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To cite this article: Anastasiya Shyrokaya *et al* 2024 *Environ. Res. Lett.* **19** 014037

ENVIRONMENTAL RESEARCH
LETTERS

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RECEIVED
13 July 2023

REVISED
17 November 2023

ACCEPTED FOR PUBLICATION
29 November 2023

PUBLISHED
11 December 2023

LETTER

Significant relationships between drought indicators and impacts for the 2018–2019 drought in Germany

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Keywords: drought, drought indicators, impacts of drought, 2018–2019 European drought, drought early warning systems

Supplementary material for this article is available online

Abstract

Despite the scientific progress in drought detection and forecasting, it remains challenging to accurately predict the corresponding impact of a drought event. This is due to the complex relationships between (multiple) drought indicators and adverse impacts across different places/hydroclimatic conditions, sectors, and spatiotemporal scales. In this study, we explored these relationships by analyzing the impacts of the severe 2018–2019 central European drought event in Germany. We first computed the standardized precipitation index (SPI), the standardized precipitation evaporation index (SPEI), the standardized soil moisture index (SSMI) and the standardized streamflow index (SSFI) over various accumulation periods, and then related these indicators to sectorial losses from the European drought impact report inventory (EDII) and media sources. To cope with the uncertainty associated with both drought indicators and impact data, we developed a fuzzy method to categorize them. Lastly, we applied the method at the region level (EU NUTS1) by correlating monthly time series. Our findings revealed strong and significant relationships between drought indicators and impacts over different accumulation periods, albeit in some cases region-specific and time-variant. Furthermore, our analysis established the interconnectedness between various sectors, which displayed systematically co-occurring impacts. As such, our work provides a new framework to explore drought indicators-impacts dependencies across space, time, sectors, and scales. In addition, it emphasizes the need to leverage available impact data to better forecast drought impacts.

1. Introduction

Central Europe experienced a severe drought during 2018–2019, whose two-year severity is likely unprecedented over the past two centuries (Hari *et al* 2020, Blauhut *et al* 2021). This event was exceptional because of both rainfall deficit and high temperatures increasing evaporation in many central European countries (Rosner *et al* 2019), leading to significant impacts on agriculture, farming and forestry in northern, central and eastern Europe (Bakke *et al* 2020, Beillouin *et al* 2020, de Brito *et al* 2020, Schuldt *et al* 2020, Bastos *et al* 2021, Blauhut *et al* 2021, Hofmann *et al* 2022). This led to some countries declaring a state of emergency (Rosner *et al* 2019). The extent of ecosystem damage and crop yield losses made the central European 2018–2019 drought a new reference event for drought risk management in central Europe (Toreti *et al* 2019, de Brito *et al* 2020, Mastrotheodoros *et al* 2020).

Drought is a complex hazard, which remains poorly understood (Quandt 2021). Its general characteristics, slow onset, prolonged duration, large spatiotemporal extent, and transboundary effects have made it difficult for researchers to define the hazard, monitor, and ensure the reduction of impacts (Sen 2015, Van Loon *et al* 2016, Hall and Leng 2019, Funk and Shukla 2020, Kreibich *et al* 2020, Tijdeman *et al* 2021). The impacts of drought are challenging to quantify because of the slow onset, lagged effects, and non-structural nature of drought events (Hall and Leng 2019, Funk and Shukla 2020, Kreibich *et al* 2020, Tijdeman *et al* 2021). Given these characteristics, drought impacts must be examined comprehensively by geographic region, temporal dimension and affected sector. Consequently, there is a lack of specific impact data solely attributed to droughts, with commonly utilized sources including agricultural statistics, insurance data, impacts bulletins (Lam *et al* 2022) and media reports (Blauhut *et al* 2015, Stagge *et al* 2015, Stahl *et al* 2016, Sutanto *et al* 2019, de Brito *et al* 2020, Torelló-Sentelles and Franzke 2021, O'Connor *et al* 2022). This research leverages media-based sources for impact data due to their capacity to encompass a wide range of drought impacts across various sectors and to provide a measure of impact severity without a near-exclusive focus on monetary metrics, as is common in economic or other conventional measures of drought impact. However, it is important to recognize that media reporting may introduce biases in terms of frequency and coverage of drought impacts in different regions. To mitigate this bias, this study normalizes the number of media resources per region and employs a fuzzy approach to ensure accurate representation of the impact magnitude.

Besides the data gap related to drought impacts, the indicators that serve to detect, monitor and forecast drought events, exhibit a number of limitations, including the choice of a reference period and probability distribution function to calculate the indicators. Furthermore, the link between drought hazards and impacts is still insufficiently understood (Sutanto *et al* 2020, Kchouk *et al* 2021). As a result, drought early warning systems (DEWSs) are currently based on physical or statistical drought indicators with no explicit link to impacts (Wanders *et al* 2017). This gap of understanding hinders preparedness and timely distribution of relief and mitigation resources to the potentially-affected sectors and areas (Merz *et al* 2020, WMO, 2021).

This study aims to fill in this gap by advancing our understanding of the relationships between drought indicators and impacts for various sectors and across different regions, focusing specifically on the case of the 2018–2019 drought event in Germany.

To this end, we first developed a fuzzy method to address the uncertainty unavoidably associated with calculation of both drought indicators and adverse impacts. Secondly, we conducted cross-correlation analysis to identify: (1) the highest and most significant/lowest and not-significant correlations between different indicators and impacts over various accumulation periods, and (2) region-specific and time-variant differences in indicator-impact relationships across multiple affected sectors. Lastly, we analysed the interconnections among sectors and identified which impacts tend to occur simultaneously in different sectors. Given the simultaneous impact of droughts on multiple sectors and their interdependencies within our complex system, it is crucial to unravel these connections to enable effective and targeted drought management (Vogt *et al* 2018, de Brito *et al* 2020).

These findings are expected to contribute to the field of impact-based forecasting (IbF), which aims to predict the impact of hazards on weather-sensitive sectors (Sutanto *et al* 2019, Boult *et al* 2022, Shyrokaya *et al* 2023). While the hazard itself can only rarely be entirely avoided, drought monitoring and early warning systems based on IbF can reduce potential losses by providing more lead time for responding to drought, anticipating and avoiding potential damage (AghaKouchak *et al* 2022).

2. Data and methods

2.1. Study area

Our research work focuses on Germany's geographical borders during the 2018–2019 central European drought event for several reasons. Firstly, the country provides consistent information about the impacts of drought for several regions across different hydroclimatic conditions. Secondly, the country has a diverse range of developed drought-sensitive sectors that allow tracking various impacts. Thirdly, Germany was the most affected country in central Europe by the 2018–2019 drought event (Toreti *et al* 2019, Mastrotheodoros *et al* 2020), with impacts over 90% of its territory across multiple sectors (de Brito 2021). Lastly, a significant part of our analysis relies on media-based information on drought impact provided by the European drought impact report inventory (EDII) database (Stahl *et al* 2016), which offers comprehensive information on the impacts of the drought event, particularly for Germany. This is partly due to the country's diverse and independent media sources, allowing for an accurate and detailed collection of impact information.

2.2. Drought indicators

Germany has a wide network of global and national tools that allow for detecting, monitoring, and forecasting droughts across various temporal and spatial scales. Among them, the observational dataset E-OBS and the European flood awareness system (EFAS) jointly offer precipitation, temperature, soil moisture and discharge data to monitor drought conditions in Germany. The European drought observatory (EDO) run by the EC's Joint Research Centre covers Germany and provides various already computed drought indicators to assess the ongoing conditions of different types of droughts. On the national level, the German weather service (DWD) and the UFZ drought monitor service (Zink *et al* 2016) provide daily drought information for multiple soil layers throughout Germany.

In this study, we employed common drought indicators standardized precipitation index (SPI) (McKee *et al* 1993) and standardized precipitation evaporation index (SPEI) (Vicente-Serrano *et al* 2010), which are recognized as standard (WMO 2016) and are further widely used in DEWS (Bachmair *et al* 2016). The main difference in the calculation of the two indicators is that SPI is based on precipitation data, whereas SPEI accounts for potential evapotranspiration by including temperature data (Vicente-Serrano *et al* 2010). The indicators were derived from the E-OBS gridded dataset with observational precipitation and temperature data (v27.0, 0.25° spatial resolution $\sim$27 km) for the period 1980–2022. For the purpose of our analysis, we first averaged precipitation and evapotranspiration data over NUTS1 (nomenclature of territorial units for statistics) administrative regions across Germany. We then estimated SPI and SPEI per each NUTS1 and considered accumulation periods of 1, 3, 6, 12 and 24 months for 2018 and 2019, obtained by applying a corresponding moving average to monthly timeseries. Different accumulation periods serve to assess different potential impacts: short periods reflect immediate impacts like soil moisture reduction, while longer ones unveil delayed impacts, including groundwater recharge rate, further influenced by local factors and human activity (EDO 2020). For detailed information on the calculation of the indices (e.g. fitting distributions, reference period etc), please refer to SM1 in the supplementary material.

We obtained volumetric soil moisture for both the top and middle soil layers, as well as discharge data from the EFAS service, to calculate drought indicators standardized soil moisture index (SSMI1), SSMI2 and standardized streamflow index SSFI (SSFI_sim), respectively. This is historical gridded simulated data provided at a 5×5 km resolution, spanning from 1991 to 2022 based on the LISFLOOD hydrological model setup (Mazzetti *et al* 2020). We then applied the same methodology as for SPI and SPEI to obtain the modeled-based SSMI and SSFI_sim indices for different regions and over the same accumulation periods ranging from 1 to 24 months.

Moreover, we utilized monthly streamflow values from 46 hydrological stations (figure 1(a)) obtained from the global runoff data center (GRDC) to additionally calculate drought indicator SSFI (SSFI_obs) for the same period (1991–2022) and with the same accumulation periods. To attribute each station to a specific region, we acquired a shapefile of the basin for each station from the respective GRDC website and weighted each station by the area of its basin intersecting different regions (figure 1(b)). Finally, we associated each region with all relevant stations according to the above weighting procedure.

2.3. Drought impact data

To conduct a comprehensive analysis, we compiled data on the impacts of drought during the entire duration of the drought events that occurred in 2018 and 2019. We gathered this data from both the text-based EDII dataset and additional data collection efforts, with detailed information provided in supplementary material SM2. Table 1 lists all the 12 categories of considered drought-affected sectors together with an example of an impact report per each category. To facilitate further analysis, we treated the number of impact reports per month per region per sector as a proxy for the magnitude of drought impacts and the severity of the drought event. This study accounted for the media biases and applied a method that helps to overcome the uncertainties related to the spatial and temporal distribution of impact reports based on media sources (see section 2.4). For detailed information on text-based impact monitoring and its challenges, please refer to SM2.

2.4. Fuzzy approach for categorization of drought indicators and impacts

Many aspects related to droughts are fuzzy with no clear boundaries, particularly when it comes to its definition, detection, categorization, and impact assessment. First introduced by Zadeh (1978), the concept of fuzzy theory has proven valuable in addressing these uncertainties by assigning fuzzy values when no objective metric can adequately gauge their relative magnitude. Over time, this approach has found extensive application within the context of drought (Pongracz *et al* 1999, Acosta-Michlik *et al* 2008, Eierdanz *et al* 2008, Huang *et al* 2015).

To cope with the uncertainty associated with both drought indicators and impact data (i.e. due to bias in impact reporting and inaccuracy in calculating drought indicators), we developed fuzzy categories for the drought impacts based on the percentile of the number of impact reports for a particular region (table 2). This must be done to preserve the magnitude of the impacts while normalizing for the several different inherent biases in media reports in each region. The terciles (33rd and 66th percentile) were used as thresholds to define the impact categories similarly to how the tercile-based below/near/above normal conditions are defined considering past climatological information (Goddard *et al* 2003, Shukla *et al* 2019). This resulted in the creation of four categories, ranging from 'No impact' for 0 reports and ending with 'Extreme impact' for the number of

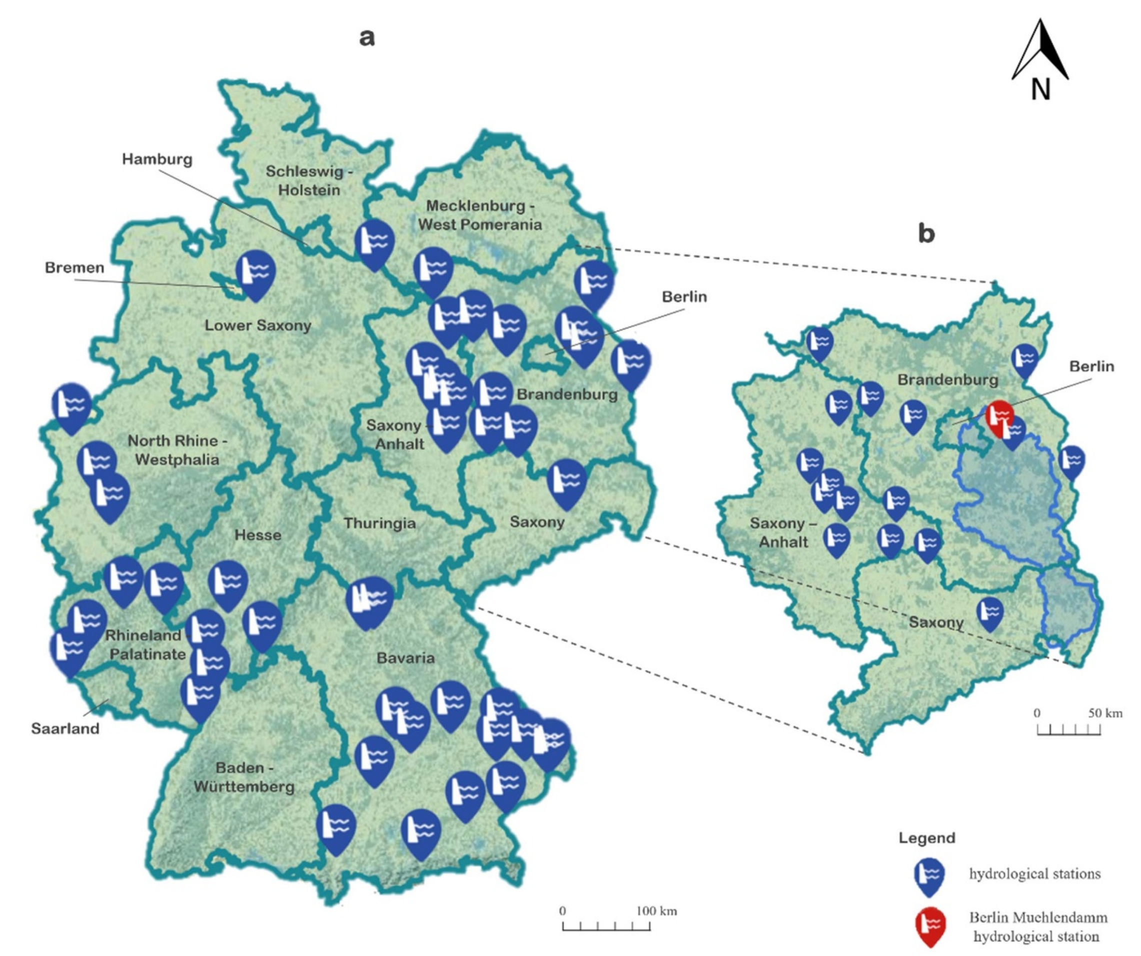

Figure 1. (a) (left) Location of hydrological stations in Germany from the GRDC; (b) (right) Basin area of the Berlin Muehlendamm station (in red) covering 3 NUTS-1 regions (Berlin, Brandenburg, Saxony).

reports falling into the top 33% of the reports distribution for the particular region. We further partitioned the analysis by sectors; a region was excluded from further analysis if the number of reports was less than 5% of the total number of reports per sector for the whole country.

Next, we grouped the drought indicators (SPI, SPEI, SSMI, SSFI) into four categories matching those adopted for the impacts, as shown in table 2. This categorization corresponds to other drought severity classifications as provided by WMO (2016), EDO (2020), and DWD.

Generally, these fuzzy categories were used to keep the magnitude of the impacts and capture their spatial, sectoral, and temporal variability, while alleviating potential biases in reporting them.

2.5. Correlation analysis

To assess the non-linear, but monotonic relationship between drought impacts and indicators, we applied the Spearman rank correlation and analysed the impacts spatially, temporally and by sectors. After transforming the data into the fuzzy categories, Spearman rank correlation coefficients and significance levels were calculated for the time series of SPI, SPEI, SSMI, and SSFI with various accumulation periods versus the number of impact reports for each region.

3. Results

3.1. Spatiotemporal distribution of drought impacts

To assess how the drought impacts propagated in space and time, we analysed the distribution of drought impacts. First, we identified the most affected regions with the highest number of drought impact reports and the most affected sector in each region as shown in figure 2.

The number of impact reports over the 2 year period varied across the regions, with North Rhine–Westphalia and Baden–Württemberg being the most affected, primarily due their higher population density (figure 2(a)). In terms of sectoral analysis (figure 2(b)), the agricultural losses were primarily concentrated in the northern part of the country, whereas forestry was most affected in the south and the water-related sectors (e.g. transportation,

Table 1. List of drought-affected sectors and an example of the impact on each affected sector, categorized according to the EDII database.

Impacted sectors by categories	Example of impact report per category
Agriculture and livestock farming	The second weak harvest (crop failure of 70% in grains and fodder) in a row is emerging in eastern Germany due to drought and the fodder reserves are now extremely scarce in many farms; some farmers had to sell cows because they could not harvest enough forage;
Energy and industry	Due to the low water levels of the Rench, the hydropower station 'Rosensäge' near Ramsach had a failure rate of about 40% over the year 2018; from june to the end of September, the station had been in operation for only a few hours and generated as much electricity as it would normally do in two days;
Forestry	Many newly planted trees did not even survive the winter, they have dried up; in regions with large spruce forests, an extreme bark beetle plague is expected as the bark beetle benefits from this severe drought, which weakens the trees' natural defences;
Freshwater aquaculture and fisheries	The fish farm in Petersheim had to begin fishing in august 2018 already, which was two months earlier than usual, to prevent the fish from dying from prolonged waiting and lack of water; due to the heat and the premature fishing, the pond keeper expects losses of about 40%;
Freshwater ecosystem	Birds at the Timmerhorn ponds are threatened by drought;
Human health and public safety	Park Sanssouci has been closed in the area of the Ruinenberg since wednesday due to falling branches affected by drought;
Public water supply	Water withdrawal from rivers prohibited in Spree and Schwarze Elster, in certain streets there is no water between 7 p.m. and 10 p.m.;
Terrestrial ecosystem	In Sandhausen, many hedgehogs starved to death because there were hardly any snails or earthworms due to the drought;
Tourism and recreation	Visitors to forests, moors and heaths are forbidden to leave the roads, motorable paths and marked hiking and horseback riding trails;
Water quality	Threat of botulism: the toxic bacteria spreads as the water lacks oxygen due to drought in Nordrhein–Westfalen;
Waterborne transportation	Ships in the Upper Rhine have to reduce their load by 50% due to the low water level caused by the drought; tankers can no longer transport their full cargo, diesel and petrol are becoming scarce at petrol stations;
Wildfire	3 000 firemen fought a fire caused by the drought for days in the south of Berlin;

Table 2. Transforming drought impact data and drought indicators to fuzzy categories.

Drought impacts		
Percentile	Fuzzy category	Interpretation
$=0$	0	No impact
$0 \div 33.33\%$	1	Moderate impact
$33.34\% \div 66.66\%$	2	Severe impact
$66.67\% \div 100\%$	3	Extreme impact
Drought indicators (SPI/SPEI/SSMI/SSFI)		
Range	Fuzzy category	Interpretation
$\geqslant 0$	0	No drought
$0 \div -1$	1	Moderate drought
$-1 \div -2$	2	Severe drought
<-2	3	Extreme drought

ecosystems) were primarily affected in the north and west of the country. The latter can be explained by the presence of the Elbe river in the north-west and the Rhine river in the west, which are important industry and water transportation hubs that have been severely affected by the drought (Rosner *et al* 2019). The severe agricultural impacts in the north of the country are in agreement with de Brito *et al* (2020), who explained this by the higher area of crop cultivation compared to other parts of Germany.

We next analysed the temporal distribution of drought impacts affecting 12 different sectors (figure 3).

As the drought event was more intense in 2018 as compared to 2019, agriculture (yellow line in figure 3(A)), as the sector with faster response, was mainly affected in the first year of the drought. de Brito *et al* (2020) also observed that agricultural drought in 2019 primarily affected the lower soil levels. Additionally, state relief efforts alleviated the impacts in the second year. To counteract the detrimental impact of drought and heat conditions on the agricultural sector in Germany in 2018, federal aid payments of 340 million Euros were provided to farmers experiencing a minimum of 30% yield loss (Reinermann *et al* 2019).

Further, wildfires (red line in figure 3(A)) were limited to the summer season in 2018. However, in 2019, they started earlier during the spring season and continued into the summer months. This extended occurrence of wildfires in 2019 can be attributed to the persistently dry conditions from the preceding

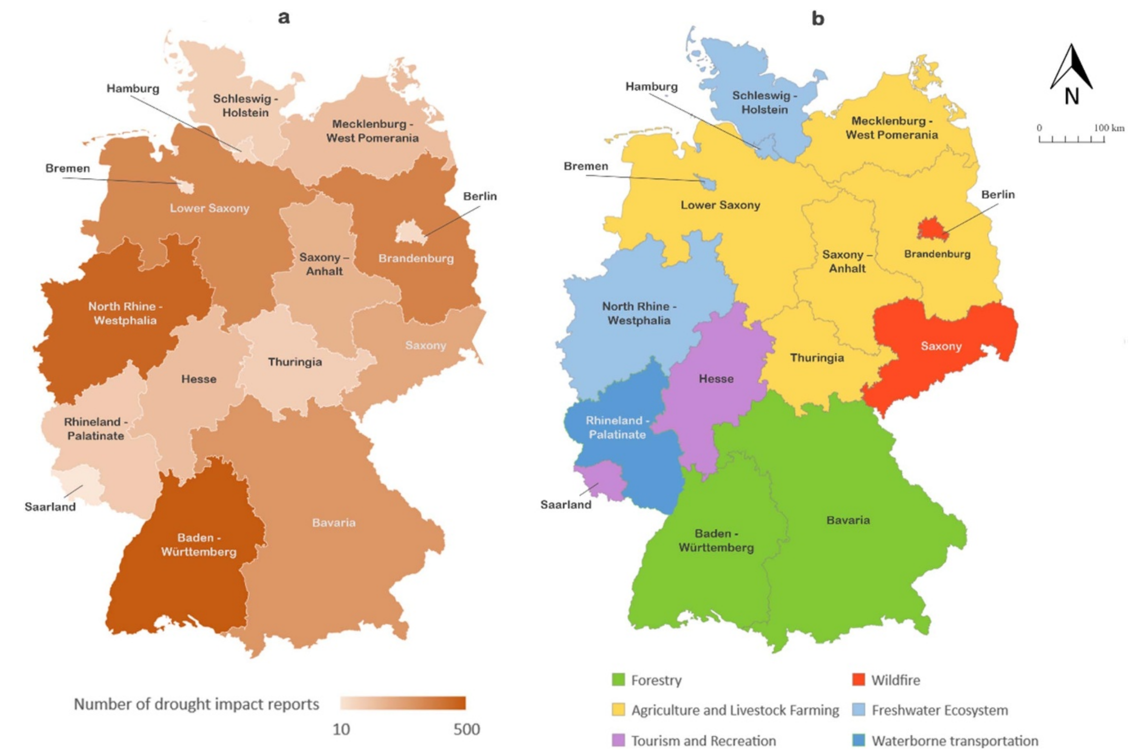

Figure 2. Spatial distribution of drought impact reports during the 2018–2019 drought in Germany: (a) (left) total number of reports; (b) (right) the most affected sector in each region.

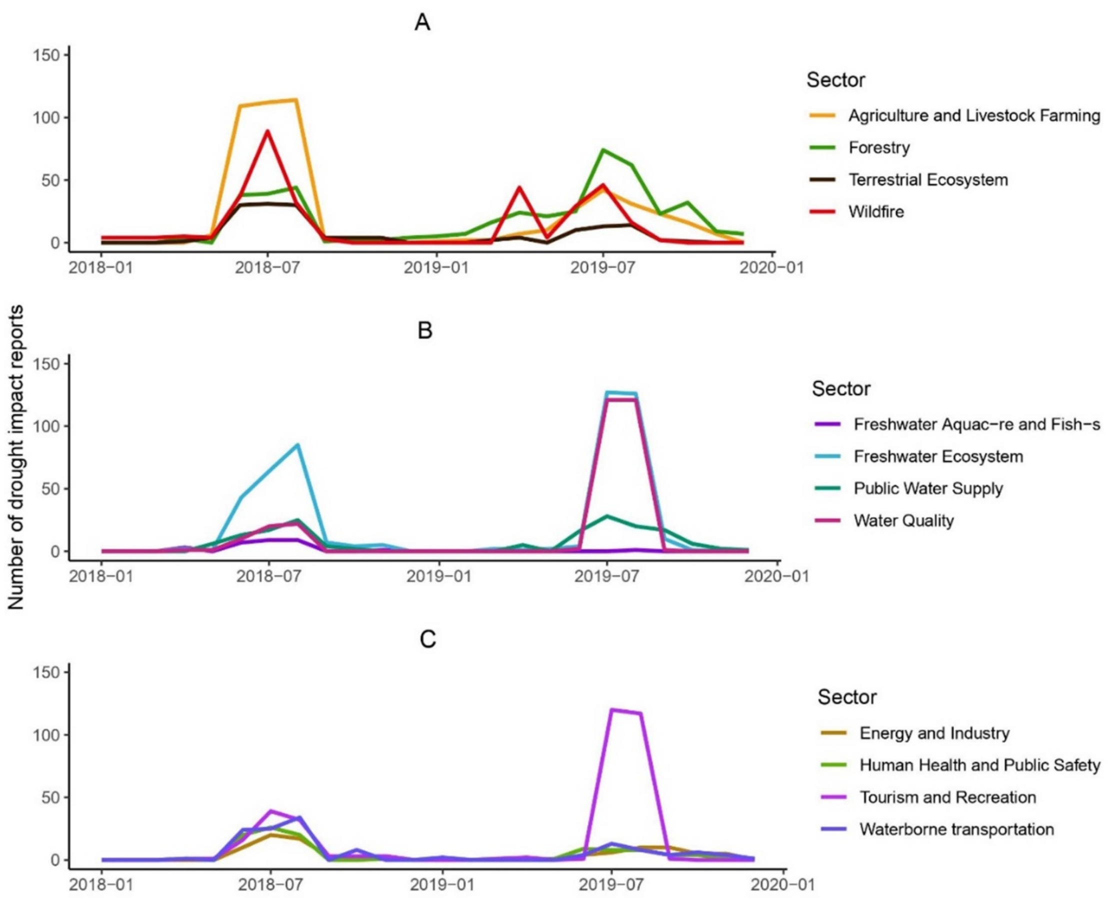

Figure 3. Temporal distribution of drought impacts by sectors over 2 years during the 2018–2019 drought in Germany.

year, which created a favorable environment for fire outbreaks. The green line for forestry (figure 3(A)) indicates that the drought had a delayed impact, as heat conditions and drought persisted and impacts were mostly reported in the second year. Additionally, the adverse effects on forestry were exacerbated by the drought conditions in the second year, particularly affecting the lower layers of soil where the tree root system is located (de Brito *et al* 2020, Bastos *et al* 2021).

On the middle timeline, the freshwater ecosystems (blue line in figure 3(B)) show that they were impacted in the summer of both years, but the impacts on water quality (pink line) were mostly seen only in the second year due to a lagged effect of hydrological drought. Finally, tourism and recreation (purple line in figure 3(C)) were affected in the second year due to swimming bans connected to the proliferation of algae blooms that generally take more than one drought season to develop.

3.2. Correlating impacts and indicators

To determine the relationship between drought indicators and drought impacts across regions, sectors, and spatiotemporal scales, a comprehensive cross-correlation analysis was performed. This analysis utilized the transformed data represented in fuzzy categories, and involved calculating Spearman rank correlation coefficients and determining their significance levels. The correlation analysis was conducted between the time series of SPI, SPEI, SSMI and SSFI drought indicators, and the number of impact reports for each region (figures 5 and 6) and drought-affected sector (figures 7 and 8), providing insights into their interrelationships within different contexts.

3.2.1. Regional correlation

We first examined the correlation between the fuzzy time series of the drought indicators and the impact reports across NUTS1 regions in Germany. Figure 4 presents two examples: the highest and most significant correlation between drought impact reports and an indicator for one region and the lowest and insignificant correlation of drought impact reports and the same indicator for another region. More specifically, we found that SPEI3 has the highest and most significant correlation with drought impact reports for Saxony, as both variables follow the same pattern and have a monotonic relationship. For the same SPEI3, the lowest correlation was observed in Mecklenburg–West Pomerania, where SPEI3 was unable to follow the reported impact frequency.

We further assessed the correlation between the analysed drought indicators and drought impacts across various NUTS1 regions in Germany (figure 5). Different accumulation periods of the various indicators (SPI, SPEI, SSMI 1st and 2nd layer) are shown on the x-axis of the same graph. As a result, the gridded cells show correlation coefficients (ρ) and significance levels between time series of drought impact reports and drought indicators (SPI, SPEI, SSMI1, SSMI2) with various accumulation periods and regions in Germany.

Overall, the highest and most significant correlation across all indicators was for the accumulation periods of 1, 3 and, in case of SPI, of 24 months. This can be explained by the ability of 1 and 3 month accumulation periods to capture the sub-seasonal to seasonal impacts of ongoing dry conditions. At the same time, the accumulation period of 24 months is able to pick up the long-term signal of dry conditions from 2 warm seasons, which gradually exacerbates the drought situation, leading to long-term impacts. It needs to be acknowledged that this observation can be case-specific as we are analyzing a 2 year drought. In contrast, the accumulation periods of 9 and 12 months do not allow capturing the dynamics of two seasons and, thus, do not show as clear a link with impacts.

Next, the SPEI exhibits the highest correlation overall across all regions. Specifically, a coefficient of 0.8 was observed for SPEI3 in Saxony, Lower Saxony and Hesse. This is likely due to its ability to account for both precipitation and evapotranspiration. It has been widely acknowledged that atmospheric evaporative demand plays a key role in drought development (González-Hidalgo *et al* 2018, Torelló-Sentelles and Franzke 2021). However, we found that SPEI cannot capture impacts across regions over long accumulation periods possibly due to the fact that these values depend on winter temperature, which is not expected to influence the impact of the summer drought.

SSMI1 and SSMI2 effectively capture impact signals in various regions, with SSMI2 demonstrating a particularly strong association with impacts in Brandenburg across accumulation periods of 1, 3, 6, and 12 months. In contrast, neither SPI nor SPEI managed to establish this link. This observation can be partially explained by the sectors reporting impacts in this region, primarily agriculture, forestry, and recreation, all of which are closely linked to soil moisture conditions. The local conditions, including the prevalence of low-quality sandy soil (Wolff *et al* 2021), which is susceptible to rapid drying in drought periods due to its high permeability (Ladányi *et al* 2021), contribute to the considerable challenges faced by all sectors reliant on soil moisture conditions (Gutzler *et al* 2015). The negative correlation of SSMI1 and SSMI2 in Saxony can be explained by the fact that the freshwater aquaculture and fisheries sector was ranked second as most affected in this region, and later itself showed a negative correlation with SSMI1 and SSMI2 for the same accumulation periods (figure 7).

Further, SSFI_obs (figure 6) was able to establish a connection to impacts for 1 and 3 month accumulations in central regions (North Rhine–Westphalia, Hesse, Thuringia, Lower Saxony) that are dependent

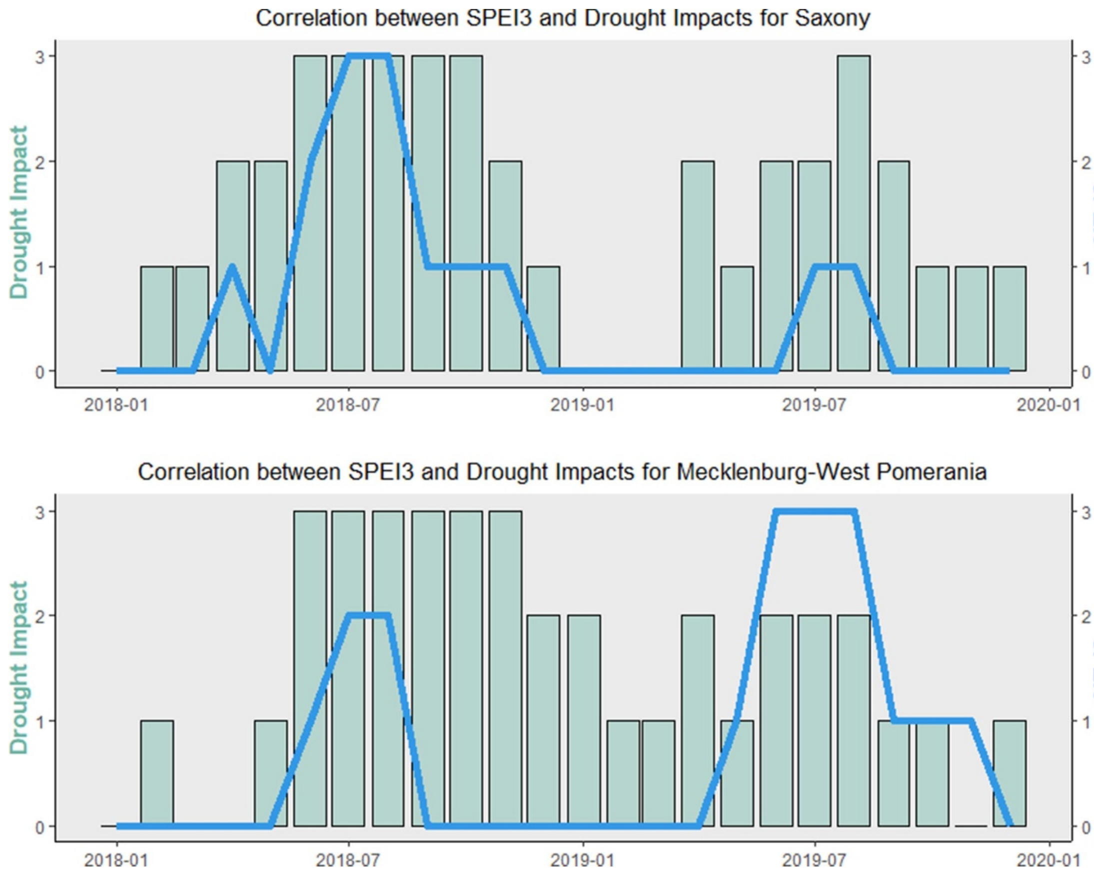

Figure 4. Correlation between time series of SPEI3 and drought impacts in Saxony (the highest correlation coefficient) and in Mecklenburg–West Pomerania (the lowest correlation coefficient).

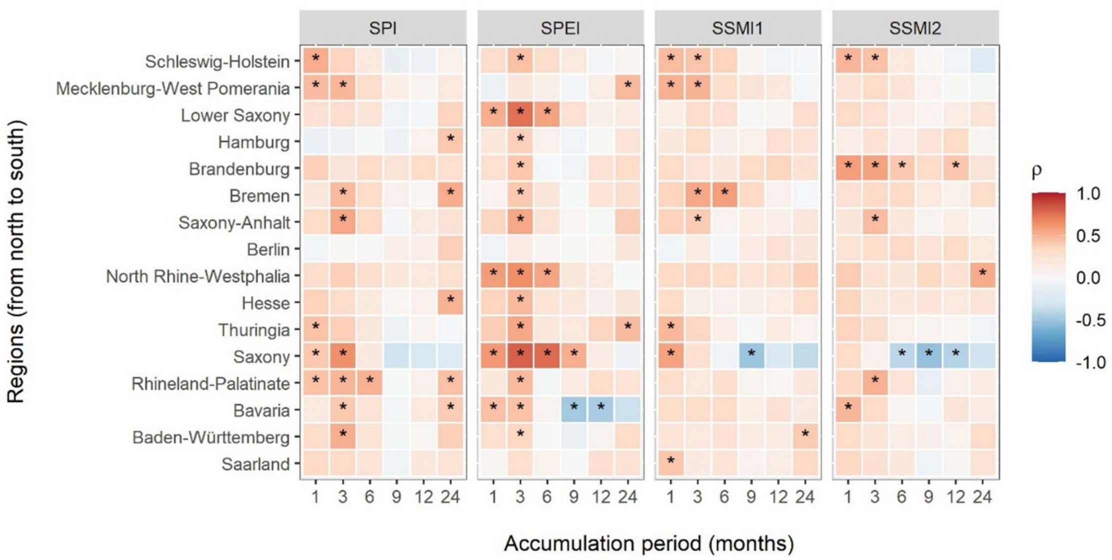

Figure 5. Correlation coefficients (ρ) and significance levels (p-value < 0.05 indicated with stars) between time series of drought indicators (SPI, SPEI, SSMI 1st and 2nd layer) with various accumulation periods and drought impacts for various NUTS1 regions in Germany.

on the Rhine basin area. Indeed, during the 2018–2019 drought event numerous sources reported various impacts associated with the extremely low flow of the Rhine (Erfurt 2019). The negative correlation values of SSFI are difficult to interpret, as they can be due to a combination of factors. In high-altitude regions (Bavaria and Saxony) with forested areas and steep topography, the annual rainfall and snowmelt season may lose its typical periodicity when impacted by drought (Wang et al 2018). Moreover, there are

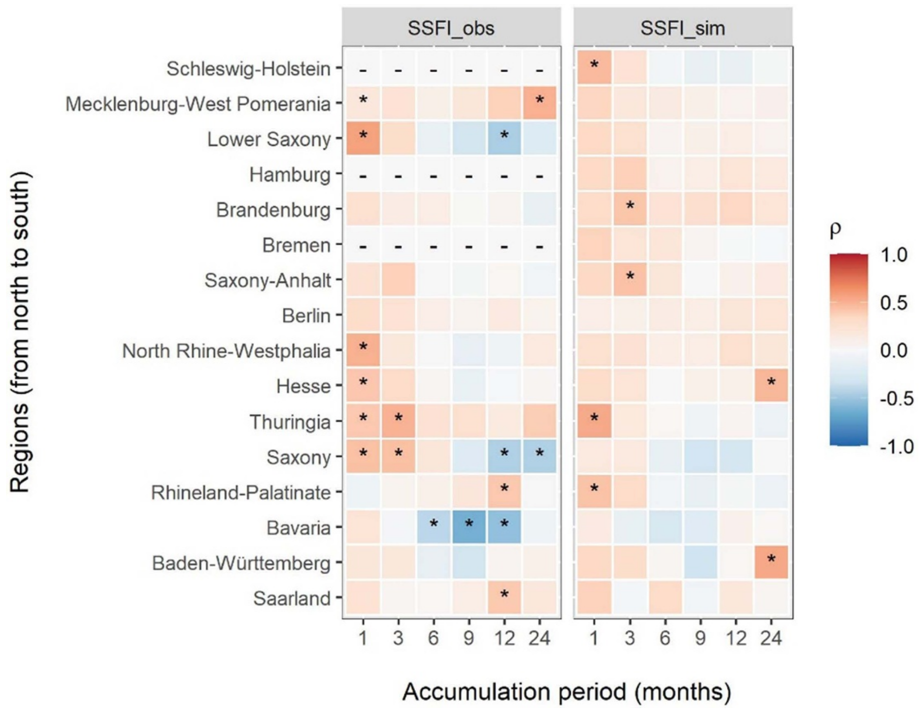

Figure 6. Correlation coefficients (ρ) and significance levels (p-value < 0.05 indicated with stars) between time series of drought indicators (SSFI_obs and SSFI_sim) with various accumulation periods and drought impacts for various NUTS1 regions in Germany. The dashed lines for SSFI_obs indicate the regions where no hydrological stations are available from the GRDC.

significant uncertainty in low flow data (Westerberg *et al* 2014) and the difficulties in averaging SSFI. These challenges include the need to average data over regions, especially when dealing with the presence of transboundary river basins and rivers of varying Strahler stream orders.

3.2.2. Sectoral correlation

Next, we explored the correlation across various sectors. Similar to figures 5, figure 7 shows different accumulation periods of the various indicators along x-axis. Further, the y-axis shows different sectors affected by the 2018–2019 drought event in Germany, listed in alphabetic order. The resulting gridded cells show the correlation coefficients (ρ) and significance levels between drought indicators with various accumulation periods and drought impacts for different drought-affected sectors in Germany.

Consistent with earlier findings, the accumulation periods of 1 and 3 months demonstrate the strongest correlation across all indicators. However, there is a noteworthy additional observation; in the case of SPI and SPEI, the 6 month and 24 month periods also display a strong association. Furthermore, as seen in figure 7, the correlation coefficients for SPEI were the highest, with a value of 0.5, for terrestrial ecosystems, wildfire, and tourism and recreation. The latter mainly comprises reports on swimming bans.

A key observation when examining the correlations across different sectors is that longer accumulation periods show the most significant correlation for the forestry sector. This reflects the delayed effect of drought when dieback occurs due to prolonged dry conditions that decrease pest and disease resistance. This further implies that the first year of a drought event can impair the physiological recovery of trees, leading to prolonged tree mortality that may persist for several years with implications for biodiversity, the carbon cycle and wood production (Messori *et al* 2019, Bastos *et al* 2020, Brun *et al* 2020, Mcdowell *et al* 2020, Schuldt *et al* 2020, Senf *et al* 2021, Wu *et al* 2022). Among all the indicators, notably SSMI2 (middle soil layer) with 12 months accumulation shows the highest correlation value of 0.47 for the forestry sector, since the middle soil layer, extending up to 30 cm, encompasses part of the root zone of trees and thus effectively captures the impact signal.

Wildfires instead appear to only have significant correlations with both indices for shorter accumulation periods of 1–6 months, since persistent dry conditions can lead to rapid fire potential even in the short term. In a study conducted by Gudmundsson *et al* (2014), similar conclusions were drawn regarding the use of SPI to detect significant impacts of wildfires in southern Europe. The study utilized the extensive European fire database and found that SPI with shorter lead times (no more than 2 months) correlated with the occurrence of major wildfire events.

Furthermore, the impacts on the agricultural sector are not adequately captured by SPI with a 1 month accumulation period, but rather by a 3 month

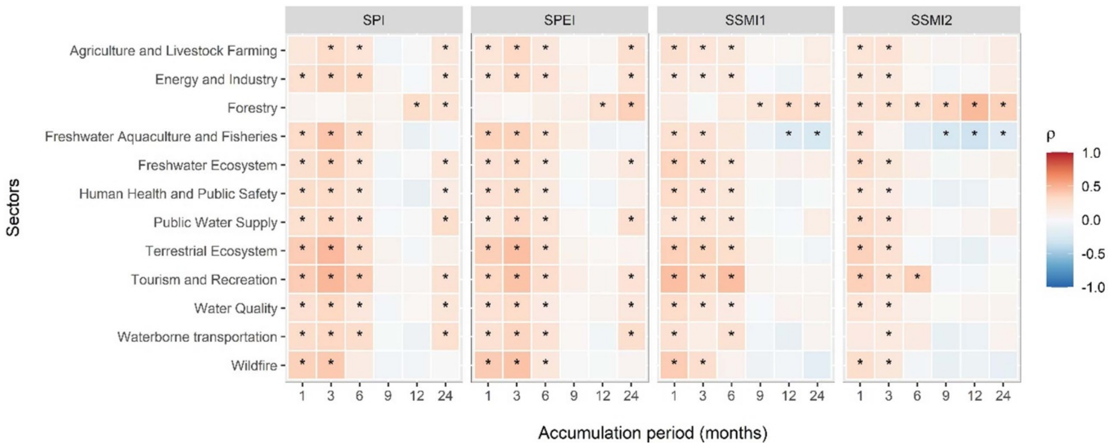

Figure 7. Correlation coefficients (ρ) and significance levels (p-value <0.05 indicated with stars) between time series of drought indices (SPI, SPEI, SSMI 1st and 2nd layer) with various accumulation periods and drought impacts for various drought-affected sectors in Germany.

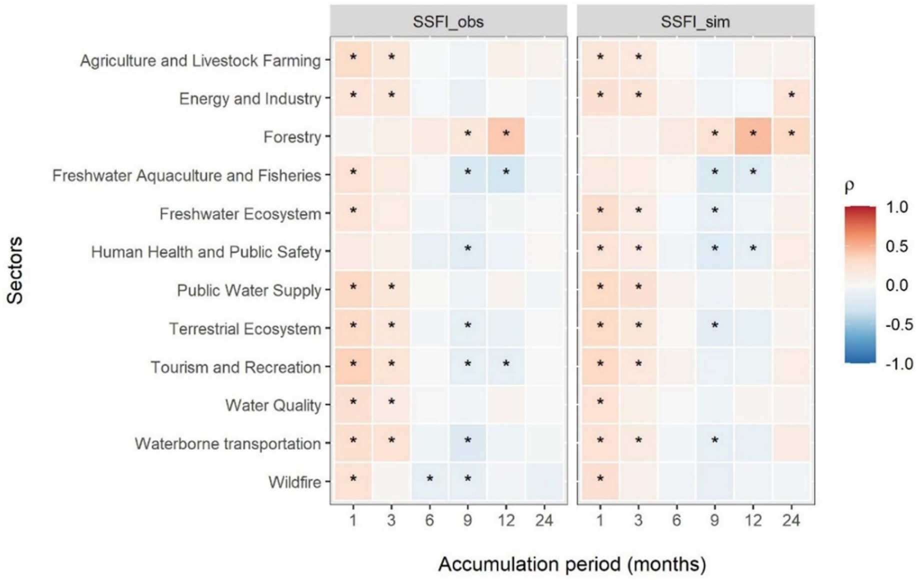

Figure 8. Correlation coefficients (ρ) and significance levels (p-value < 0.05 indicated with stars) between time series of drought indices (SSFI_obs and SSFI_sim) with various accumulation periods and drought impacts for various drought-affected sectors in Germany.

accumulation period. In contrast, SPEI is already capable of capturing agricultural impacts from a 1 month accumulation period, as evapotranspiration plays a crucial role in soil conditions. According to some studies (Stagge *et al* 2015), agricultural impacts are explained by anomalies aggregated over shorter periods, whereas anomalies greater than 9 months are likely related to agricultural management practices and various hydrological regimes.

The negative correlation of SSMI1 and SSMI2 for longer accumulation periods with the freshwater aquaculture and fisheries sector has no intuitive explanation and, therefore, requires further investigation.

SSFI (figure 8) appears to have, similarly to SSMI2, notable correlation of 0.4 for the forestry for 12 months accumulation period, highlighting the connection between streamflow and forestry within the water cycle. The negative values of drought indicators, particularly for the 9 month accumulation period, which does not span the full annual cycle, can be explained by multiple factors. These include the higher altitude and the source of water supply for some regions or the role of snow accumulation/melting for other regions.

3.3. Co-occurrences of impacts across sectors

Drought impacts have historically affected almost all parts of the society, the economy, and the environment, all of which are deeply intertwined (Di Baldassarre *et al* 2017, Poljansek *et al* 2017). As shown in figure 3, droughts tend to cause multiple

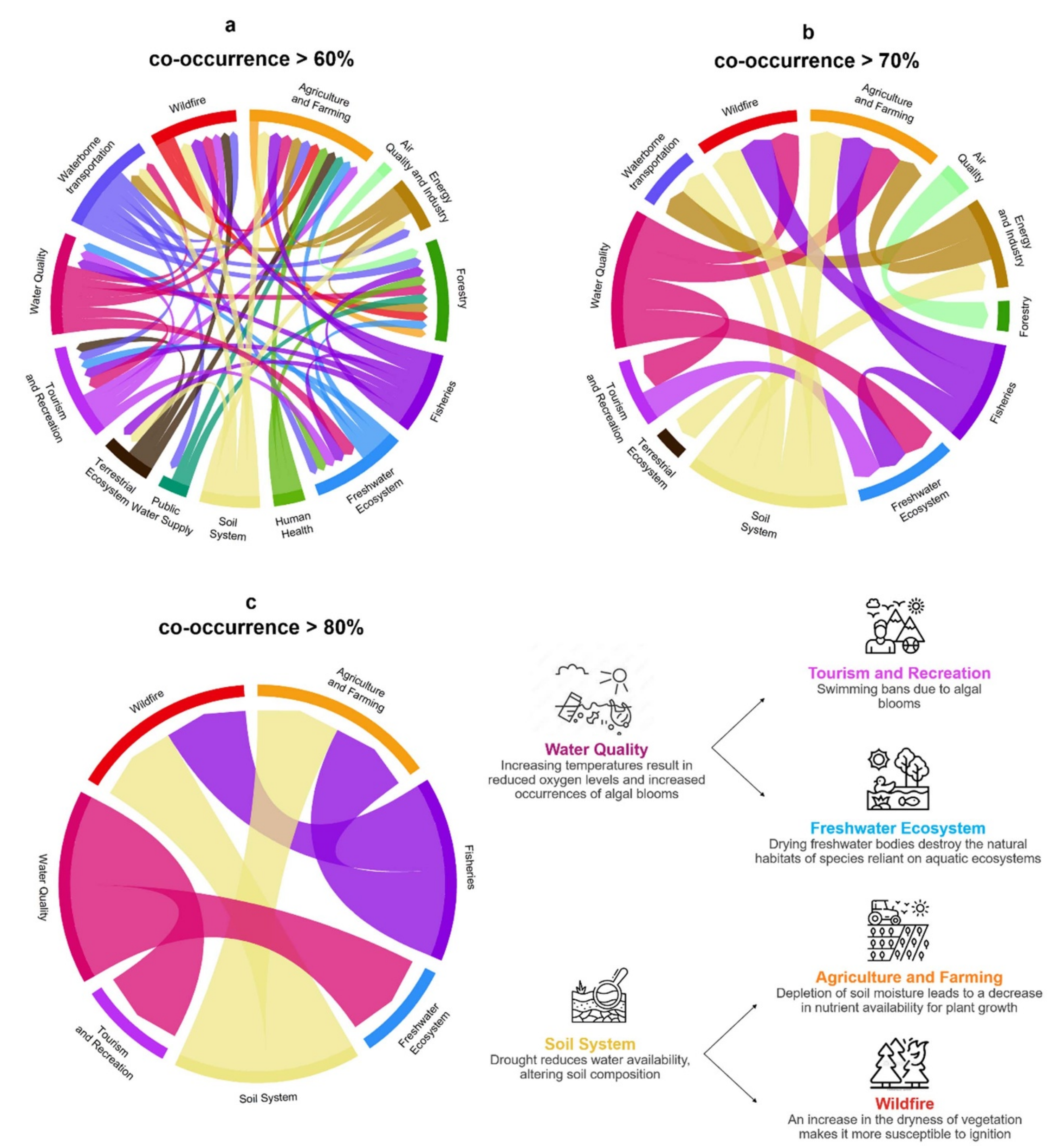

Figure 9. Co-occurring impacts during the 2018–2019 drought event in Germany across 14 affected sectors with the proportion of co-occurrences above: (a) (top left) 60%; (b) (top right) 70%; (c) (bottom left) 80% with specific notable connection among sectors with the proportion of co-occurrences above 80% (bottom right).

impacts across different sectors simultaneously. It is common for a single impact to trigger a chain reaction, affecting other sectors through hydrological and socio-economic systems (AghaKouchak *et al* 2021, de Brito 2021). Failure to understand which impacts occur together can lead to underestimating the risk and failing to provide appropriate drought relief to the affected sectors.

We, therefore, utilized the impact dataset described in section 2.3 to determine which sectors were reported to be affected simultaneously in the same region and the same month over the considered two-year drought period. SM3 in supplementary material gives an overview of the proportions of impacts occurring during the same months and within the same regions, categorized by sectors. To visualize results, figure 9 presents the co-occurrences among all 14 explored sectors that experience impacts simultaneously in a particular region with the proportion of co-occurrence above 60% (figure 9(a)), 70% (figure 9(b)), and 80% (figure 9(c)), with the latter showing specific notable connections between the sectors with the proportion of co-occurrence exceeding 80% (refer to SM3 for the calculation details).

Examining figure 9, it becomes evident that certain sectors, such as fisheries, water quality, waterborne transportation and soil system, tend to have impacts co-occurring with impacts reported in agriculture, freshwater ecosystem, wildfire, and forestry sectors, which are also among the most frequently reported sectors.

Moreover, the recreation, water quality and water ecosystem sectors together as well as soil system, agriculture and wildfire together exhibit a noticeable relationship and tend to experience impacts concurrently in more than 80% of cases of their occurrence. Notably, impacts in the water quality are often (91% of co-occurrences; refer to table SM3.1) attributed to changes in water ecosystem conditions caused by rising temperatures. Additionally, water quality exhibits a strong link (87% of co-occurrences; refer to table SM3.1) with the recreation sector, likely due to reports of algal blooms leading to swimming bans.

The soil system sector and agriculture exhibit strong connection (86% of co-occurrences; refer to table SM3.1) as both sectors rely on suitable soil conditions and moisture levels. These factors are critical for microbial activity and plant growth, ultimately sustaining ecosystems and crop cultivation. Additionally, the soil system sector frequently experiences concurrent impacts with wildfire (86% of co-occurrences; refer to table SM3.1) due to the higher risk of ignition of vegetation in moisture-deficient soil conditions.

4. Discussion—limitations and practical implications

This study has a number of caveats. First, the categorization of indicators and impacts involved subjective decisions, as fuzzy categories were defined. While this approach was justified to mitigate potential media biases, it is important to note that certain impacts may have been alleviated through drought relief measures, resulting in underreporting by the media. Secondly, the research scope and data availability were restricted to a two-year period of drought. This timeframe facilitated detailed analysis of the studied drought event due to the abundance of available data. However, drawing more robust conclusions (including a rigorous attribution of the correlations) would require longer time-series data. Lastly, a longer time-series would enable the utilization of statistical methods to assess the predictive power of different indicators in relation to the impacts. This information could directly contribute to the establishment of IbF models for droughts and adaptation to support decision-making.

Further, a more practical extension of this analysis might involve an assessment of the economic costs of drought impacts. As estimated by Cammalleri *et al* (2020) drought-related losses in the European Union account for about 9 billion Euros annually with 75% of these losses seen in agriculture, energy and public water supply sectors. Given this, such quantitative information on the losses due to droughts by sectors can support policy-makers in prioritization and enacting drought mitigation efforts in a timely manner.

It is also important to note that establishing the connection between drought indicators and impacts at both regional and sectoral levels is crucial to support IbF of droughts. While some research has explored regional connections and the combined impacts on multiple sectors (Sutanto *et al* 2019), there is a need to investigate these relationships individually for each sector. The emerging field of IbF of droughts holds the potential to estimate the impacts of droughts across different sectors, enabling the development of accurate impact-based DEWS and facilitating timely and effective distribution of relief aid for drought-stricken areas (Göber *et al* 2022, Shyrokaya *et al* 2023).

5. Conclusions

Efficient and integrated drought management often requires knowledge on the time that different drought types take to propagate through different water resource systems and the extent to which they impact various sectors. This study investigates the relationships between drought indicators and impacts, identifying patterns across regions and sectors, focusing on the 2018–2019 drought in Germany. This study has implications for developing sector- and region-specific drought management policies by applying different drought indicators with varying accumulation periods. The main findings of this study are:

- **A fuzzy approach to address uncertainties associated with drought indicators and impacts**. The developed and applied fuzzy categories can effectively reduce these uncertainties and contribute to the advancement of drought-related studies.
- **Strong correlation between drought indicators and impacts with very short or very long accumulation periods depending on regions and sectors**. The strongest associations between drought indicators and impact reports were observed for very short (1 or 3 months) or very long (24 months) accumulation periods. In particular, the forestry sector was found to be closely linked to longer accumulation periods, while wildfires and fishery sectors with shorter accumulation periods.
- **SPEI is overall the indicator most strongly correlated to impacts across regions and sectors**. For sectors notably, the highest correlation was found with agriculture, fisheries, recreation, terrestrial ecosystems, and wildfires. SPEI considers both precipitation and evapotranspiration, and the atmospheric evaporative demand plays a large role in drought development.
- **Forestry strongly correlates with long accumulation periods for the drought indicators due to its slow response**. By gaining insights into the long-term connections between droughts and forestry

sector, proactive measures can be taken well in advance to anticipate and adapt forests to the increasingly hot and dry conditions, which are expected to result in more frequent disturbances.

- **Co-occurring impacts across drought-affected sectors**. Several patterns of co-occurrences among sectors were identified. Specifically, water quality, water ecosystem, and recreation were found to experience impacts simultaneously, as did agriculture, soil systems, and wildfire. This understanding is valuable for accurately estimating the occurrence of multiple impacts across different sectors that occur simultaneously, with each impact triggering another.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

The authors would like to thank Kerstin Stahl (University of Freiburg) for providing the updated version of the EDII database and Ruth Stephan (University of Freiburg) for insightful discussions regarding it. We further thank Elise Jonsson (Uppsala University) for sharing the SSFI data and Herminia Torelló-Sentelles (University of Lausanne) for providing the script to generate the correlation matrix plot.

Conflict of interest

The authors have declared no conflicting interests.

Funding

Anastasiya Shyrokaya, **Giuliano Di Baldassarre**, and **Gabriele Messori** received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie Grant Agreement No. 956396 (EDIPI Project). **Gabriele Messori** further acknowledges support from the Swedish Research Council Vetenskapsrådet (Proj. No. 2022-03448) and from the European Union's Horizon Europe research and innovation programme under the European Research Council (ERC) Grant Agreement No. 101112727 (ICE-MOT).

Giuliano Di Baldassarre further received funding from the European Research Council (ERC) for his consolidator Grant Agreement No. 771678 (HydroSocialExtremes).

Ilias G Pechlivanidis was funded by the EU Horizon 2020 Project CLINT (Climate Intelligence: Extreme events detection, attribution and adaptation design using machine learning) under Grant Agreement 101003876 and by the EU Horizon Europe Project MedEWSa (Mediterranean and pan-European forecast and Early Warning System against natural hazards) under Grant Agreement 101121192.

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