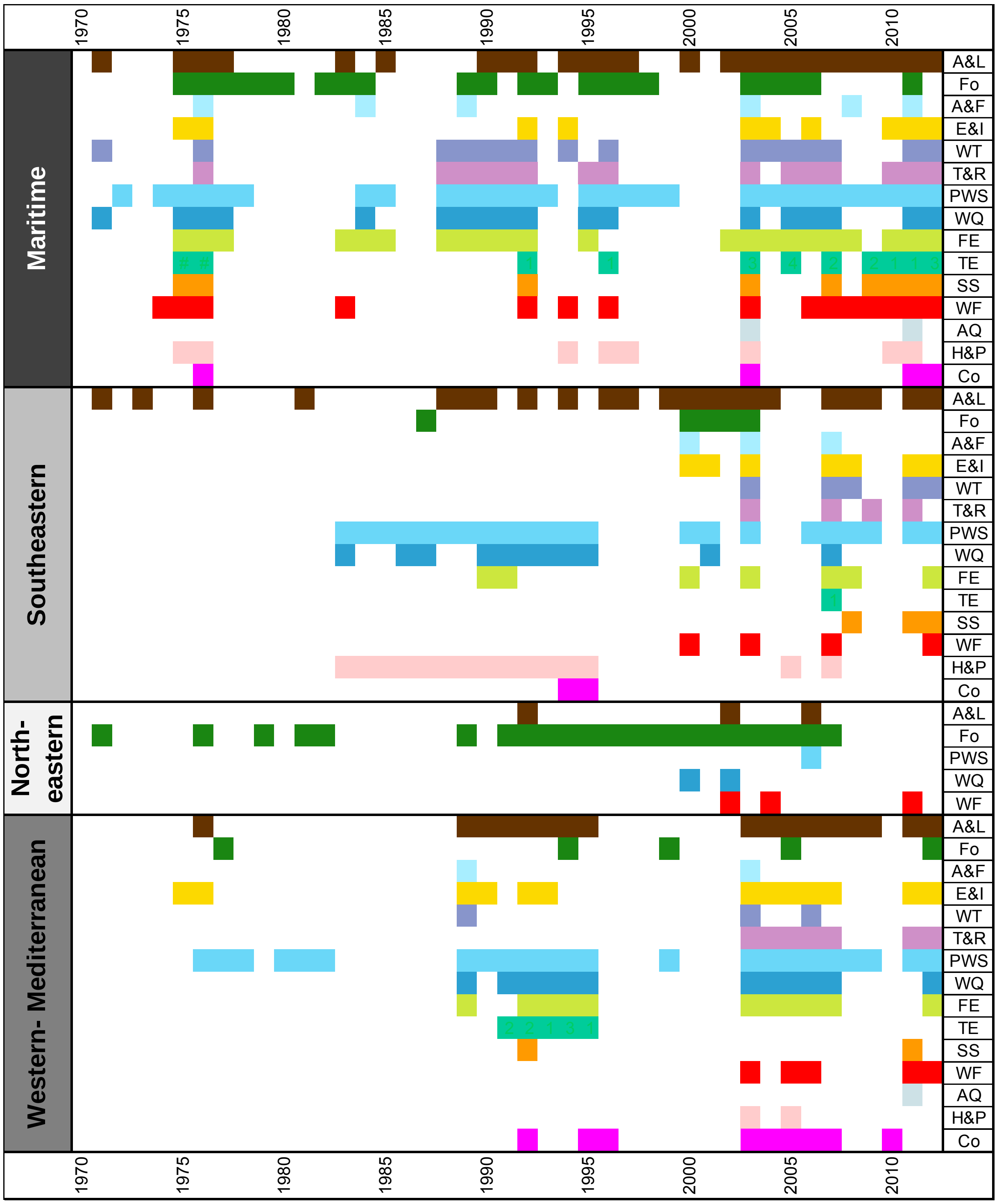

Figure 2 Annual drought impact occurrence by European macro region and impact category

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.

	Impact category	Hazard		Vulnerability		
		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 best performing predictors, yellow: SPEI with short temporal accumulation, light yellow to brown: SPEI with increasing temporal aggregation (short-, medium-, with 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

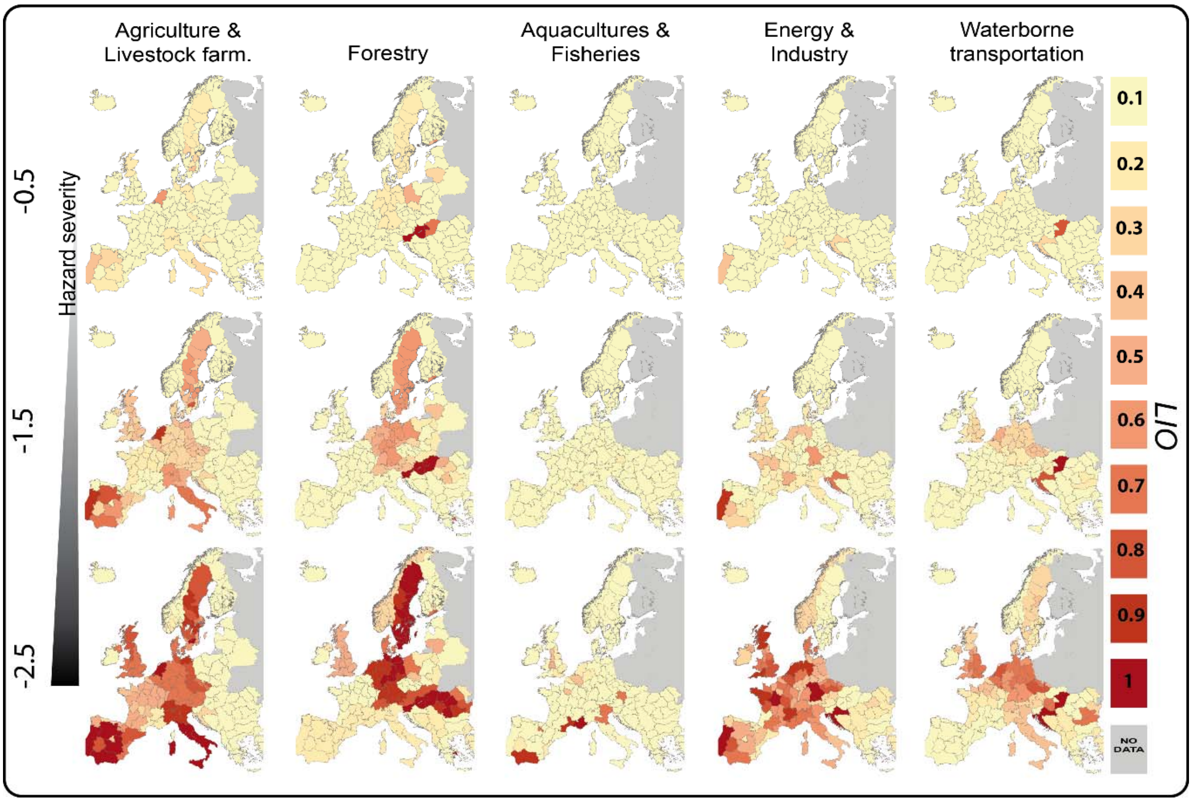

Figure 4 Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Agriculture and Livestock Farming, Forestry, Aquaculture and Fisheries, Energy and Industry, and Waterborne transportation (columns) for three hazard levels of SPEI with -0.5: 'near normal', -1.5: 'severely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

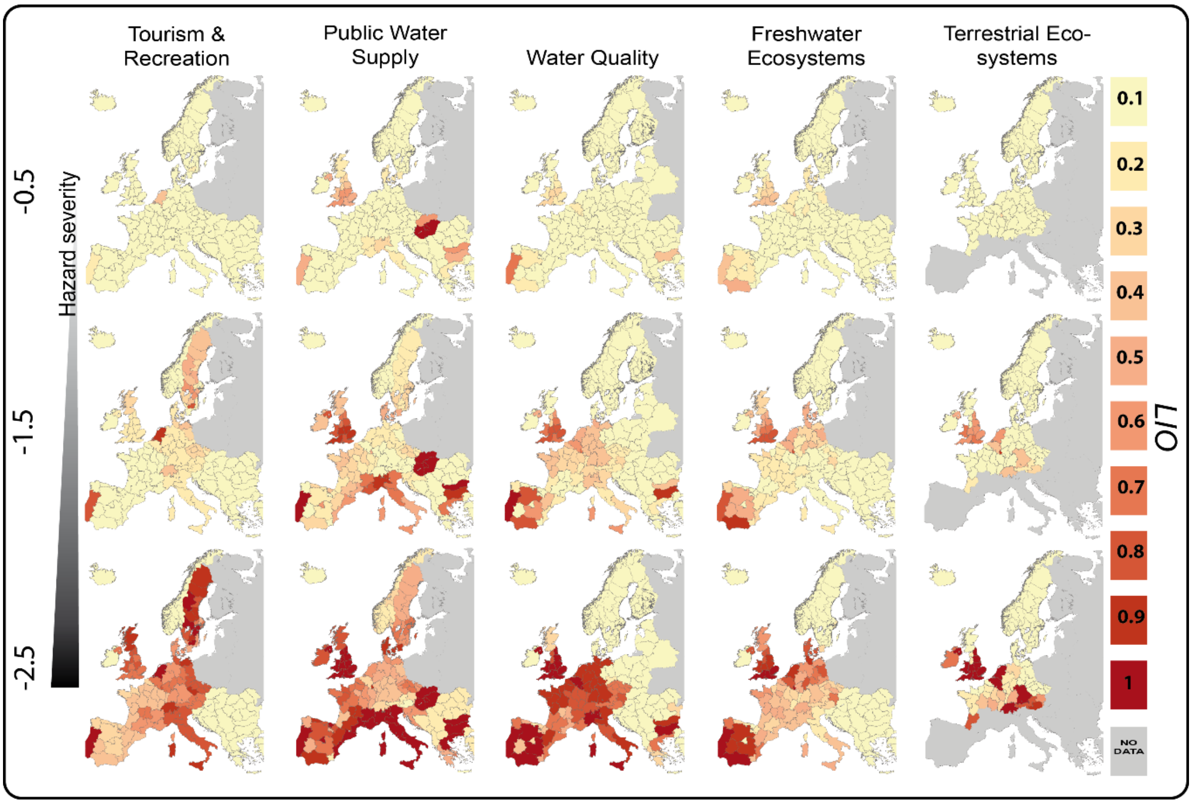

Figure 5 Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Tourism and Recreation, Public Water Supply, Water Quality, Freshwater Ecosystems and Terrestrial Ecosystems (columns) for three hazard levels of SPEI with -0.5: ‘near normal’, -1.5: ‘severely dry’, -2.5: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

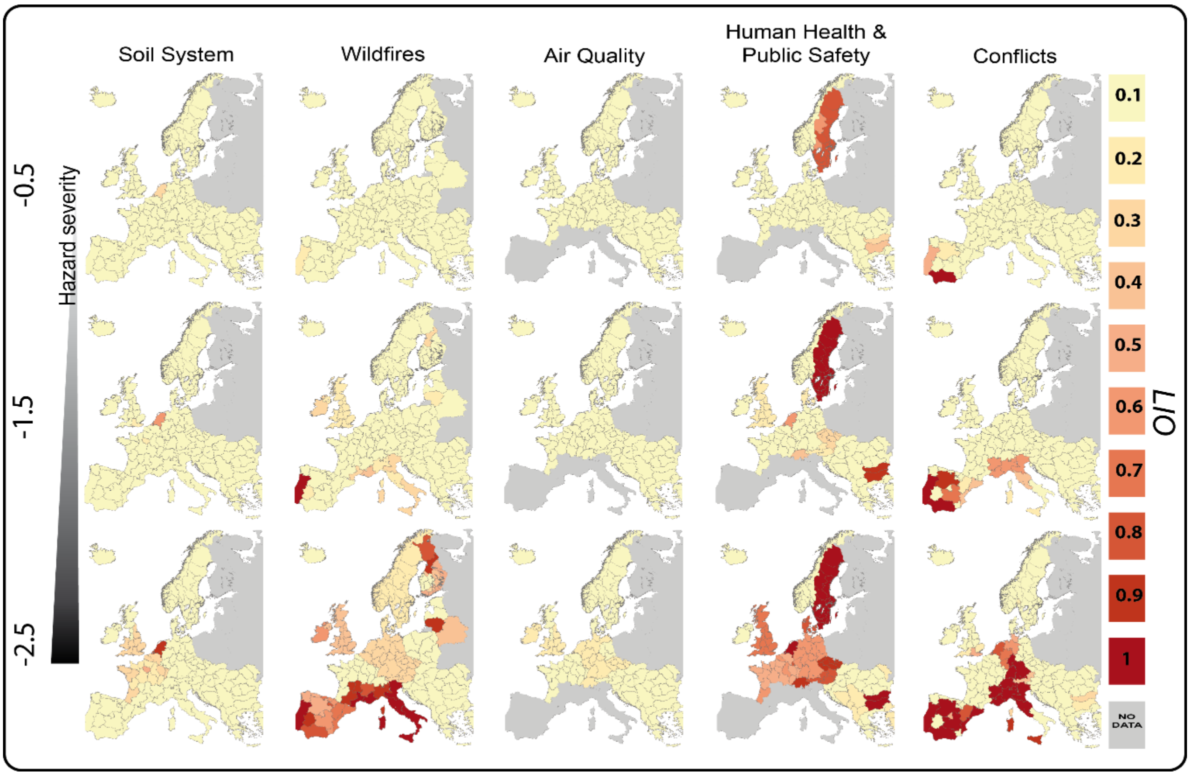

Figure 6, Drought risk maps with the likelihood of impact occurrence (LIO) in the impact categories Soil System, Wildfires, Air Quality, Human Health and Public Safety and Conflicts; (columns) for three hazard levels of SPEI with -0.5: ‘near normal’, -1.5: ‘severely dry’, -2.5: ‘extremely dry’ (rows).