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How good is my drought index? Evaluating predictability and ability to estimate impacts across Europe

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LETTER

How good is my drought index? Evaluating predictability and ability to estimate impacts across Europe

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Abstract

Identifying drought indices that effectively predict future drought impacts remains a critical challenge in seasonal forecasting, as these indices provide the necessary actionable information that enables stakeholders to better anticipate and respond to drought-related challenges. This study evaluates how drought indices balance forecast skill and relevance for estimating impacts across Europe. Using European Centre for Medium-Range Weather Forecasts SEAS5 seasonal predictions and ERA5 reanalysis as benchmarks, we assessed the predictability skill of drought indices over various accumulation periods and their relevance in estimating drought impacts across Europe, with the aim of enhancing impact-based forecasting. To evaluate these relationships, we built upon the findings from a study that utilized drought impact data from the European Drought Impact Report Inventory and employed random forest models to evaluate the significance of various drought indices in predicting sector-specific impacts. Our findings reveal higher predictability in Northern and Southern Europe, particularly during winter and summer, with some regions showing extended predictability up to six months, depending on the season. Focusing on case studies in the UK and Germany, our results highlight regions and seasons where accurate impact predictions are possible. In both countries, high impact predictability was found up to six months ahead, with sectors such as Agriculture, Water Supply, and Tourism in the UK, and Agriculture and Water Transportation in Germany, depending on the region and season. This analysis represents a significant step forward in identifying the most suitable drought indices for predicting impacts across Europe. Our approach not only introduces a new method for evaluating the relationship between drought indices and impacts, but also addresses the challenge of selecting indices for estimating impacts. This framework advances the development of operational impact-based drought forecasting systems for Europe.

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1. Introduction

Droughts are an escalating concern in Europe, exacerbated by climate change and increasing variability in weather patterns (Cook *et al* 2020, IPCC 2021, Faranda *et al* 2022, Schumacher *et al* 2022, Montanari *et al* 2023). In recent years, Europe has experienced a series of severe drought events, including those in 2003, 2007, 2010–2013, 2015, 2017–2022 (Caloiero *et al* 2018, Biella *et al* 2024), with a predicted increase in the frequency and severity of such events (Cook *et al* 2020, IPCC 2021). Amplified by human activities and unsustainable water usage (Di Baldassarre *et al* 2018, AghaKouchak *et al* 2021, Van Loon *et al* 2022, Rusca *et al* 2023), they have caused widespread impacts on agriculture (Heinrich and Bailey 2020), water resources (Mosley 2015), energy production (Herrera-Estrada *et al* 2018, Byers *et al* 2020), ecosystems (Bastos *et al* 2020, Wu *et al* 2022), public health (Charnley *et al* 2021, Mora *et al* 2022), and tourism and recreation (Koutroulis *et al* 2018, Dube *et al* 2022). While the socio-economic and environmental consequences are far-reaching, the full scope of quantifiable and non-quantifiable impacts remains unknown. Addressing this growing challenge requires the development of improved drought forecasting systems that incorporate both robustly forecasted and impact-relevant indices. In this context, impact-based forecasting (IbF) has emerged as a vital approach, enhancing early warning systems and enabling more effective, targeted decision-making frameworks (Sutanto *et al* 2019, AghaKouchak *et al* 2023, Shyrokaya *et al* 2024).

Effective drought management hinges on accurately defining drought conditions and standardizing indicators to monitor and predict events reliably. At the European level, a plethora of drought forecasting products is currently available operating for the national, regional or local needs. Among these, the European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecasting system 5 (SEAS5) system, offers critical data for drought prediction by providing global forecasts of climate variables up to seven months ahead. These include precipitation and temperature, which are crucial for predicting drought conditions, enhancing both short-term and long-term preparedness globally (Sutanto *et al* 2019, Kowal *et al* 2022, Busker *et al* 2023).

Drought forecasting services offer information across various time horizons, from a few weeks to several months, with the predictive skill generally decreasing with increased lead time (LT) and varying depending on the initialization month, geographic domain and its physiographic characteristics (Lavaysse *et al* 2015, White *et al* 2017). There are known variations in the skill of forecasts of temperature and precipitation at seasonal timescales across Europe. At a 1 month LT, SEAS5 demonstrates enhanced skill in predicting seasonal temperature anomalies over Southern and Eastern Europe during summer, whereas precipitation forecasts generally exhibit low skill across Europe in both winter and summer (Johnson *et al* 2019). Predictions of temperature are known to be skillful at shorter LTs (1 month) but decrease in accuracy for longer LTs (up to 6 months) (Prodhomme *et al* (2022), and precipitation predictions show a similar decrease in skill with increasing LT (Johnson *et al* 2019). Likewise, the skill of seasonal drought indicator forecasts in Europe varies spatially but has been shown to effectively predict drought onset and severity beyond 2 months ahead (Turco *et al* 2017, Sutanto *et al* 2020).

However, the relationship between drought indicators and sectoral impacts, such as agricultural losses (Parsons *et al* 2019, Lam *et al* 2023) or water supply shortages (Torelló-Sentelles and Franzke 2021, Busker *et al* 2023), can also vary significantly by region and season (Bachmair *et al* 2015, Shyrokaya *et al* 2023). This underscores the complexity of using drought indices to predict real-world impacts (Kreibich *et al* 2020), and highlights the need for a more nuanced approach to linking drought forecasts with sectoral impacts. Addressing this, an IbF system for Germany has been developed (Sutanto *et al* 2019), integrating machine learning with seasonal forecasts and demonstrating the potential of combining different approaches for impact predictions with considerable skill up to 3–4 months ahead. Hence, to forecast the impact of droughts, there is a need of indices that can be both accurately and reliably forecasted, and significantly and systematically associated with drought impacts. However, a critical gap remains: systematic assessments of SEAS5's skill across various drought indices and their relevance to predicting sectoral impacts.

This study addresses this gap by introducing a comprehensive framework that evaluates both the predictability skill of drought indices and their ability to estimate sectoral drought impacts. This framework aims to bridge the gap between hydro-meteorological drought forecasts and real-world impacts, providing a more robust, sector-specific approach to impact-based drought forecasting, ultimately equipping stakeholders with actionable information to better anticipate and respond to drought-related challenges (Shyrokaya *et al* 2024). Specifically, this study addresses two key questions: (1) how do forecast skill and impact relevance of drought indices vary across Europe? (2) How can these insights improve operational drought forecasting systems?

To achieve this, we assessed the predictability of drought indices calculated from SEAS5 forecasts at different LTs and accumulation periods, analyzed spatiotemporal variations at both grid and regional levels, and explored trade-offs between each index's forecast skill and its relevance for predicting drought impacts. This was demonstrated through two case studies: the UK and Germany, where drought-sensitive sectors closely linked to specific indices were mapped, highlighting regions and seasons with potential for accurate impact predictions.

The manuscript is structured as follows: section 2 outlines the datasets, while section 3 describes the methodologies for calculating drought indices, evaluating forecasts, and linking them to impacts. Section 4 presents the results on seasonal predictability and case studies. Finally, sections 5 and 6 discuss the key findings, highlight limitations, and provide conclusions.

2. Data

2.1. Study area

The study area covers Europe (the domain of analysis is limited to land surface grid points between 30 °–75° N, 15° W–42.5° E), which spans a vast range of latitudes and has a wide variety of climates. The southern parts of the domain, particularly around the Mediterranean Sea, experience a warm, dry climate with hot summers and mild, wet winters. Moving northward, the climate transitions to a temperate zone with moderate rainfall and more pronounced seasonal temperature variations, typical of Western and Central Europe. Further north, the climate becomes increasingly cold, with long, harsh winters and short, cool summers, particularly in Scandinavia and the Arctic regions. The Atlantic Ocean significantly influences the western parts of Europe, moderating temperatures and bringing more precipitation, while the eastern areas, further from the ocean, experience more continental climates with hotter summers, colder winters, and less precipitation.

Despite these climatic variations, much of the European analysis domain has faced extreme drought conditions in recent years, resulting in increasing impacts across various sectors (Cammalleri *et al* 2020). Consequently, there is a growing need for proactive drought management strategies, including forecasting the potential impacts of drought.

2.2. Seasonal data and proxy of reality

The drought indicators were calculated using the ECMWF's SEAS5 (Johnson *et al* 2019) and validated with ECMWF's Copernicus Climate Change Service reanalysis data (ERA5) (Hersbach *et al* 2020). The description of both datasets is provided in table 1.

SEAS5, operational since November 2017, provides a 51-member ensemble of real-time forecasts starting each month and integrated for approximately seven months (referred to as target months or LTs 1–7). For periods before 2017, SEAS5 offers a 25-member ensemble of hindcasts. These hindcasts, which are retrospective seasonal forecasts for past years (up to 1981), are used to calibrate real-time forecasts. Both hindcast and real-time forecast (each with 25 ensemble members) are used as one continuous time series for assessing the skill since they belong to the same cycle (5, in our case) with further assumption that with normalization and averaging involved in computing drought indices and accumulation periods, the difference in initialization between hindcast and real-time forecast will not affect the skill significantly.

ERA5 is a high-resolution reanalysis dataset (∼28 km grid) providing globally consistent weather variables derived from observations processed using ECMWF's Integrated Forecasting System. ERA5 is considered a reliable proxy for reality, as it incorporates approximately 95 billion observations obtained from both ground-based measurements and remote sensing (Hersbach *et al* 2020). A recent evaluation confirmed ERA5's reliability for precipitation data in extratropical regions (Lavers *et al* 2022), the focus of this study. Employing products from the same system, such as SEAS5 and ERA5, minimizes bias and ensures consistency.

This study utilized ECMWF SEAS5 surface data, including seasonal forecasts of monthly total rainfall and 2 m temperature (Johnson *et al* 2019), and ERA5 (pseudo-observations) provided corresponding data directly (Hersbach *et al* 2020). Both datasets covered the period from 1990 to 2024 at a spatial resolution of 0.25° (∼28 km). Although earlier data is available, it was intentionally excluded to minimize the influence of a strong long-term climate change signal. Monthly and tri-monthly means were calculated, focusing on the seasons March–April–May (MAM), June–July–August (JJA), September–October–November (SON), and December–January–February (DJF). Consequently, the monthly and seasonal means are based on 825 integrations (25 members over 33 years). Predictions focused on the trimesters starting from the second month after forecast initiation (LT1 where the initialization month is LT0). For example, for estimating the MAM trimester at LT1, three forecast values were used: the forecast initialized on 1 February (LT0) for March (LT1), the forecast initialized on 1 March (LT0) for April (LT1), and the forecast initialized on 1 April (LT0) for May (LT1). These three values were then averaged to obtain a single value representing the MAM trimester at LT1. The study primarily examined LT1, LT3, and LT6.

2.3. Drought indicators and impacts

In this study, we utilized the standardized precipitation index (SPI) (McKee *et al* 1993) and the standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano *et al* 2010), both of which are widely used as drought indicators (WMO 2016) and are frequently employed in drought monitoring (Peng *et al* 2024) and early warning systems (Bachmair

Table 1. Summary of datasets, precipitation and temperature variables, and their purposes in the analysis.

Dataset	Variables used	Period covered	Resolution	Purpose
SEAS5	Mean total precipitation rate (converted to total rainfall), 2 m temperature	1990–2024	0.25° (∼28 km)	Used to forecast drought indicators
ERA5	Total rainfall, 2 m temperature	1990–2024	0.25° (∼28 km)	Serves as a reference dataset representing the 'ground truth' for drought indicators

et al 2016b). The key difference between these indicators is that SPI relies solely on precipitation data, while SPEI also factors in potential evapotranspiration (PET) by including temperature data (Vicente-Serrano *et al* 2010). We computed SPEI using the Thornthwaite method to estimate the climatic water balance (Thornthwaite 1948). These indicators were selected for their widespread use and their ability to compare the effects of precipitation alone versus the combined influence of precipitation and temperature on drought conditions.

We then estimated SPI and SPEI at the grid and NUTS1 scale (nomenclature of territorial units for statistics, v.2016) and considered accumulation periods of 1, 3, 6, 12 and 24 months, derived by applying a corresponding moving window to monthly time series. Different accumulation periods serve to assess various potential drought impacts: shorter periods capture immediate impacts, such as increased fire risk leading to wildfires, while longer periods reveal delayed impacts, like forest dieback from prolonged dry conditions and increased tree mortality (Shyrokaya *et al* 2023), which are further influenced by local factors and human activity (European Drought Observatory (EDO) 2020).

Data on drought impacts and their links to drought indicators were obtained from Bachmair *et al* (2016a), sourced from the publicly accessible European Drought Impact Report Inventory (Stahl *et al* 2012). For further details, refer to SM1 in the supplementary material.

3. Methodology

3.1. Calculation of drought indicators

Two methods were considered to calculate the indicators: (1) forecast-based method which evaluates the predictability of drought indicators using forecasts alone when the LT is equal to or greater than the accumulation period, and (2) combined method which combines forecasts with observational proxies (ERA5) when LT is shorter than the accumulation period. These approaches provide a comprehensive assessment of the forecasting system, with the latter approach simulating how a forecaster would use available observational data up to a certain point and rely on forecast data thereafter.

For the first forecast-based method, the calculation of SPI/SPEI with 3 month accumulation period (SPI3/SPEI3) at LT3 was done by taking the forecasts at LT3 for the target month, the LT2 from the previous month, and LT1 from 2 months previously. For instance, to calculate SPI3 at LT3 targeting May, we used the forecasted precipitation for May (LT3), April (LT2), and March (LT1), all from initialization in February (LT0). Figure 1(a) demonstrates the calculation of SPI3 with LT3, taking month 5 (May) as an example. This approach ensured that only the forecasting system is evaluated when the LT is greater than the accumulation period, and allowed us to evaluate SPI1 at LT1, SPI1 and SPI3 at LT3 (involving other LTs for aggregation as explained), SPI1 and SPI3 and SPI6 at LT6.

For the second combined method, the calculation of SPI3/SPEI3 at LT1 for May was done by using forecasts at LT1 for May and pseudo-observations (e.g. ERA5) for April and March to complete the 3 month accumulation (figure 1(b), Method 2). This approach allowed us to evaluate the following combinations: LT1 SPI3 to 24 accumulation periods; LT3 SPI6 to 24 accumulation periods; LT6 SPI12 to 24 accumulation periods.

3.2. Forecast evaluation

The verification of drought indicators computed based on SEAS5 with those calculated from ERA5 was conducted for each grid point and NUTS1 region by evaluating both their performance and skill. Performance was assessed using 4 deterministic metrics (correlation coefficient, mean squared error (MSE), root MSE (RMSE), mean absolute error) and 2 probabilistic metrics (brier score and ranked probability score (RPS)), along with their skill scores calculated relative to a baseline (see table SM2 in the supplementary material).

Specifically, for the deterministic metrics, we focused on the mean of SEAS5 ensemble members and used it to assess the precision (or accuracy) in forecasting drought indices. We tested whether using the median instead of the mean would impact the results and found no significant difference. In

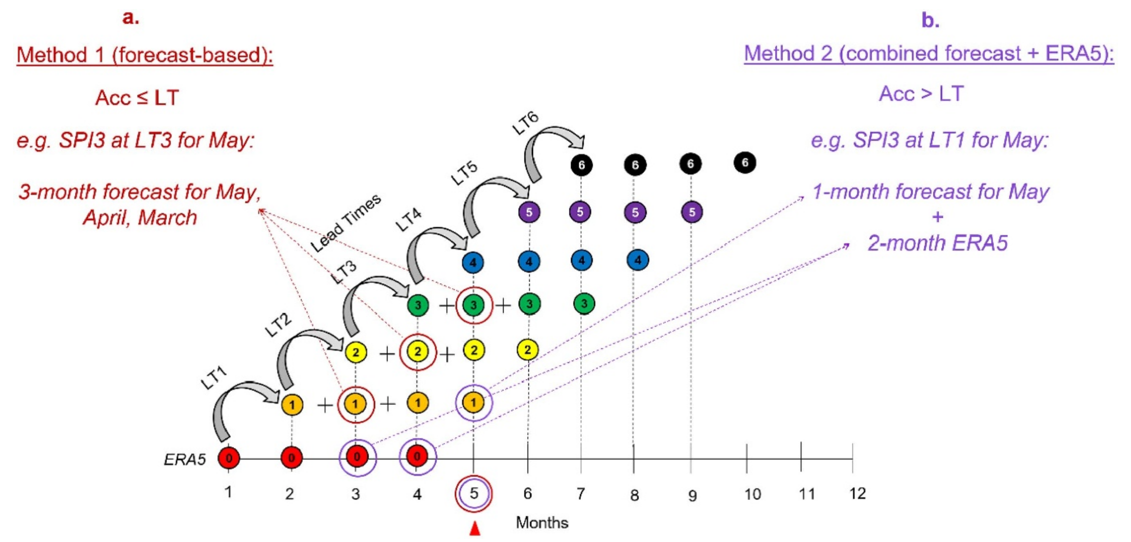

Figure 1. The forecast-based method ((a), method 1 in red) of calculating SPI3 at LT3 and the combined method ((b), method 2 in purple) of calculating SPI3 at LT1, both for the target month of May. Acc refers to the accumulation period.

calculating skill scores, the forecasting system was compared against ERA5 climatology as a benchmark. Particularly for the BS, we set thresholds for moderate, severe, and extreme drought categories (<0, <−1, and <−2 respectively), which corresponds to drought severity classification by WMO (2016) and European Drought Observatory (EDO) (2020). The ERA5 observational data were transformed into binary format (event 1/no event 0) with respect to each threshold separately, and SEAS5 probabilities were computed accordingly. For the RPSS, we categorized drought into four levels (>0: no drought, [−1, 0]: moderate drought, [−2, −1]: severe drought, <−2: extreme drought). We generated a matrix with probabilities for each category from SEAS5 and converted the ERA5 drought indices to one of these categories (1, 2, 3, 4) for each data point.

Here, this study presents three key chosen metrics: the deterministic correlation coefficient and RMSESS, and the probabilistic RPSS (table SM2 in the supplementary material). The correlation coefficient identifies regions where the forecasting system closely aligns with the pseudo-observations. Given the multiple correlation tests performed in grid-specific analyses, we apply the Benjamini–Hochberg procedure to control the False Discovery Rate (Benjamini and Hochberg 1995, Wilks 2016). This method accounts for multiple testing, minimizing the risk of false positives while maintaining the integrity of grid-specific analyses. RMSESS provides insight into the forecast quality compared to climatology in these areas. Additionally, RPSS analysis reveals whether and where the probabilistic forecasting system exceeds climatology in accuracy and reliability for predicting drought categories. Skill ranges from $-\infty$ to 1, with 1 indicating perfect skill and negative values indicating superiority of the benchmark system (climatology).

Additionally, the study assessed if bias-adjusted SEAS5 forecasts could improve drought indicator predictability against ERA5. Two approaches were considered: applying a simpler quantile-mapping (‘QUANT’) and a more sophisticated fitting probability-transformation function (‘PTF’) method to SEAS5 data (Enayati et al 2021, Golian and Murphy 2022).

3.3. Trade-off analysis: the UK and Germany case studies

After verifying the forecasting performance and skill of drought indicators at the grid scale, the next step was to aggregate them and assess their predictability at the NUTS1 level, and finally evaluate how well each index reflects actual drought impacts. This enabled us to conduct a trade-off analysis, comparing the forecasting performance of these drought indicators with findings from existing studies that ranked their predictive importance for various impacted sectors at the NUTS1 level. By combining these analyses, we established a complete chain, enabling the development of drought IbF for the impacted sectors which are linked to forecastable drought indicators in specific locations.

Due to the lack of gridded quantitative drought impact data for Europe, we focused on two case studies involving the UK and Germany, drawing on the study by Bachmair et al (2016a), which assessed the performance of the drought indices (SPI, SPEI) in terms of estimating drought impacts. The authors' approach involved adjusting the ranks of predictor importance during the construction of random forest models for assessing drought impacts across various sectors, as shown in figure 6 (for the UK) and figure 7 (for Germany) in Bachmair et al (2016a) and in SM3 and SM4 in the supplementary material.

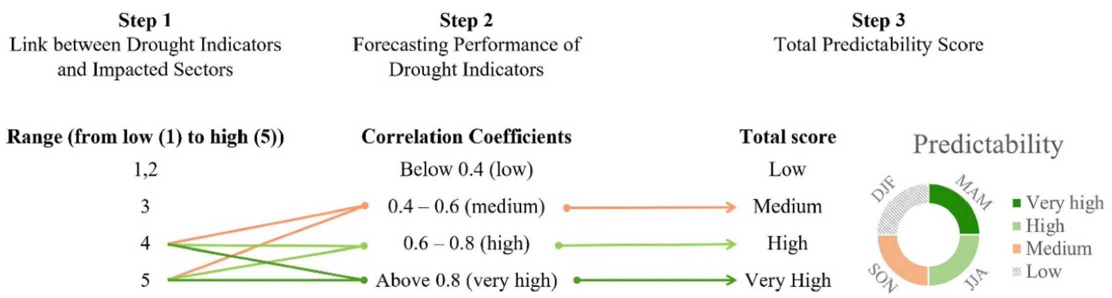

Figure 2. Conceptual figure presenting the total predictability score, involving 3 steps in its calculation (where DJF: winter, MAM: spring, JJA: summer, and SON: autumn).

We then estimated the total predictability score, which encompassed both the correlation coefficient from forecast evaluations and the relationship between specific drought indicators and their corresponding accumulation periods within each NUTS1 region in the UK or Germany (drawn from Bachmair *et al* 2016a). Correlation coefficients were chosen because they offer an intuitive interpretation, clearly demonstrating whether the model captures the temporal variability and patterns of drought indicators. This process followed the methodology depicted in figure 2.

1. **Link between Drought Indicators and Impacted Sectors**: We transformed the ranks of predictor importance from SM3 (for the UK) and SM4 (for Germany) into a scale of 1–5, considering values of 4 and 5 as indicative of a strong link.
2. **Correlation Coefficients for Forecasting Performance of Drought Indicators**: We calculated the correlation coefficients for the SPI/SPEI predictability in LT1, LT3, and LT6 for the corresponding NUTS1 regions in the UK and Germany. Correlation coefficients were classified as medium (0.4–0.6), high (0.6–0.8), and very high (above 0.8). In cases where a proxy for observed data (ERA5) was partially used, a perfect correlation of 1 was weighted proportionally to the number of observational months relative to the total accumulation months. For example, SPI3 LT1 was calculated as the correlation coefficient for SPI1 LT1 * 1/3 + 1 (perfect correlation of proxy for observed) * 2/3.
3. **Total Predictability Score**: We combined the results from the previous two steps to determine the overall predictability score:
   (a) Medium: When the link (Step 1) is 4 or 5, and the correlation coefficient (Step 2) is medium (0.4–0.6).
   (b) High: When the link (Step 1) is 4 or 5, and the correlation coefficient (Step 2) is high (0.6–0.8).
   (c) Very High: When the link (Step 1) is 4 or 5, and the correlation coefficient (Step 2) is very high (above 0.8).

4. Results

4.1. Seasonal drought predictability across Europe

Drought predictability across Europe (figures 3 and 4, table 2) varies by region and season, reflecting differences in climatic conditions and the performance of forecasting indices. Northern Europe exhibits high predictability, with SPI slightly outperforming SPEI, particularly in winter and spring. This higher predictability may stem from less climatic variability and more accurate precipitation forecasts. While, Southern Europe, particularly the Iberian Peninsula, maintains strong forecast skill in winter, spring and summer, with SPI performing slightly better in winter and SPEI in summer, driven by the region's higher temperature predictability during summer (Turco *et al* 2017). Western and Central Europe show moderate predictability, with higher performance of SPEI in spring and autumn, while Eastern Europe achieves consistent, moderate correlations across seasons, with some indices extending predictability into longer LTs. Notably, SPI3/SPEI3 at LT6 shows a very low correlation and is therefore included only in the supplementary material (see figure SM5 in the supplementary material).

These regional differences emphasize the need to tailor drought forecasting approaches to the specific climatic conditions of each area. Understanding these nuances is key to maximizing the utility of long-term forecasts, offering significant potential for planning and adaptation, particularly in sectors such as water management and agriculture. Regions with high predictability at LT6, such as parts of Northern Europe in spring (SPI6, SPEI6) and summer (SPI6), as well as parts of Western, Central, Southern, and Eastern Europe in autumn (SPEI6), could support long-term water resource planning.

4.2. Difference in SPI and SPEI: error propagation between ERA5 and SEAS5

We next examine the error propagation during the calculation of SPI and SPEI by comparing the correlation coefficients between ERA5 and SEAS5 for several variables used to compute these indices (figure 5). For SPI, a gamma distribution was fitted to precipitation

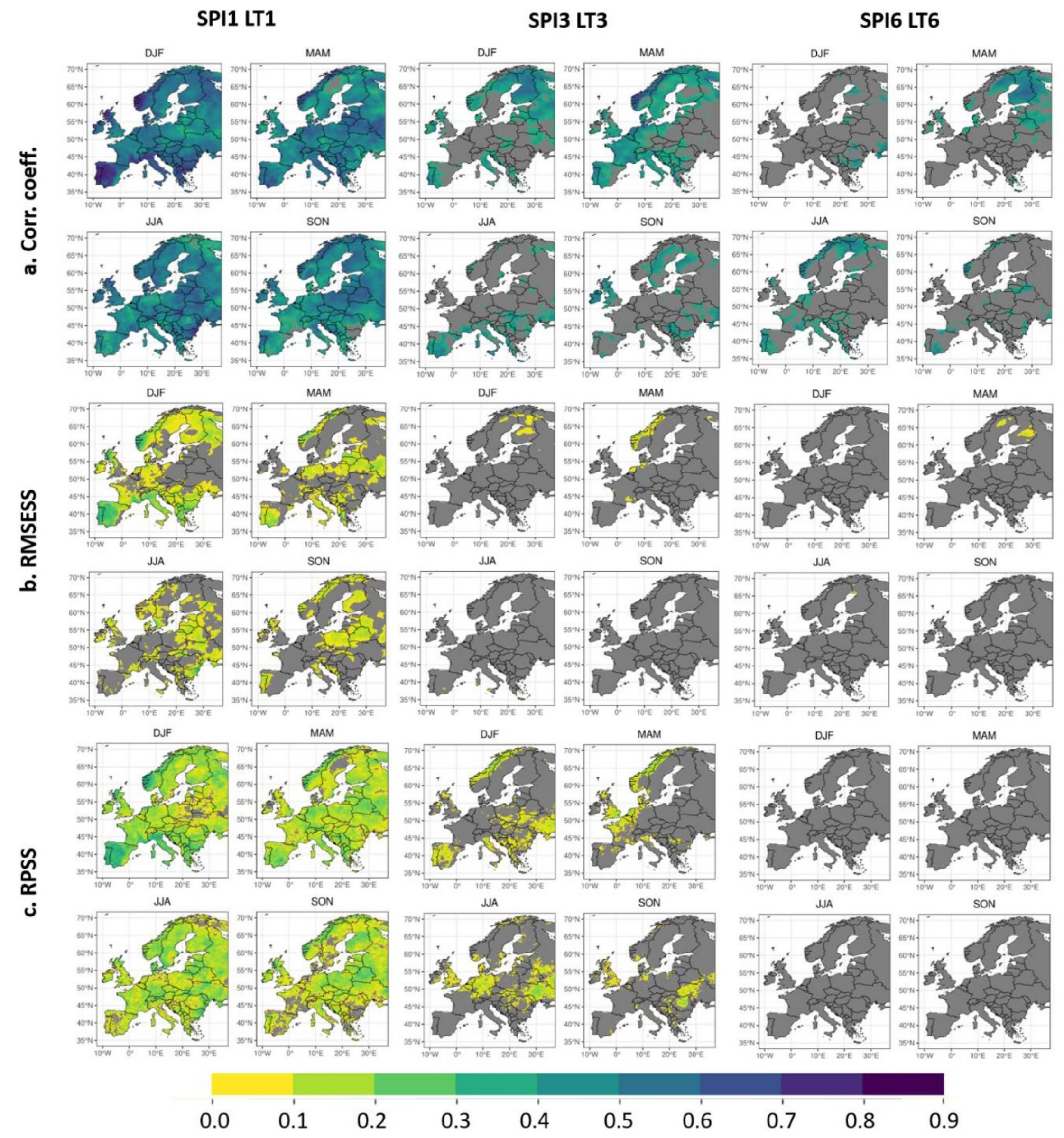

Figure 3. Forecasting performance (a. Correlation Coefficient) and skill (b. RMSESS and c. RPSS) assessment for SPI1 LT1, SPI3 LT3, SPI6 LT6. The grey areas for Correlation Coefficients denote correlations that are not statistically significant (adjusted p-value > 0.01). The grey areas for RMSESS and RPSS indicate skill below 0. The results are presented for each target season (DJF: winter, MAM: spring, JJA: summer, and SON: autumn). Refer to SM5 in the supplementary material for SPI3 at LT6.

(P) data, while SPEI calculations involved the additional step of using temperature (T) to estimate PET, subtracting PET from precipitation to determine the climatic water balance (BAL), and fitting a log-logistic distribution to compute SPEI.

Panels I and II reveal that precipitation exhibits the lowest correlation between ERA5 and SEAS5, reducing the accuracy of the water balance (P minus PET). This leads to large errors in the later steps of the SPI and SPEI calculations. Despite these issues, SPEI still shows marginally higher correlations than SPI (mean correlation coefficient of 0.5 for SPEI compared to 0.44 for SPI) suggesting for this slight improvement to be accounted to the more predictable temperature (Weisheimer and Palmer 2014). In Panel III, the strong correlation between SPI and SPEI reflects their reliance on partially shared data, although the methods of derivation differ.

4.3. Bias-correction: forecast only

The improvement gained from bias-correcting precipitation (SM7) is substantially reduced when applied to SPI1 (SM8). This is evident in the results presented in the supplementary material, where SM7 illustrates the bias correction of raw precipitation data, and SM8 shows the bias correction applied to SPI1 at LT1. Both figures reveal that while bias-correction enhances the precipitation data, the improvement diminishes significantly during the transformation to drought indices, with the correlation coefficient improvement being within 0.1 (SM8).

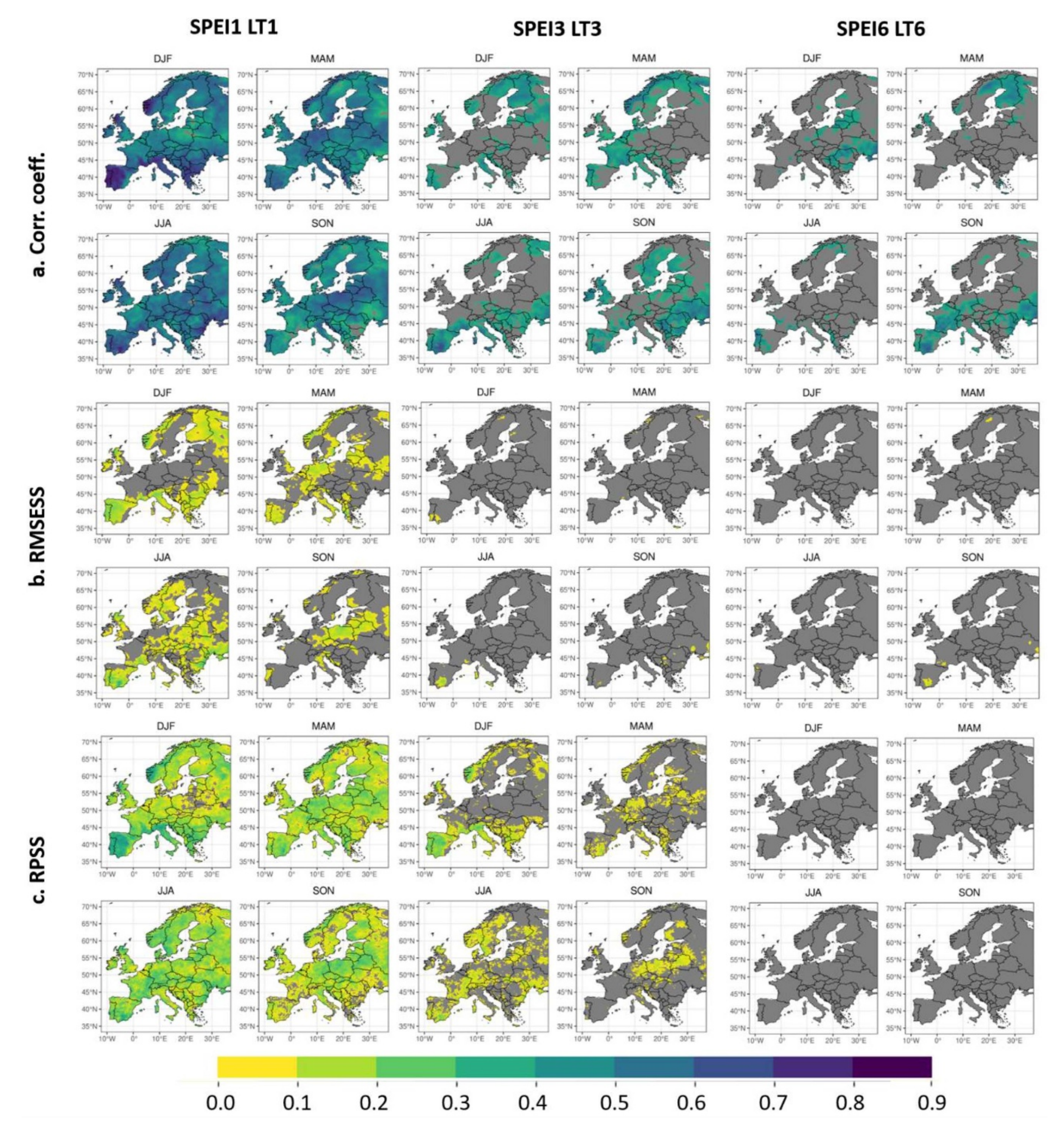

Figure 4. Forecasting performance (a. Correlation Coefficient) and skill (b. RMSESS and c. RPSS) assessment for SPEI1 LT1, SPEI3 LT3, SPEI6 LT6. The grey areas for Correlation Coefficients denote correlations that are not statistically significant (adjusted p-value > 0.01). The grey areas for RMSESS and RPSS indicate skill below 0. The results are presented for each target season (DJF: winter, MAM: spring, JJA: summer, and SON: autumn). Refer to SM5 in the supplementary material for SPEI3 at LT6.

This pattern is consistent across SEAS5 data corrected using both tested approaches: the simpler quantile-mapping (‘QUANT’) method and the more sophisticated fitting ‘PTF’ method, applied to SEAS5 hindcasts and real-time forecasts from 1990–2024.

These findings suggest that improvements achieved through bias correction are diminished during the transformation to drought indices. While quantile mapping adjusts the statistical distribution of model outputs to align with the reference dataset (ERA5), it might not address temporal or spatial variability issues in precipitation predictions. If the SEAS5 model has inaccuracies in timing, sequence, or intensity of precipitation events, quantile mapping alone cannot correct these critical aspects for accurate SPI representation. Therefore, alternative methods should be explored to either bias-correct raw precipitation data from SEAS5 while preserving improvements through drought index transformations or directly bias-correct drought indices. Correcting raw precipitation data helps the transformation process (e.g., SPI, SPEI) more accurately capture precipitation variability—a critical factor in drought assessments. In turn, post-processing the resulting drought indices can directly adjust the final signals, improving alignment with observed conditions and simplifying the overall workflow.

4.4. IbF: the UK and Germany as case studies

Aggregating grid-scale data to the NUTS1 administrative level enables comparison with drought indicators that have previously been linked to

Table 2. Seasonal performance (correlation coefficient) and skill (RMSESS and RPSS) of SPI and SPEI across European Regions.

Region	Index	Performance	Skill
Northern Europe	SPI	High correlations for SPI1 and SPI3 across most seasons (except SPI3 in summer). SPI6 shows notable correlations in spring and summer (parts of Scandinavia).	RMSESS and RPSS show positive skill in winter and spring, particularly in Norway for LT3. Reduced skill in summer and autumn; some areas show no skill.
	SPEI	Similar performance to SPI, with slightly higher correlations in spring for SPEI1, but worse for SPEI6 in summer over Scandinavia.	Lower skill than SPI in winter and spring, but slightly better in summer (skill extends to LT3 in Scandinavia).
Western and Central Europe	SPI	SPI1 shows moderate to high correlations across all seasons, while SPI3 maintains moderate correlations during spring only. For SPI6, correlations tend to decrease in all seasons.	Skill peaks in winter and spring for SPI1 but diminishes for SPI3, with no significant skill in winter and autumn.
	SPEI	Slightly higher correlations than SPI, particularly in autumn extending to SPEI6.	Similar skill to SPI, with lower skill in winter, but slightly higher in summer.
Southern Europe (Iberian Peninsula and Mediterranean/ Balkan)	SPI	*Iberian Peninsula*: High correlations for SPI1 and SPI3 in winter and spring. Stronger performance in summer compared to other areas in Southern Europe. *Mediterranean/Balkan*: Lower correlations compared to the Iberian Peninsula, especially during summer.	*Iberian Peninsula*: Positive skill across most seasons, particularly winter and spring. The positive skill of SPI3 in summer only. *Mediterranean/Balkan*: The skill is generally slightly lower, with some areas showing skill for SPI3 in winter.
	SPEI	*Iberian Peninsula*: Aligns with SPI, with higher correlation coefficients in summer and autumn. *Mediterranean/Balkan:* Similar performance to SPI, with slightly better skill for SPEI3 in winter.	*Iberian Peninsula*: SPEI3 skill extends into winter, capturing both precipitation and temperature influences effectively. *Mediterranean/Balkan*: Similar to SPI.
Eastern Europe	SPI	Moderate correlations across seasons for SPI1 and SPI3. SPI3 correlations extend to LT3 in winter and autumn; SPI6 correlations extend to LT6 in spring.	Generally moderate to high skill, but notably lower in winter.
	SPEI	Similar to SPI, with slightly better correlations for SPEI3 in autumn.	Comparable skill to SPI.

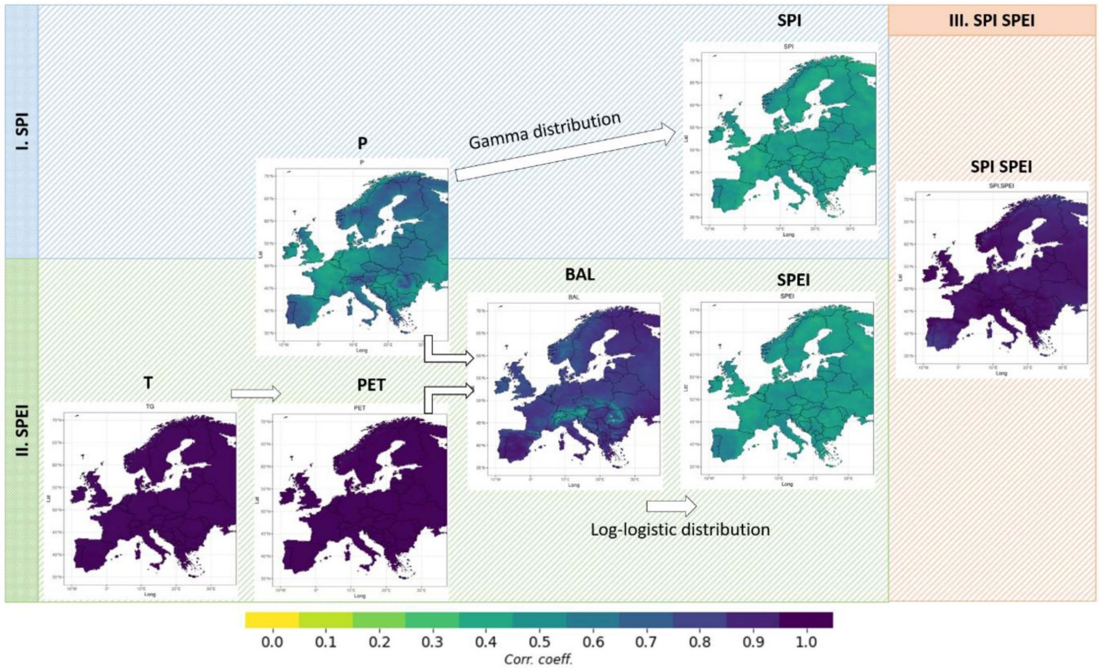

Figure 5. Grid point correlation between ERA5 and SEAS5-based calculations for various variables involved in computing SPI (panel (I)) and SPEI (panel (II)), including precipitation (P), 2 m temperature (T), potential evapotranspiration (PET), water balance (BAL). Panel (III) shows the correlation between SPI and SPEI, both computed from SEAS5. All variables were calculated with LT1 and averaged across all seasons.

impacts across various sectors at the same NUTS1 level, as outlined by Bachmair *et al* (2016a). The correlation coefficients for SPI1/SPI3/SPI6 and SPEI1/SPEI3/SPEI6 at LT of 1, 3, and 6 months are presented in figure SM9 in the supplementary material. After aggregation, these performance metrics became smoother, while generally reflecting the trends discussed in section 4.1. The RMSESS plots are not shown, as the results become statistically insignificant during aggregation, while the RPSS for SPI1/SPEI1 at LT1 is included in SM6 in the supplementary material.

The forecast-based method alone offers moderate predictability for certain sectors in the UK and Germany, including Agriculture, Tourism, and Water Transportation, up to LT3 depending on a season. In contrast, the combined method, which integrates SEAS5 forecast data with ERA5 proxy data (section 3.2), significantly improves accuracy, achieving very high predictability across various NUTS1 regions in both countries throughout all seasons, with some variation at LT6 depending on the reliability of forecasted data. The total predictability scores for these regions, with a focus on sectors linked to drought impacts (Bachmair *et al* 2016a), are presented in Tables Zenodo 1 and Zenodo 2, available at https://zenodo.org/records/14447608. These color-coded tables (orange for medium, light green for high, and dark green for very high predictability) highlight the sectors that can be predicted accurately, considering season, region, and LT.

The results presented below illustrate the total predictability of impacts for the two methods across various sectors at three LTs (LT1, LT3, and LT6) and four seasons for different NUTS1 regions in the UK (figure 6) and Germany (figure 7). The figures show the best available combination of results, without specifying which drought indicator was used for each specific result. For the forecast-based method, the specific drought indicators used in the calculation are detailed below figures 6 and 7, as well as in table 11 of the supplementary material. All underlying data supporting these calculations for both methods are available in Tables Zenodo 1 and Zenodo 2.

In the case of the UK (figure 6; upper panel), the forecast-based method achieves moderate predictability of impacts on Agriculture in Yorkshire and the Humber (UKE) (based on SPEI1) and Tourism in the South East (UKJ) (based on SPI1 and SPEI1) at LT1 across all seasons. Similarly, moderate predictability is observed for Water Supply in the South East and Water Quality and Tourism in the South West (UKK) at LT3 (all based on SPI3), but this is limited to spring. However, the combined method (figure 6; lower panel), allowing for longer accumulation periods, substantially improves predictability across multiple sectors, including Agriculture, Water Supply, Water Quality, Freshwater Ecosystems, and Tourism. This results in very high predictability for all seasons across various NUTS1 regions in the UK in the short-to-medium term (LT1 and LT3). The predictability at LT6 varies by sector depending on the NUTS1 region

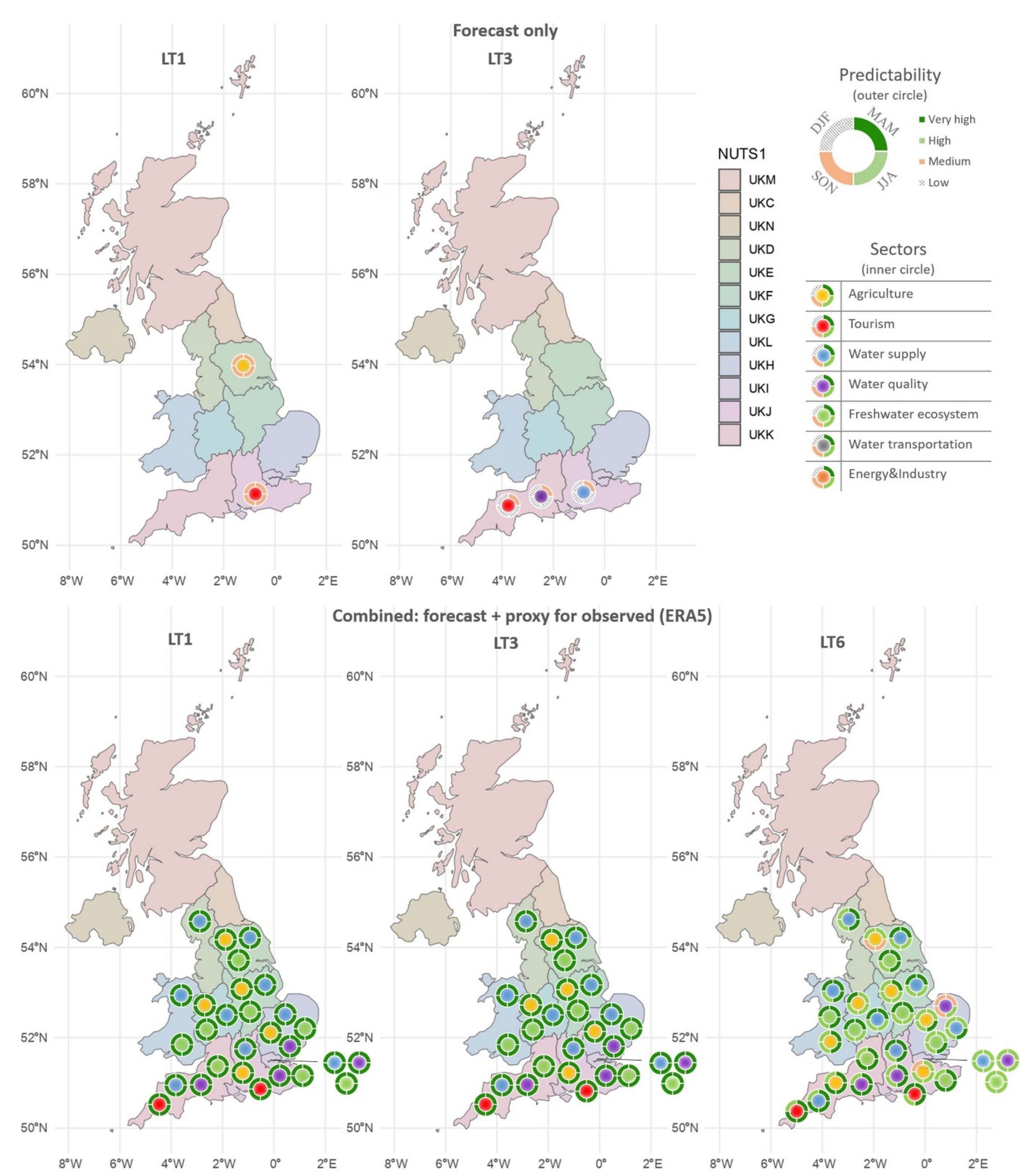

Figure 6. The total predictability scores for impacts on various sectors across different NUTS1 regions in the UK (refer to table SM10 in the supplementary material for the abbreviated list of NUTS1 regions). The analysis is split between two methods: forecast-based (upper panel) and combined method (lower panel). For each method, predictability is evaluated at three lead times (LT1, LT3, and LT6) and across different seasons (MAM: Spring, JJA: Summer, SON: Autumn, DJF: winter).

and season. For example, in the South West (UKK), all sectors show very high predictability in summer, spring, and autumn, with slightly lower yet still high predictability in winter. In contrast, Water Quality in the East of England (UKH) shows high predictability in spring, but only moderate predictability in other seasons.

Similarly, in Germany, the forecast-based method (figure 7; upper panel) shows medium predictability for Agriculture in regions such as Baden–Württemberg (DE1), Schleswig–Holstein (DEF), and Mecklenburg-Vorpommern (DE8) at LT1 across all seasons (all based on SPI1 and SPEI1), with high predictability in spring for Mecklenburg-Vorpommern (based on SPEI1). Similarly, Water Transportation impacts in Baden–Württemberg and Rhineland–Palatinate (DEB) (all based on SPEI1) are also predicted with medium accuracy at LT1 across all seasons. However, at LT3, only impacts on Agriculture in Schleswig–Holstein, Mecklenburg-Vorpommern, and Lower Saxony (DE9) can be predicted with medium accuracy, and only in spring (all based on SPI3). When combining forecast data with ERA5 proxies (figure 7; lower panel), the predictability for all sectors increases to very high across all seasons at LT1 and LT3. However, at LT3, some regions, such as Schleswig–Holstein, Lower Saxony, and Saxony (DED), experience a slight decline in predictability

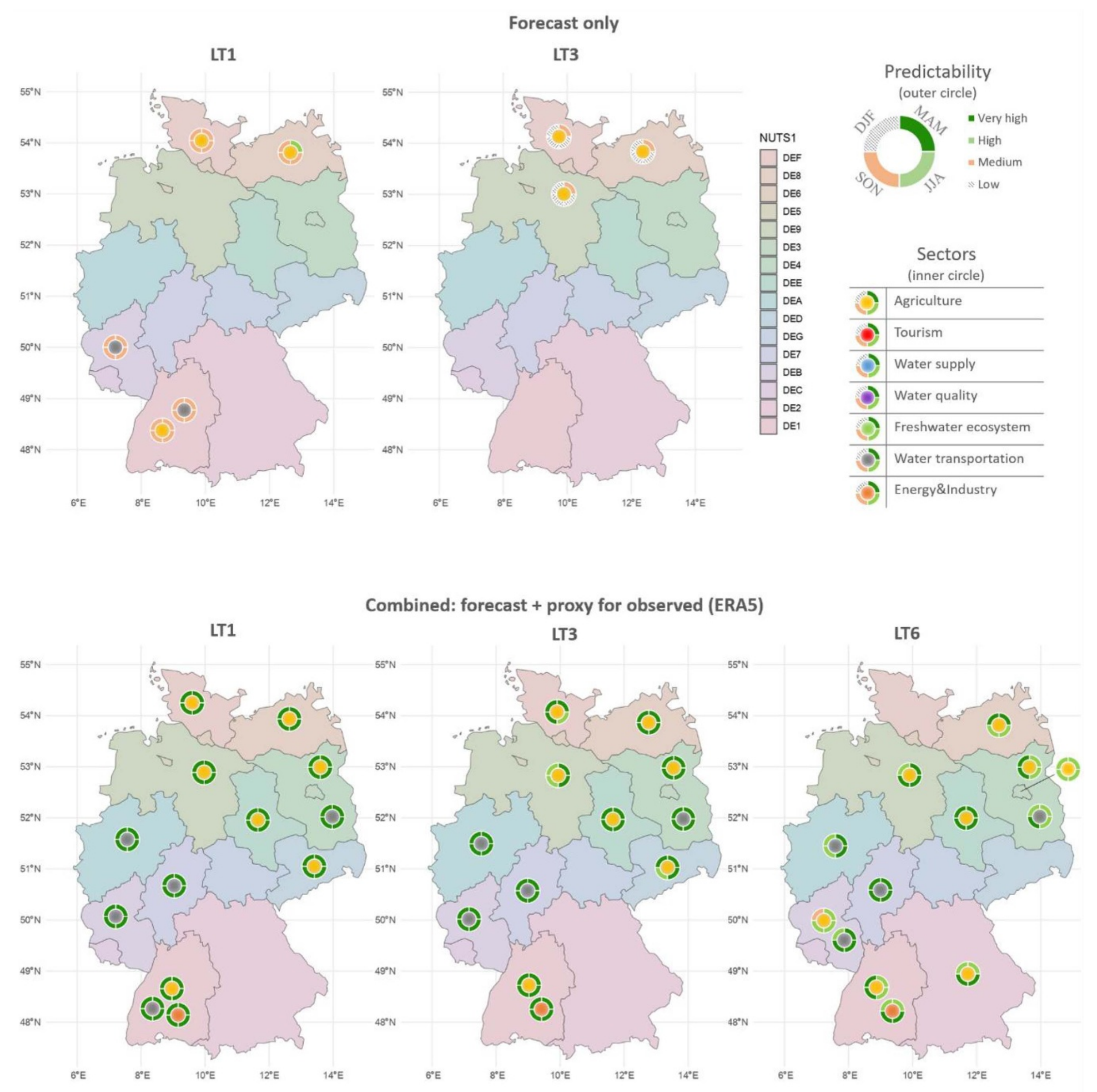

Figure 7. The total predictability scores for impacts on various sectors across different NUTS1 regions in Germany (refer to table SM10 in the supplementary material for the abbreviated list of NUTS1 regions). The analysis is split between two methods: forecast-based (upper panel) and combined method (lower panel). For each method, predictability is evaluated at three lead times (LT1, LT3, and LT6) and across different seasons (MAM: Spring, JJA: Summer, SON: Autumn, DJF: winter).

for Agriculture, from very high to high, especially in winter and autumn. At LT6, predictability varies by region and sector. For example, in southern regions like Bavaria (DE2) and Baden–Württemberg, very high predictability is observed in summer and autumn, with slightly lower (but still high) predictability in winter and spring. In contrast, northern regions like Mecklenburg-Vorpommern show higher predictability in winter and spring for Agriculture, with predictability slightly lower but still high in summer and autumn. This regional variability is likely due to differences in temperature patterns, with lower temperature variability observed in southern Germany during the summer months compared to higher latitudes.

5. Discussion—limitations and practical implications

This study demonstrates that the predictability of drought indicators (SPI and SPEI) varies significantly across Europe, with clear regional and seasonal patterns that provide actionable insights for IbF. The framework presented in this study offers great potential for developing operational IbF systems by mapping climate-sensitive sectors closely linked to drought indices, and identifying regions and seasons where accurate impact predictions are feasible.

The relationship between drought indicators and sector-specific impacts is complex, requiring robust data pipelines between forecast models and impact observations to enable widespread adoption. Our approach can be adapted to assess drought impact predictability in various case studies across and beyond Europe, serving as a flexible tool for different geographical contexts. The variability in results between SPI and SPEI underscores the need for users to carefully select the appropriate drought indices based on regional climate characteristics and the specific sectors being forecasted, which may limit the practical application of IbF in certain areas. We note though that the successful implementation of such systems relies on the availability and integration of impact data.

Our findings confirm increased predictability of SPEI in summer for Southern Europe. This generally aligns with Turco *et al* (2017), although we find a maximum LT of 3 months in our study compared to 6 months in theirs. Similarly, SPEI6 shows comparable predictability in spring for Northern Europe and remains limited for Central Europe. For LT6, our results highlight autumn predictability over Western and Southern Europe, consistent with Turco *et al* (2017)'s observation of SEAS4's stronger performance in these regions. Regarding impacts, our findings align with Sutanto *et al* (2019), indicating predictability of agricultural impacts at longer LTs in Lower Saxony (DE9) and water transportation impacts in Baden–Württemberg (DE1) at shorter LTs.

While short LTs yield better accuracy, long LTs are vital for decision-making in sectors such as water management and agriculture. However, one major limitation is the reduced performance of the forecasting models at long LTs (e.g., 6 months), where both SPI and SPEI exhibit low skill across all regions. Here we improved long-term predictability by integrating pseudo-observational data, leveraging longer accumulation periods to extend forecasts up to six months with region-, season-, and sector-specific reliability.

Bias correction techniques, while helpful, provided limited improvement in forecast skill, indicating a need for alternative methods. Future efforts could explore advanced bias correction methods, alternative drought index formulations, or machine learning approaches to correct raw precipitation data while preserving temporal patterns critical for SPI/SPEI calculations or to directly predict impacts from the raw data.

Additionally, ERA5, while commonly used as a ground truth, has limitations, including biases in precipitation, particularly during heavy precipitation events. To enhance reliability, the forecasts could be verified against higher-resolution datasets like Multi-Source Weather (Beck *et al* 2022). Extending reforecasts to cover the full ERA5 period could also improve spatial coherence.

Lastly, future research could extend this approach to include other important drought indicators like soil moisture or streamflow. Some studies (e.g. Sutanto *et al* 2020, Du *et al* 2023) suggest that these may offer better predictability due to catchment memory effects, and they can better describe agricultural and hydrological droughts and their socioeconomic impacts. However, the lack of studies linking soil moisture and streamflow indices to sectoral impacts limits the ability to conduct a comprehensive analysis in data-scarce regions, unlike the SPI and SPEI application demonstrated here for the UK and Germany. Addressing the limited availability of impact data is crucial to further advancing the operationalization of IbF systems. Equally important, these systems must uphold ethical principles by ensuring equitable access to drought forecasts and preventing the misinterpretation of indices, particularly in regions with limited data, to avoid exacerbating vulnerabilities or inequalities.

6. Conclusions

There is an urgent need to effectively integrate drought forecasting with sectoral impact prediction, as current systems often struggle to reliably connect drought indices like SPI and SPEI to real-world consequences, thereby limiting the development of actionable, IbF systems across Europe. This study offers a comprehensive evaluation of drought forecasts, identifying seasons, regions and sectors where SPI and SPEI show strong predictability. The developed framework provides a solid foundation for operationalizing IbF by combining forecast data with pseudo-observed data, which enhances predictability for critical sectors. These findings significantly contribute to advancing operational IbF by enabling accurate, actionable drought impact predictions. Key insights include:

- *Regional and Seasonal Insights*: Across Europe, drought forecasting predictability varies significantly by region and season, with notable differences between SPI and SPEI. In general, Northern Europe tends to have better predictability, especially in winter and spring, with SPI slightly outperforming SPEI in these 2 seasons. The Iberian Peninsula stands out in Southern Europe, with relatively high predictability, particularly in winter and spring for both SPI and SPEI, and additionally in summer for SPEI only. Western and Central Europe also show reasonable predictability for both indices during these seasons, although skill declines significantly in spring and autumn, with SPEI showing slightly higher value. While forecasting skill typically declines with increased LT, certain areas maintain skill at LT6. Notably, parts of Northern Europe in spring (SPI6, SPEI6) and summer (SPI6), as well as areas in Western, Central, Southern, and Eastern Europe in autumn (SPEI6), exhibit sustained skill, offering a potential window for long-term water resource planning.

- *Impact Predictability for the UK and Germany*: In the UK and Germany, the study demonstrates establishing a complete chain, enabling the development of drought IbF for the impacted sectors which are linked to forecastable drought indicators in specific locations. The combined method, which integrates forecast data with pseudo-observed data, extends prediction accuracy over longer periods (up to LT6), improving sector-specific impact predictions depending on LT, region, and season. In the UK, the method yielded very high predictability for Agriculture, Water Supply, Water Quality, Freshwater Ecosystems, and Tourism across multiple NUTS1 regions. In Germany, central regions demonstrated very high predictability for Water Transportation, while southern and northern regions showed similarly high predictability for Agriculture, depending on the season. However, in some regions and seasons, predictability varied, underscoring the complex interplay between sector-specific impacts and drought indices. Overall, the findings emphasize the value of combining forecast data with observed proxies to enhance the reliability and timing of drought impact predictions.

This framework lays the foundation for advancing drought management systems, particularly in regions vulnerable to climate change. By supporting more effective decision-making, it enables stakeholders to anticipate and mitigate drought impacts across key sectors. Ultimately, it enhances the ability of policymakers and resource managers to implement proactive strategies, building resilience to climate change and alleviating the socio-economic and environmental impacts of droughts.

Data availability statement

The ERA5 monthly averaged data, provided by ECMWF, is freely accessible through the Climate Data Store: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means. The ECMWF SEAS5 dataset can be accessed from the operational archives of the MARS catalogue www.ecmwf.int/en/forecasts/dataset/operational-archive.

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

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Conflict of interest

The authors have declared no conflicting interests.

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