

Multiscalar and nonlinear controls of drought impacts in Spain revealed by media-reported data

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15 **Abstract.** This study assesses the multiscalar and nonlinear relationships between drought severity, characterised by the
Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI), and media-
reported hydrological and agricultural impacts across Spain during 1976–2023. Drought indices were derived from a high-
resolution gridded climate dataset (1.1 km), while impact data were obtained from standardised monthly frequencies of
drought-related newspaper articles at the provincial scale. Results demonstrate robust temporal coherence between drought
20 conditions and impacts, with major drought episodes associated with anomalies exceeding +1 to +2 standard deviations.
Drought–impact relationships strengthen markedly with accumulation timescale, reaching maximum correlations at 12–24
months ($|r| \approx 0.6$ – 0.8), while short timescales (1–3 months) show weak associations ($|r| < 0.3$). Hydrological impacts are
primarily associated with accumulated medium- and long-term moisture deficits (12–48 months), whereas agricultural impacts
are associated with shorter accumulation timescales (3–12 months). However, for both sectors, dominant accumulation
25 timescales lengthen as drought severity increases. Sensitivity analyses reveal pronounced nonlinear responses, with media-
reported impact frequency increasing disproportionately during severe drought conditions, peaking at 12–36 months. The
consistently stronger association of SPEI relative to SPI, especially for agricultural impacts, suggests a dominant contribution
of atmospheric evaporative demand. Our results indicate that media-reported impact frequency is associated with accumulated
moisture deficits across timescales and temperature-dependent processes and provide a framework for improved impact-based
30 drought monitoring in a warming climate.

1 Introduction

Drought is a complex and cyclical natural hazard that can lead to severe impacts on ecosystems, water resources, agriculture and economies (Vicente-Serrano et al., 2016; Slette et al., 2019; McGlade et al., 2019; El Kenawy et al., 2023). Unlike rapidly
35 developing hazards, drought evolves gradually over months to years and thus detection and assessment of drought impacts is more difficult (Vicente-Serrano, 2016). Climate change has led to severe droughts and their consequences for the world's population (Spinoni et al., 2021; Runde et al., 2022; Wang et al., 2023). Increased temperature and increased atmospheric evaporative demand have been reported to be linked with increased frequency, severity and duration of droughts for Southern Europe (Vicente-Serrano et al., 2014; Stagge et al., 2017).

40 To monitor and characterise drought severity, researchers use drought indices, which provide objective measures across meteorological, agricultural, and hydrological domains (Keyantash, 2021). The relationship between most drought indices and their actual impacts can be non-linear, even though they are highly correlated (Bachmair et al., 2015; Kchouk et al., 2022). The magnitude and nature of drought impacts are largely influenced by local environmental and socioeconomic conditions (Kamali et al., 2019; Wijitkosum et al., 2025). These impacts are diverse, including hydrological impacts such as reduced river
45 flows, reservoir depletion, and groundwater decline, as well as agricultural impacts such as crop failure, livestock losses, and food insecurity (Vicente-Serrano et al., 2021; Walker et al., 2024).

Hydrological impacts are primarily controlled by accumulated precipitation deficits, driven by mechanisms including soil moisture depletion, reduced groundwater recharge and reduced reservoir storage (Melo et al., 2016; Álvarez-Garretón et al., 2021; Liu et al., 2024). Thus, hydrological impacts are largely the cumulative effects of a prolonged deficit of moisture.
50 Hydrological systems primarily respond to medium- and long-term drought conditions and therefore exhibit delayed yet persistent responses (Van Loon et al., 2024). Agricultural impacts are more closely associated with short- to medium-term droughts because soil moisture and atmospheric water demand respond rapidly during the growing season (Kimm et al., 2020; Rigden et al., 2020). These sectoral differences highlight the importance of the drought accumulation timescale for the link between climate anomalies and impacts. Warm conditions can intensify water stress through increased atmospheric
55 evaporative demand, leading to larger differences between precipitation-based and temperature-sensitive drought indicators (Vicente-Serrano et al., 2014; Tomás-Burguera et al., 2020; Ji et al., 2026). Similar drought conditions do not necessarily produce similar impacts depending on regional vulnerability, adaptive capacity and land and water management protocols (Welsh et al., 2013; Engström et al., 2020; Van Schmidt et al., 2023). Together, these controls introduce nonlinear behaviour into drought-impact relationships and may induce disproportionate effects in the event of severe or extended droughts.

60 Media coverage plays an important role in shaping the societal interpretation of drought impacts. Newspaper articles provide information on the timing, location, and sectoral manifestation of drought impacts (Bachmair et al., 2016; Murphy et al., 2017; Wang et al., 2020; O'Connor et al., 2023; Jobbová et al., 2024), which allows us to understand physical conditions and social

responses. They are often used for reconstruction of past droughts and interpretation of human behaviour in relation to climate change (Brazil et al., 2018; Nash et al., 2019). Drought indices in Europe and the Mediterranean are highly correlated with reported impacts (e.g., in agriculture and water supply systems) (e.g., Stahl et al., 2015; Blauhut et al., 2016; Shyrokaya et al., 2023). Such media reports have been important for documenting regional drought dynamics and public perceptions in Spain (Llasat et al., 2009; Ruiz Sinoga and León Gross, 2013; Serrano-Acebedo et al., 2026).

Recent advances in natural language processing and machine learning have enabled the development of long-term multi-sectoral datasets (Dayrell et al., 2022) for systematic extraction of drought impact information from a large text corpus. However, there are large differences in the variation of drought-impact relationships across accumulation timescales, the role of atmospheric evaporative demand in shaping those relationships, and the change in impact sensitivity with increasing drought severity. These gaps are particularly relevant for Spain, a region with amplified hydro-climatic gradients, high interannual variability and high sensitivity to both precipitation deficits and drought intensification driven by temperature (Domínguez-Castro et al., 2019; Vicente-Serrano et al., 2019; Noguera et al., 2022). Despite extensive use of drought indices, the spatial organisation of drought impacts and the dominant timescales controlling hydrological and agricultural responses remain poorly constrained. Addressing these challenges is critical for improving impact-based drought monitoring and early warning systems, which increasingly require information on when, where, and how impacts occur. Spain provides an ideal case study due to its climatic heterogeneity and recurrent exposure to drought.

The aim of this study is to quantify the multiscale relationship between drought severity (SPI and SPEI) and media-reported hydrological and agricultural impacts across Spain (1976–2023). Specifically, we (1) assess the temporal coherence and timescale dependence of drought–impact relationships, (2) evaluate the role of atmospheric evaporative demand (SPEI vs SPI) and the nonlinear sensitivity of impacts to drought severity, and (3) identify the dominant timescales and spatial patterns controlling impact responses across sectors. The results provide new insights into the temporal, nonlinear, and spatial dynamics of drought impacts and contribute to advancing impact-based drought monitoring under changing climatic conditions.

2 Data and methods

2.1 Drought impact data

Drought impact information was extracted from El País, the general-interest newspaper with the largest circulation in Spain. All articles published from its foundation on 11 May 1976 to 31 December 2023 were analysed. Articles were initially pre-filtered for drought relevance using a supervised classifier based on a fine-tuned Longformer model within the SeqIA

90 framework (López Otal et al., 2025). This binary classifier identified 15,102 drought-relevant news articles over the study period.

Drought impact extraction from these articles was conducted using a schema-guided Generative Information Extraction (GenIE) approach implemented within the CienaLLM framework (https://github.com/lcsc/ciena_llm/). This method enables the extraction of structured information from unstructured text by prompting a large language model (LLM) to generate outputs (e.g., in JSON format) based on a predefined schema specifying the target information.

The first schema incorporated the four most common drought-impact categories in Spain: crops (e.g., reduction in yield of crops, crop failure, planting delays), livestock (e.g., reduced productivity, feed shortage, increased mortality), hydrological resources (e.g., reduced river discharge, reservoir depletion, decline in groundwater level) and energy (e.g., reductions in hydropower generation). We performed the extraction locally using the gemma2:9b model, aiming to balance computational cost and extraction performance. The extraction resulted in 6,852 articles reporting crop-related impacts and 1,268 articles reporting livestock-related impacts. These were eventually combined into one category of agricultural impacts comprising 7,009 articles. Hydrological resources (6,408 articles) and energy (1,106 articles) were merged into a broader category of hydrological impacts. These aggregations were introduced to reduce data sparsity and support consistent province-by-timescale comparisons at a broad sectoral level. They represent operational groupings rather than an assumption that all constituent impacts share identical mechanisms or response timescales. The resulting sector-level patterns should therefore be interpreted as broad reporting signals.

Temporal attribution was based on the publication date of each article. Specifically, an article contributed to the calendar month in which it was published; temporal expressions within the article text were not used to back-date an impact to an inferred occurrence month. The monthly series therefore represent the timing of media reporting, which may differ from the timing of impact onset because of delays between impact occurrence, recognition, and publication.

Repeated coverage was intentionally retained at the article level. No event-level de-duplication was applied across consecutive articles or months, so multiple reports of an ongoing condition (for example, persistently low reservoir levels) contribute multiple observations. Consequently, the resulting monthly series quantify reporting intensity or societal salience rather than the number of unique drought-impact events.

Province extraction was performed separately from impact extraction to identify the Spanish provinces referenced in drought-related articles. Because impact labels and province labels were extracted independently, the workflow did not establish sentence-level one-to-one links between a particular impact and a particular province when an article contained multiple impacts and multiple locations. Such articles can therefore contribute to more than one province–sector combination, and province-level results should be interpreted as spatial patterns of drought-related reporting rather than perfectly resolved

geocoded impact events. The province names were standardized by mapping the different model outputs to the official names, reconciling spelling differences between co-official languages, and manually assigning frequently mentioned municipalities or geographical features to their corresponding provinces. The final dataset is a monthly count of articles referring to each impact category (agriculture and hydrology) in each province. Monthly impact frequencies were quantified as the number of drought-related articles published for each province and impact category. Article publication month was used for temporal attribution, and repeated reporting of persistent impacts was retained; consequently, the response variable represents reporting intensity and societal visibility rather than a count of unique impact events or a direct measure of physical damage magnitude. The extraction was multi-label rather than mutually exclusive. Therefore, a single article could contribute to more than one impact category when it reported multiple drought consequences, such as crop losses together with reservoir depletion or water-use restrictions. The agricultural and hydrological series should therefore be interpreted as sector-specific monthly reporting frequencies, not as disjoint sets of articles. To assess the possible influence of co-reporting, we quantified the article-level overlap between the two broad sectors and considered this overlap when interpreting the relationship between agricultural and hydrological impact series.

2.2 Drought quantification

To compute drought indices, this study used a high-resolution gridded drought indices dataset developed by Vicente-Serrano et al. (2017a) with SPI and SPEI information for the whole of Spain at a resolution of 1.1 km. SPI and SPEI, which are based on precipitation and on the difference between precipitation and atmospheric evaporative demand, respectively, have been widely used in agricultural, ecological and socioeconomic studies (e.g., Abatzoglou et al., 2014; Bachmair et al., 2015; Barker et al., 2016; Kumar et al., 2016; Peña-Gallardo et al., 2018). The monthly SPI and SPEI series were computed for the 48 provinces comprising mainland Spain and the Balearic Islands, as well as at the national scale. The SPI and SPEI were computed for accumulation periods from 1–48 months. While SPI is useful for its simplicity and availability of data (McKee et al., 1993), it does not take into account atmospheric demand and may underestimate the intensity of drought during warm periods, which is considered by the SPEI (Tomas-Burguera et al., 2020). The joint use of SPI and SPEI therefore offers a complete characterization of the drought severity and variability over Spain for the analysed period (1976–2023), useful for both climatological assessments and impact attribution.

2.3 Relating drought to impact data

To allow a robust comparison of the temporal dynamics of drought indices (SPI and SPEI) and the frequency of reported impacts of drought, we standardized the time series of the monthly relative frequency of drought-related news across the provinces of Spain for the period 1976–2023. The dataset includes information about hydrological and agricultural droughts reported in newspapers. Because the raw data are proportional frequencies, which are often missing in months with no reports, a statistical transformation was needed to normalize the distribution of the data and to make it comparable to standardised drought indices. We applied the method proposed by Vicente-Serrano et al. (2025). We focused on a non-parametric empirical

standardization technique for non-climatic impact indicators (e.g., media-based records) that may not satisfy normality or distribution assumptions. It deals with important issues of discrete and zero-inflated time series and provides a flexible yet rigorous framework to convert impact frequencies into standardised values. This approach preserves the ordinal structure of the original series while accommodating repeated values and months without drought reports. This yields a standardised impact index directly comparable to SPI and SPEI, with negative values indicating below-average impact frequency (i.e., little or no reported drought activity) and positive values indicating above-average impact frequency, with increasing magnitude indicating increasing reporting frequency or visibility of drought conditions. This transformation placed all provincial time series on a common scale (mean = 0, standard deviation = 1), facilitating comparison among provinces and with SPI/SPEI. However, standardization does not remove possible long-term changes in newspaper production, editorial priorities, digital publication practices, or drought newsworthiness. These sources of non-climatic temporal variation are therefore treated as limitations of the media-derived record rather than assumed to have been eliminated by standardization. The analysis was contemporaneous: impact reporting in month (t) was compared with SPI or SPEI whose accumulation period ended in the same month (t). Thus, the analysis evaluates climatic accumulation windows associated with reporting rather than explicit temporal lags between drought conditions and subsequent impacts or reporting.

2.4 Spatial regionalization of drought impact data

To reduce dimensionality and identify dominant spatial-temporal patterns in drought-related impact reporting, we applied Principal Component Analysis (PCA) to the standardised monthly drought-impact time series. PCA was conducted separately for hydrological and agricultural impacts. In each sector-specific analysis, the input matrix consisted of monthly observations from 1976–2023 as rows ($n = 572$) and Spanish provinces as columns ($n = 48$). Therefore, the covariance matrix represented covariation among provincial impact-reporting time series within a given sector. SPI and SPEI were analysed subsequently in the drought–impact correlation and sensitivity analyses. The PCA was used only to identify the dominant spatial modes of reported impact variability and the provinces contributing most strongly to those modes. Spatial patterns were used to visualise the loadings to recognize regions with similar behaviour of drought impacts. We examined the temporal evolution (scores) of each principal component to illustrate the dominant temporal mode of variability among provinces.

2.5 Drought–reporting sensitivity coefficient

To quantify how media reporting varies with drought magnitude, we calculated a drought–reporting sensitivity coefficient (β) from a log–log relationship between drought magnitude and monthly media-reporting counts. This coefficient provides a scale-independent measure of the elasticity of reporting intensity with respect to drought magnitude across sectors, provinces, drought-severity classes, and accumulation timescales.

For the sensitivity analysis, only months with dry index values (SPI or SPEI < 0) were retained, and the drought index was sign-reversed so that larger positive values represent greater drought magnitude ($D_t = -\text{SPI}_t$ or $-\text{SPEI}_t$). This means that the

185 magnitude of drought was represented by the absolute value of the drought index (López-Moreno et al., 2013; Barker et al., 2016; Conradt et al., 2023). Unlike the standardized impact series used for the temporal comparison, correlation analysis, and PCA, the response variable in the log–log regression was the unstandardized monthly article count for the corresponding province and sector. Thus, I_t denotes the number of media reports in month t . Because $\ln(0)$ is undefined, months with $I_t=0$ were excluded from this specific regression step; months with positive counts were transformed as $\ln(I_t)$, and drought
190 magnitude was transformed as $\ln(D_t)$. The resulting coefficient therefore describes the elasticity of reporting intensity conditional on at least one report being present. It does not model the probability of whether any report occurs, and exclusion of zero-report months can affect the estimated coefficient, particularly in sparsely reported province–sector combinations.

To examine whether the reporting–drought association changes across drought severity, monthly observations were stratified
195 by the sign-reversed drought index into near-normal dry conditions (>0 to 0.5), mild (0.5 – 0.84), moderate (0.84 – 1.28), severe (1.28 – 1.65), and extreme (>1.65) drought, together with a category containing all dry conditions (>0) (Agnew, 2000). Regressions were fitted separately within each class. This stratification is intended to reveal broad changes in reporting sensitivity across severity ranges, but the width of the predictor range and the number of observations differ among classes. In particular, severe and extreme classes can contain relatively few observations, so isolated class-specific slopes may be unstable.
200 As such, the number of observations supporting each regression, as well as the resulting sample-size distributions, was quantified across provinces, accumulation timescales, drought indicators, sectors, and severity classes.

For each province, the ordinary least squares (OLS) estimator for β was computed, following:

$$\ln(I_t) = \alpha + \beta \ln(D_t) + \epsilon_t$$

205 where I_t represents the monthly media-reporting count in month t , D_t is the sign-reversed drought index in month t . Under this log–log formulation, the coefficient β quantifies the relative response of reporting frequency to changes in drought magnitude, indicating the proportional change in reporting intensity associated with a proportional change in drought magnitude (e.g., a 1% increase in drought magnitude is associated with an approximate $\beta\%$ change in reporting intensity). This statistic provides a dimensionless measure of drought-reporting sensitivity. As a result, comparisons can be made across sectors
210 (hydrological vs. agricultural), provinces, and timescales (1–48 months). This enables a multiscale assessment of drought–impact relationships. Moreover, this framework enables the identification of the timescales, as well as provinces, at which drought conditions show the strongest association with reporting. For each sector, sensitivity coefficients were first estimated at the provincial level and then aggregated to the national scale by computing the arithmetic mean across provinces.

215 Prior to inferential interpretation of the correlation and regression analyses, temporal autocorrelation was evaluated for the drought-index and impact-reporting series, with particular attention to the longer SPI/SPEI accumulation periods for which successive monthly values contain strongly overlapping climatic information. Serial dependence was assessed using the autocorrelation function (ACF). Autocorrelation of the regression residuals was additionally examined to assess whether

temporal dependence materially affected the statistical inference from the fitted models. To evaluate the role of atmospheric evaporative demand in drought severity and subsequent drought impacts, sensitivity coefficients were calculated independently using SPI and SPEI. Differences between SPI- and SPEI-based coefficients (i.e., $SPI - SPEI$) were used to assess the contribution of temperature-driven processes to drought impacts. Negative sensitivity values (i.e., $SPEI > SPI$) indicate a stronger influence of atmospheric evaporative demand, whereas positive values (i.e., $SPI > SPEI$) suggest precipitation-dominated responses.

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Regional patterns of impact response were determined by analysing the spatial distribution of drought impact sensitivity at the province level. In addition, the dominant accumulation timescale was defined as the timescale for which the sensitivity coefficient was the maximum in the range 1–48 months for each province and drought severity class. All drought indices were aligned with media reporting in the same month; therefore, the identified accumulation timescale represents the climatic integration window most strongly associated with reporting at time (t), rather than drought-event duration or an explicit impact-response lag. In cases where multiple timescales exhibited similar values, the smallest timescale among the maxima was selected to ensure consistency.

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3. Results

3.1. Drought impacts track climate variability across timescales

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Fig. 1 depicts the temporal evolution of standardised drought indices (SPI-12 and SPEI-12) and media-reported drought impacts in Spain from 1976 to 2023. Hydrological reporting closely tracks multi-year drought variability, with major peaks in drought-impact reporting occurring in the early 1980s, mid-1990s, early 2000s and early 2010s associated with significant positive anomalies. In contrast, wet periods are associated with negative anomalies (< -1), indicating a decrease or no reported impacts. Although both sectors exhibit coherent variability, important sectoral differences emerge. Negative SPEI anomalies have become more frequent than SPI anomalies in recent decades (after 2000) and are more consistent with variability in reporting. However, some inconsistencies are observed, such as moderate drought conditions (-0.5 to -1) are not always associated with significant reporting anomalies, indicating nonlinear and context-dependent responses. The strong relationship between agricultural and hydrological impacts ($r = 0.89$, Fig. 1c) should be interpreted with caution because the impact categories are not mutually exclusive at the article level. Some articles report multiple drought consequences simultaneously and therefore contribute to both sectoral series. Accordingly, Fig. 1c reflects both genuine temporal co-occurrence of sectoral impacts during major drought episodes and partial co-reporting within the same media articles. We therefore interpret this relationship as coherent cross-sector drought reporting and impact co-occurrence, rather than as fully independent evidence of causal propagation between sectors.

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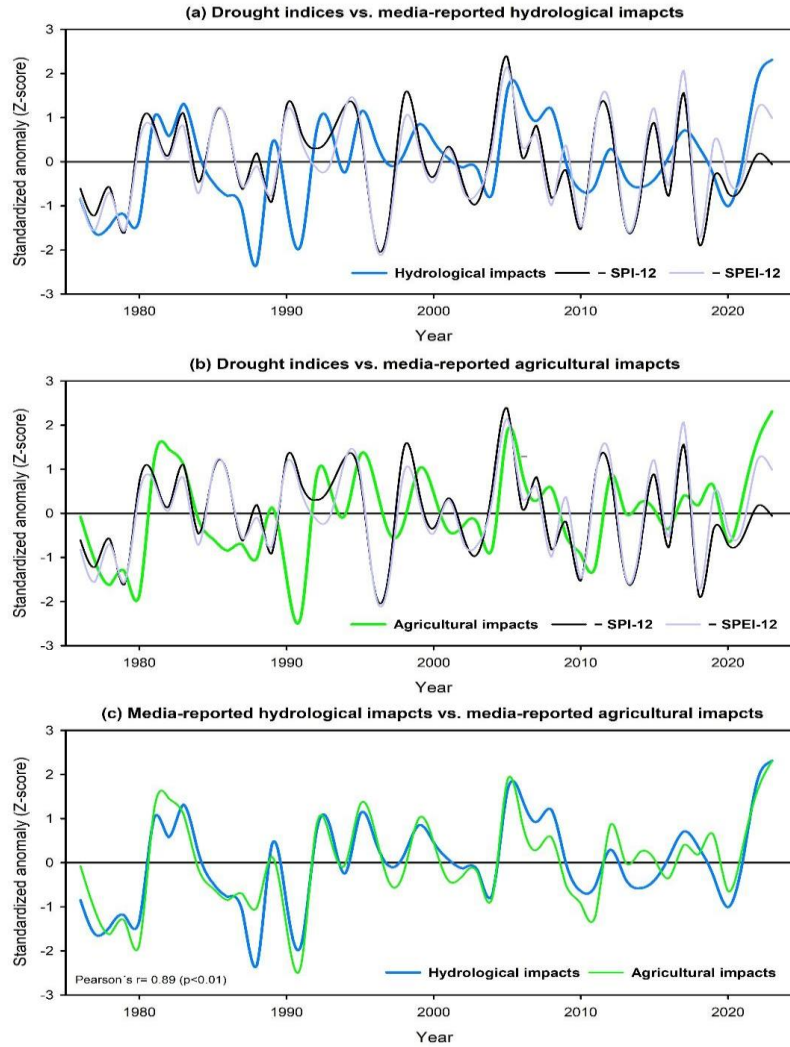


Fig. 1: Temporal evolution of standardised drought indices and media-reported drought impacts in peninsular Spain over the period 1976–2023. (a) Hydrological impacts and (b) agricultural impacts are compared with SPI-12 and SPEI-12, while (c) illustrates the relationship between hydrological and agricultural impacts. All series are expressed as standardised anomalies (Z-scores). In panels a and b, drought indices were sign-reversed (multiplied by -1) to facilitate direct comparisons with drought impacts (i.e., drought severity $\uparrow$, reported-impact frequency $\uparrow$).

The relationship between drought indices and impacts across accumulation timescales (1–48 months) over Spain is summarized in Fig. 2. Consistent negative correlations indicate that drier conditions correspond to increased reported impacts. Correlations increase significantly with increasing timescale, reaching maximum values at 12–30 months for both sectors ($|r| \approx 0.6$ – 0.8), while short timescales (1–3 months) indicate weak and inconsistent relationships ($|r| < 0.3$). These relationships are further modulated by seasonal variability, with higher correlations during summer months and early autumn when water

demand and agricultural sensitivity peak. Hydrological impacts have the highest correlations at longer time scales (12–32 months), whereas agricultural impacts respond mainly over a slightly broader range, especially in late spring and early summer. SPEI has slightly stronger correlations than SPI across most conditions and especially for agriculture. The results indicate that reported-impact frequency is more strongly associated with persistent moisture deficits than with short-term anomalies.

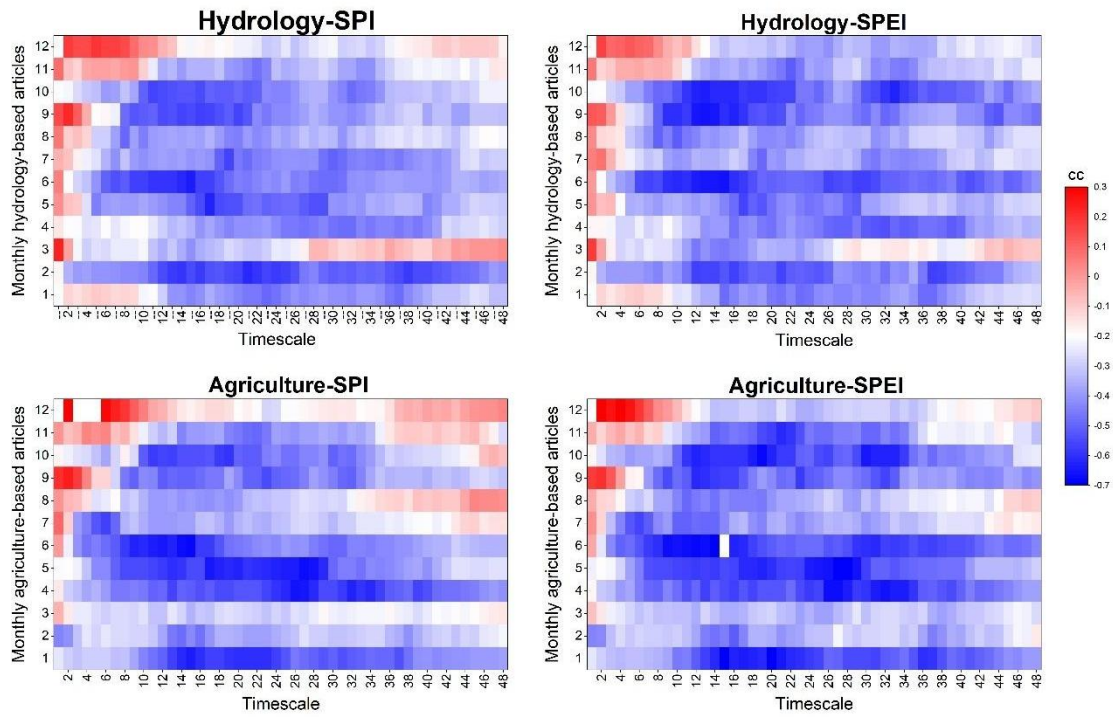


Fig. 2: Correlation matrix (Pearson coefficient) between standardised monthly frequencies of drought-related newspaper impacts and drought indices (SPI and SPEI) computed at accumulation timescales from 1–48 months. Absolute Pearson correlation coefficients ($|r|$) exceeding 0.28 are statistically significant at $p < 0.05$.

3.2. Mechanisms and nonlinear sensitivity of drought–impact relationships

Fig. 3 illustrates the drought-reporting sensitivity coefficient of media-reporting frequency to drought severity across accumulation timescales. Reporting sensitivity varies markedly with timescale and drought intensity, and the strongest response coefficient is found at 12–24 months. The sensitivity coefficient values are consistently larger for SPEI than for SPI, especially for hydrological impacts, indicating that temperature-driven processes amplify impact responses. While the sensitivity coefficient for hydrological impacts indicates smoother, more gradual increases, agricultural reporting displays higher and more variable sensitivity, which reflects their faster reaction to soil moisture deficits. At short timescales (1–3 months) the sensitivity coefficient is low, confirming the limited role of short-term anomalies. These findings highlight the nonlinear response of media-reported impact frequency to drought severity and the dominant role of sustained moisture deficits.

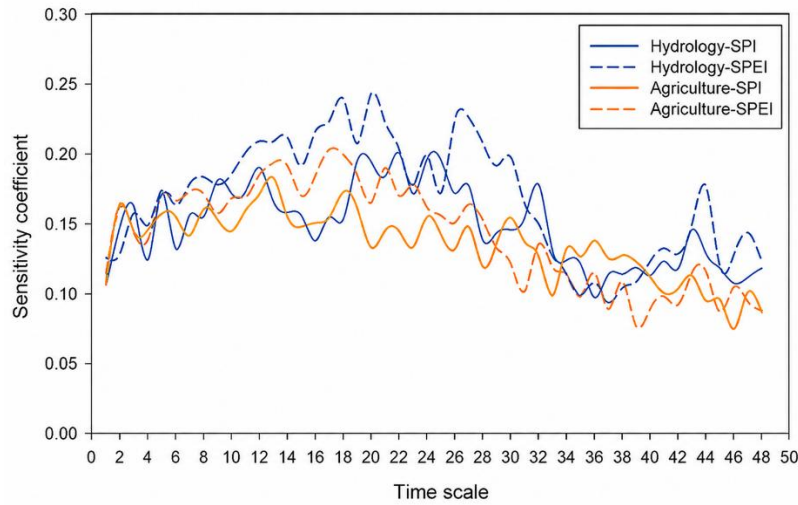


Fig. 3: Drought-reporting sensitivity coefficient response curves linking drought indices (SPI and SPEI) with media-reported hydrological and agricultural drought impacts across accumulation timescales from 1–48 months. Lines represent mean drought-reporting sensitivity coefficient values averaged across Spanish provinces for each sector-index combination.

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Because stratification by drought-severity class reduces the number of observations available for individual regressions, we examined the sample size underlying the sensitivity estimates across sectors, drought indicators, and accumulation timescales (Supplementary Figs. S1–S3). As expected, for hydrological (Supplementary Fig. S1) and agricultural (Supplementary Fig. S2) impacts, the number of observations decreases from normal and moderate conditions toward severe and extreme drought classes. Nevertheless, the severe and extreme regressions retain observations across the full 1–48-month accumulation range for both SPI and SPEI and for both hydrological and agricultural impacts. Median sample sizes generally remain around or above 10 observations across most timescales, and frequently approach or exceed 15 observations over the intermediate accumulation periods where many of the strongest sensitivity responses occur (Supplementary Fig. S3). The largest reductions in sample size are more evident toward the longest accumulation periods, particularly for some extreme-drought combinations.

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The interquartile ranges further indicate appreciable spatial variability in the number of observations available among provinces, confirming that some province-timescale regressions are less well supported than others. Importantly, however, the sample-size curves vary smoothly with accumulation timescale rather than showing isolated collapses at the accumulation periods associated with the principal sensitivity maxima. This suggests that the broad timescale-dependent patterns are not simply artefacts of a single or very small number of sparsely sampled regressions.

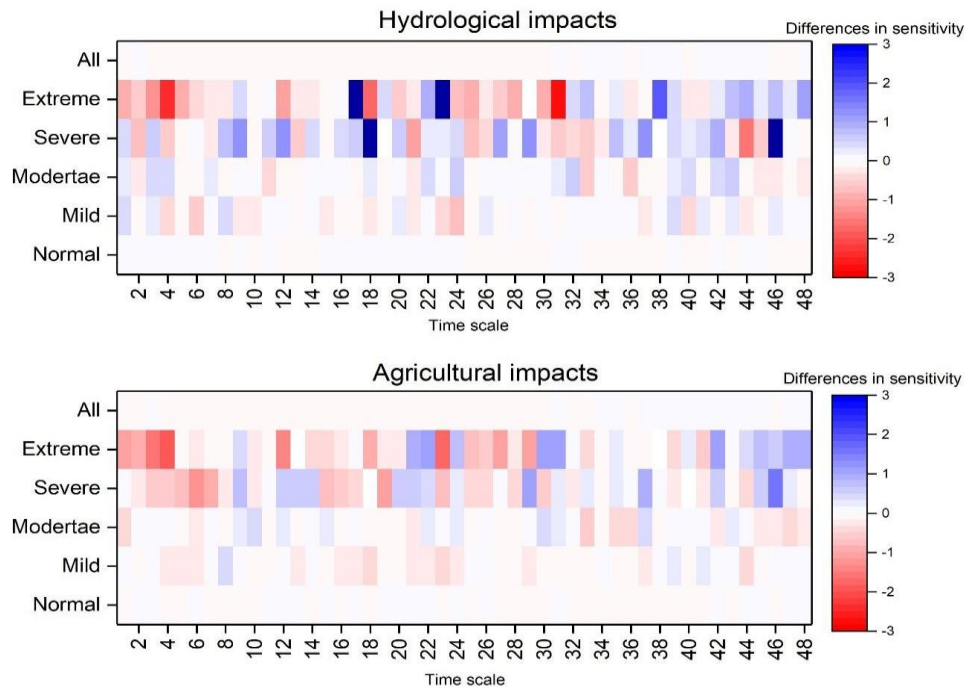


Fig. 4: Differences in national-scale mean drought-reporting responses between SPI and SPEI across accumulation timescales (1–48 months). Differences between SPI and SPEI responses indicate the contribution of temperature-driven evaporative demand across drought severity classes.

Results suggest that impact sensitivity is dependent on accumulation timescale (Fig. 4), with the highest sensitivity at 12–36 months. Differences between SPEI and SPI based responses are negligible at short timescales (1–3 months) but increase with increasing timescales, with consistently stronger responses from SPEI, particularly for moderate to severe droughts. Results reveal some sectoral differences. Specifically, for hydrological impacts, negative differences emerge primarily at medium to long timescales (12–36 months). In contrast, agricultural impacts suggest earlier divergence, with amplified negative differences already at shorter to intermediate timescales (6–24 months), indicating higher sensitivity to atmospheric demand.

Fig. 5 reveals clear spatial heterogeneity in drought-reporting sensitivities. SPEI-dominated responses prevail over large areas, especially at longer timescales (12–36 months), indicating a widespread influence of atmospheric evaporative demand on drought impacts. This effect is especially evident for agricultural systems, whereas hydrological responses exhibit greater spatial coherence at longer accumulation periods. At shorter timescales (3–6 months), differences are weaker and more fragmented, reflecting the dominant role of precipitation variability. Collectively, these results indicate a transition from precipitation-driven to temperature-influenced drought impacts at longer accumulation timescales.

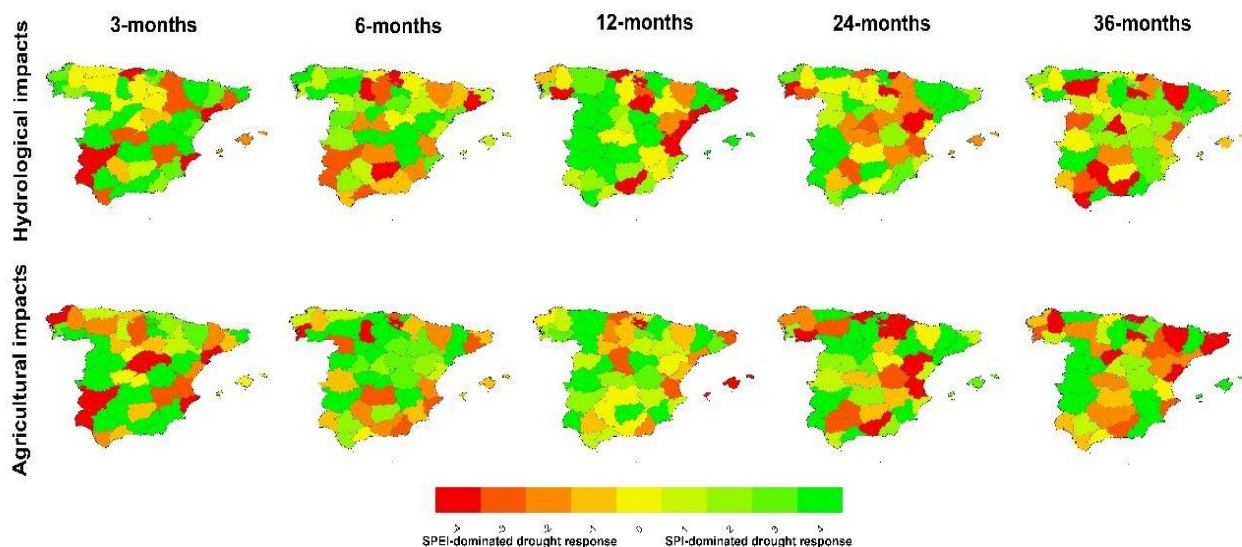
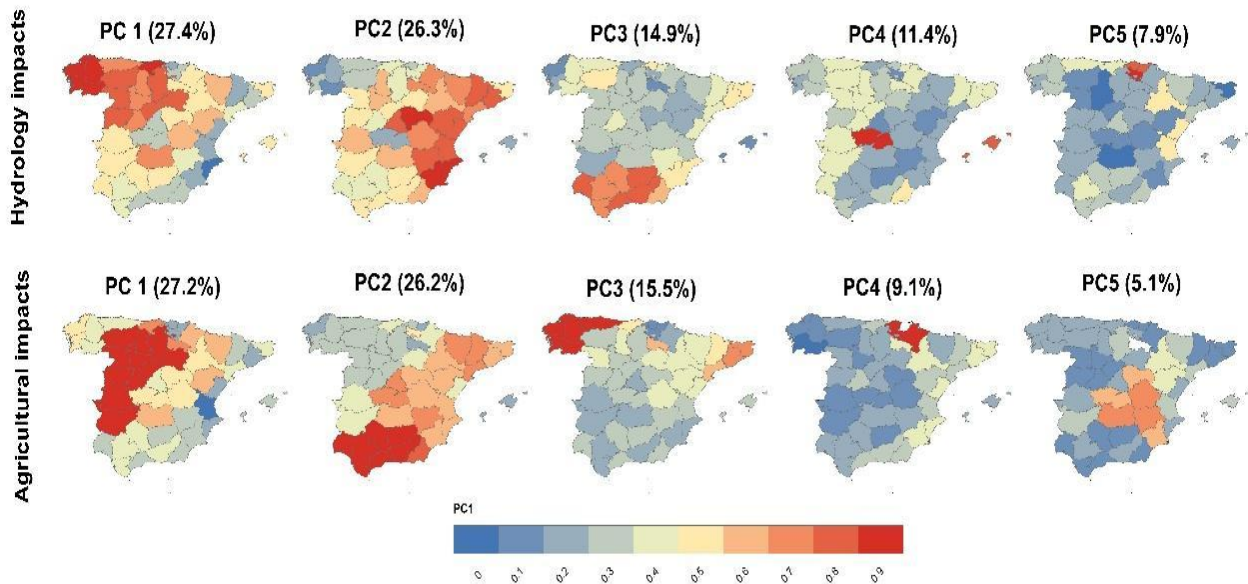


Fig. 5: Spatial differences in drought-reporting sensitivity between SPI and SPEI across peninsular Spain at multiple accumulation timescales. The relative dominance of SPEI-driven versus SPI-driven drought responses for hydrological impacts (top row) and agricultural impacts (bottom row) is presented at 3-, 6-, 12-, 24-, and 36-month timescales.

The leading spatial modes of drought impacts obtained from principal component analysis are illustrated in Fig. 6. The first principal component (PC1) embodies a prevailing national mode in the two sectors with positive loadings indicating coherent large-scale variability of drought impacts. The most evident hydrological impacts are in north-western and central Spain, consistent with basin-scale water storage responses, while agricultural impacts are more important in western and south-western regions, reflecting sensitivity to soil moisture deficits. PC2 demonstrates a clear east-west contrast with the Mediterranean and southern regions having stronger loadings and the interior and north having weaker or opposite patterns, a contrast that is more sharply defined for hydrological impacts. PC3–5 are higher order components that represent more local variation. Hydrological impacts seem to show structured regional differences, mainly related to catchment characteristics, whereas agricultural impacts are more patchy and spatially heterogeneous. Overall, hydrological impacts are more spatially coherent while agricultural impacts are more locally modulated.



335 **Fig. 6: Spatial loadings of the principal components (PCs) derived from standardised monthly hydrological (upper row) and**
agricultural (lower row) drought impact time series across Spanish provinces (1976–2023). Numbers in parentheses indicate the
percentage of total variance explained by each principal component.

Drought sensitivity coefficients were assessed under different drought severity classes for the different PCs for both
340 hydrological and agricultural impacts (Fig. 7). As illustrated, for hydrological impacts, sensitivity increases with both drought
severity and accumulation period, peaking during severe and extreme droughts at 12–36 months. SPEI consistently exhibits
larger drought–reporting sensitivity coefficients than SPI, especially under extreme conditions, suggesting an increased
sensitivity to atmospheric evaporative demand. At the regional scale, PC1, the dominant large-scale signal over northwestern
and central Spain, exhibits a growing sensitivity with timescale and drought severity reaching its maximum at 12–36 months,
345 in agreement with the integrative behaviour of large river basins and storage systems. PC2, which is related to the
Mediterranean and southern regions, is more sensitive to severe and extreme drought, especially at the longer timescales,
implying a higher vulnerability to prolonged moisture deficits in these regions. In contrast, higher order components (PC3–5)
that represent more localized variability have more irregular and spatially restricted responses with the sensitivity peaks
differing by timescale.

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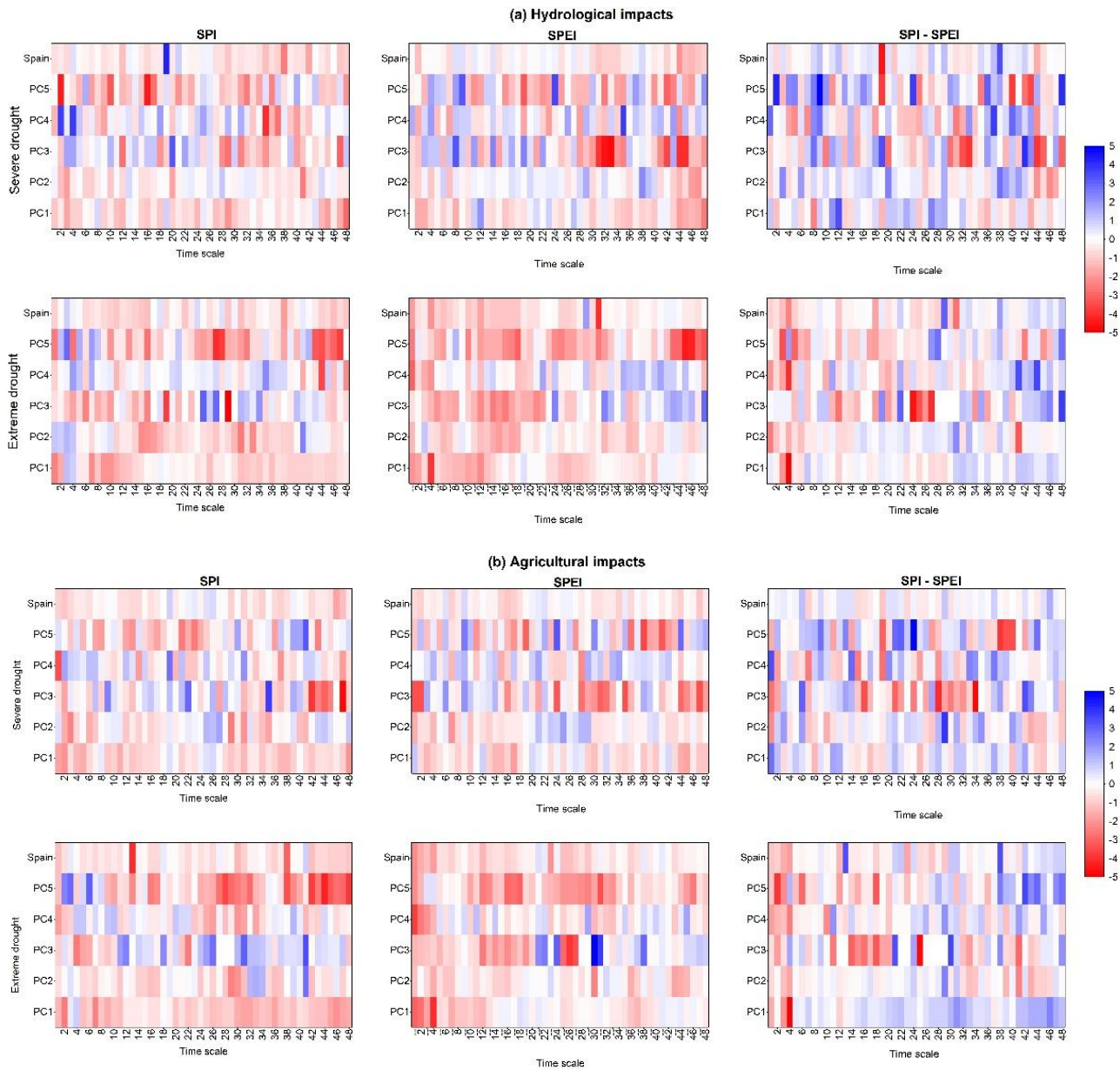


Fig. 7: Drought-reporting sensitivity coefficient between drought indices (SPI and SPEI) and (a) hydrological and (b) agricultural drought impacts across accumulation timescales (1–48 months) under different drought severity classes. Panels show coefficient patterns for severe and extreme drought conditions derived for the main principal components (PC1–PC5), as well as peninsular Spain. Warmer colours indicate stronger responsiveness of reported impacts to drought severity. Differences between SPI and SPEI highlight the influence of temperature-driven evaporative demand under extreme drought conditions.

Agricultural reporting shows higher sensitivity, with the peak drought-impact sensitivity coefficient occurring at shorter to medium timescales (6–24 months) (Fig. 7). In addition to the hydrological responses, the drought-impact sensitivity coefficient sharply increases from moderate to extreme drought conditions, considering the higher vulnerability of agricultural systems.

SPEI reveals stronger responses than SPI across all severity classes again highlighting the importance of temperature-driven stress. For agricultural impacts (Fig. 7), there are also marked sub-regional differences. The first principal component (PC1, west and southwest) exhibits rapid increases in sensitivity at short to intermediate time scales (6–24 months). PC2 and PC3, linked to eastern and northern areas, are characterized by a greater variability and earlier sensitivity peaks. Higher order components (PC4–PC5) have very local and variable responses with steep increases under extreme drought conditions indicating robust local modulation by soil properties, irrigation practices and crop type. These results demonstrate that SPEI yields higher sensitivity than SPI for all PCs and the differences tend to increase for severe and extreme drought. However, this effect tends to be more spatially structured in hydrological systems and more fragmented in agricultural ones.

3.3. Dominant drought accumulation timescales associated with impacts

Fig. 8 synthesizes the dominant accumulation timescales associated with maximum impact sensitivity. Specifically, the spatial distribution of the dominant drought accumulation timescale associated with maximum drought–reporting sensitivity across Spanish provinces for hydrological and agricultural impacts is presented for different drought severity classes (normal, mild, moderate, severe, extreme, and all dry conditions). A clear sectoral contrast emerges. Hydrological impacts are predominantly controlled by medium- to long-term timescales (12–48 months), but with a widespread dominance of 12–24 months under moderate conditions and a shift toward longer timescales (24–48 months) under severe and extreme drought. In contrast, agricultural impacts are mainly associated with shorter to intermediate timescales (3–12 months), particularly under normal to moderate drought, consistent with stronger associations at shorter accumulation timescales and sensitivity to soil moisture deficits (Fig. 8). However, in extreme conditions, agricultural systems suggest a partial shift towards longer timescales, but still shorter than hydrological responses. Hydrological patterns are spatially more homogeneous, while agricultural impacts demonstrate greater regional variability, pointing to a stronger local modulation. SPEI exhibits, in general, longer dominant timescales than SPI in both sectors, especially for severe and extreme droughts, indicating stronger SPEI-based associations at longer accumulation timescales. This effect is more pronounced for agricultural impacts, especially for severe and extreme drought, where SPEI is associated with a shift toward longer dominant accumulation timescales.

These patterns are summarized in Fig. 9, which indicates the percentage of Spanish provinces associated with the dominant drought accumulation timescale obtained from the maximum drought–reporting sensitivity coefficient between drought indices (SPI and SPEI) and reported impacts for hydrological and agricultural sectors. Fig. 9 shows that most provinces fall within the 12–48-month range for agricultural and hydrological impacts. However, agricultural impacts indicate higher concentrations in the 1–6-month range. Short-lived anomalies, on the other hand, have a limited impact, as the short timescales (1–6 months) contribute little to the hydrological impacts. With increasing drought severity, both sectors indicate a shift towards longer dominant timescales, but this shift is more pronounced for agricultural systems. However, SPEI consistently shifts the distribution to longer dominant timescales than SPI in both sectors, especially in severe and extreme drought categories. This difference remains limited under mild drought conditions but increases substantially during severe and extreme droughts,

indicating stronger SPEI-based associations at longer accumulation timescales. The effect is particularly striking for
395 agricultural impacts, where SPEI enhances the role of seasonal to long-term timescales (6–48 months) while diminishing the
contribution of short-term scales (1–6 months).

In hydrological systems SPEI further supports the dominance of long storage timescales (24–48 months), reflecting cumulative
water deficits. These results indicate that SPEI shifts the dominant associations toward longer accumulation timescales.
400 Collectively, these results demonstrate a systematic shift from shorter to longer dominant accumulation timescales with
increased severity and highlight contrasting temporal sensitivities of hydrological and agricultural impacts.

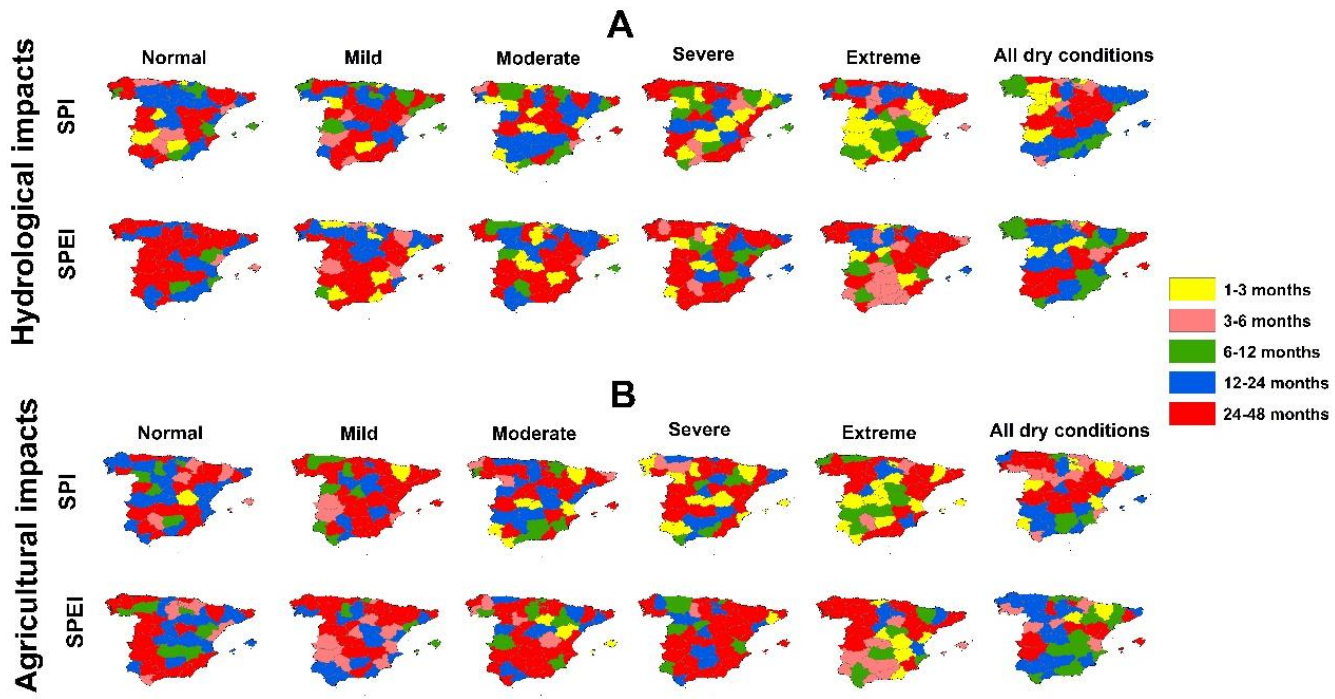
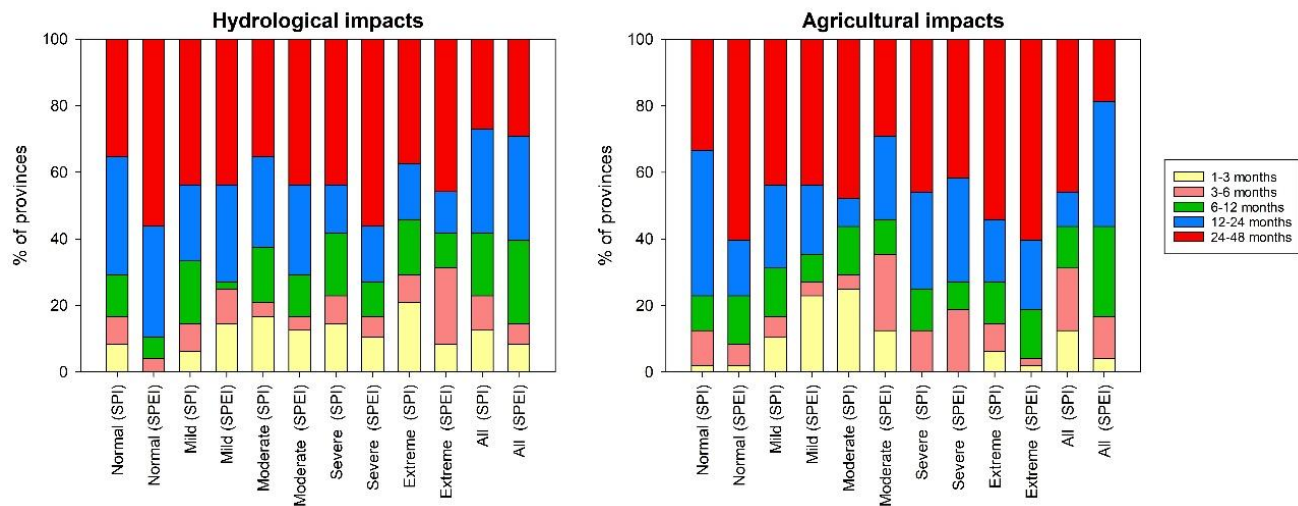


Fig. 8: Spatial distribution of the dominant drought accumulation timescale corresponding to maximum drought-reporting
405 sensitivity coefficient between drought indices (SPI and SPEI) and (a) hydrological and (b) agricultural drought impacts across
Spanish provinces. Each panel corresponds to a drought severity class (normal, mild, moderate, severe, extreme, and all dry
conditions). Colours represent the timescale at which drought conditions show the strongest association with reported impacts,
ranging from meteorological drought (1–3 months) to long-term water storage deficits (24–48 months).



410 **Fig. 9: Percentage of Spanish provinces associated with the dominant drought accumulation timescale derived from the maximum drought-reporting sensitivity between drought indices (SPI and SPEI) and reported impacts. Stacked bars show the distribution of provinces across five drought timescale categories, meteorological (1–3 months), agricultural (3–6 months), seasonal (6–12 months), hydrological (12–24 months), and long-term storage (24–48 months), for different drought severity classes (normal, mild, moderate, severe, extreme, and all dry conditions). Results are shown separately for hydrological impacts (left) and agricultural impacts (right).**

415 **4. Discussion**

This study provides a comprehensive assessment of the links between drought severity and observed impacts across Spain through the combination of multiscale drought indices (SPI and SPEI) based on a high-resolution gridded climate dataset and standardised media-reported hydrological and agricultural impacts for the period 1976–2023. This study reveals the temporal, nonlinear, and spatial dynamics of drought impacts through a scale-independent measure of impact response, providing new
 420 insights into drought-reporting relationships across accumulation timescales and sectors.

The multiscale analysis reveals weaker associations with short-term anomalies, whereas medium- and long-term accumulation periods show stronger associations with both hydrological and agricultural reporting. This pattern aligns with growing evidence that the impacts of drought are a function of the accumulation and duration of moisture deficits (e.g., Peña-Gallardo et al.,
 425 2019; Altın et al., 2021). Peña-Gallardo et al. (2019) observed stronger relationships between meteorological and hydrological droughts at larger timescales in U.S. basins. Aryal et al. (2024) also demonstrated an increase in the duration of propagation of droughts with the accumulation period which implies an increase in system memory. These findings are consistent with earlier studies that have identified drought duration and persistence as important impact drivers (Orth et al., 2020; Álvarez-Garretón et al., 2021; Tonetto et al., 2024). Our results in Spain also suggest that hydrological reporting is more strongly
 430 associated with longer accumulation periods, whereas agricultural reporting shows stronger associations with intermediate accumulation periods, consistent with their differing dependence on accumulated water deficits, soil moisture, and seasonal

variability. The analysis indicates that isolated precipitation deficits are less strongly associated with media-reported impacts than persistent deficits. Importantly, although newspaper reports often describe drought consequences when they become observable or socially salient, the temporal delay between physical impact occurrence and publication was not quantified in this study. For many reported impacts, this delay may be relatively short compared with the multi-month climatic accumulation windows examined here; however, drought impacts are often gradual and persistent, and some reports may describe conditions that began earlier. We therefore use publication month as the timing of reporting rather than as an exact estimate of impact onset. Accordingly, any temporal offset between climatic conditions and the media record may reflect a combination of physical drought-impact response time, recognition of the impact, and reporting delay.

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The study demonstrates that SPEI is more strongly associated with media-reported impacts than SPI, consistent with an important role of atmospheric evaporative demand in the determination of drought-reporting relationships. This contrast becomes more evident during prolonged and severe droughts. This suggests that temperature-driven processes are magnifying the effect of precipitation deficits, especially in the case of prolonged drought. This finding is in agreement with other global (Woodhouse et al., 2016; Ogunrinde et al., 2026), Mediterranean (Dong et al., 2019; Avanzi et al., 2020) and Spanish research (Noguera et al., 2021). Atmospheric evaporative demand is particularly important for agriculture because increased atmospheric demand intensifies plant water stress and induces a large moisture loss from soil (Rigden et al., 2020; Qing et al., 2023). Hydrological systems respond more gradually and cumulatively, leading to long-term reductions in groundwater recharge and water storage. The higher atmospheric demand can enhance agricultural and ecological droughts (Vicente-Serrano et al., 2022). Terrestrial water storage is strongly controlled by imbalances between water supply and atmospheric demand (Chang et al., 2020). The consistently stronger performance of SPEI relative to SPI further suggests that future droughts will increasingly reflect the combined effects of precipitation deficits and enhanced atmospheric evaporative demand associated with regional warming. This finding is particularly important in the Mediterranean basin, identified as a climate-change hotspot where temperatures are projected to rise faster than the global average, accompanied by increased drought severity and reduced water availability (Lionello and Scarascia, 2018).

Our findings further demonstrate a marked nonlinear drought-reporting relationship, with reporting sensitivity increasing disproportionately under severe and extreme drought. Nonlinear responses have been well documented for many regions and systems (Lobell et al., 2014; Chen et al., 2022; Wu et al., 2025; Liu et al., 2025). These findings suggest a threshold-like increase in reporting sensitivity; however, this should not be interpreted as direct evidence that physical impact magnitude increases at the same rate. Hydrological systems respond more slowly but exhibit stronger cumulative sensitivity, possibly related to the buffering effects of groundwater storage and reservoir regulation. However, studies in Spain indicate that these buffering mechanisms are insufficient to offset severe drought impacts. Previous studies have indicated that streamflow and water storage are highly sensitive to climate variability in Spanish basins (Berghuijs et al., 2016) and that reservoir regulation continues to alter but not offset the frequency and severity of droughts (Vicente-Serrano et al., 2014, 2017b). Moreover, greater

reliance on water storage and transfers increases vulnerability (Lorenzo-Lacruz et al., 2012) and risks of drought are high despite better management (Vargas et al., 2019). On the other hand, agricultural systems exhibit stronger and more variable increases in exposure with a limited ability to buffer this shift. These findings highlight the nonlinear amplification of media-reported impact frequency and underscore the need to incorporate nonlinear dynamics into drought risk assessments.

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We report a dominant large-scale signal of drought impacts, but with a large spatial heterogeneity in sensitivity and dominant timescales. The first principal component indicates that a large part of the variability of the impacts is due to a coherent climatic forcing over the whole of Spain. Several processes could plausibly contribute to the observed geography. Large-scale atmospheric circulation structures drought variability across Spain. Previous studies have linked drought variability in Spain to large-scale atmospheric circulation patterns (Vicente-Serrano et al., 2006; Russo et al., 2015; Bakke et al., 2023; Noguera et al., 2024). However, basin storage, groundwater exchange, irrigation dependence, crop composition, water-allocation rules, and adaptive capacity can alter how the same climatic deficit is experienced and reported. Numerous studies demonstrate that local hydro-climatic conditions, water management practices and socio-economic factors modulate drought responses, with regional differences in sensitivity and dominant timescales (Grau-Satorras et al., 2016; Urquijo et al., 2015; Estrela et al., 2016; Iglesias et al., 2021; Junquera et al., 2025). In addition, province-specific reporting intensity and the geographic focus of a national newspaper may contribute to apparent spatial contrasts. The spatial heterogeneity therefore likely combines hydro-climatic, management, exposure, and reporting effects and should not be attributed to climate alone. Taken together, this spatial variability further demonstrates that drought impacts cannot be fully understood without considering both large-scale climatic forcing and local environmental conditions.

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Dominant timescales are identified to offer further insight into the temporal organisation of drought impacts. Hydrological reporting is predominantly associated with medium to long-term accumulation timescales, while agricultural reporting is more linked to short to medium-term accumulation timescales (Wan et al., 2018). Both sectors exhibit a shift toward longer dominant timescales with increasing drought severity, indicating stronger associations with longer climatic accumulation windows. This change is particularly evident in hydrological systems, but it also emerges in agricultural systems under severe conditions, where agricultural reporting also becomes associated with longer accumulation timescales. Altieri et al. (2025) reported similar results indicating that even resilient agricultural systems can collapse under prolonged water stress. The limited contribution of short-term timescales further supports the conclusion that media-reported impacts are more strongly associated with persistent rather than transient anomalies.

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These findings are relevant for drought detection and the development of early warning systems. Impact dynamics are strongly controlled by drought accumulation timescales; hence, multiscale monitoring strategies are required to achieve a complete picture of the evolution of drought. A number of studies have underscored the need to choose suitable drought timescales given by sector-specific responses to assess their severity (Vicente-Serrano et al., 2021). The relatively greater impact of atmospheric

500 evaporative demand indicates the requirement for integrated temperature-sensitive indicators like the SPEI in operational monitoring networks. Although news articles are written for purposes other than systematically documenting drought impacts, they provide a credible, though not exhaustive, record of drought's effects at specific places and times (Dow, 2010). In contrast to SPI and SPEI, which quantify meteorological moisture deficits and atmospheric evaporative demand, media-reported impact data document how drought was observed, narrated, and experienced through effects on people, livelihoods, ecosystems, water
505 resources, agriculture, and socio-economic systems. In this study, these records are therefore treated not as direct physical measurements of drought damage or as a comprehensive inventory of all impacts, but as a best-available proxy for the societal visibility, timing, location, and sectoral framing of drought events. Persistent conditions could generate repeated reports because no event-level de-duplication was applied. Thus, high reporting frequencies may partly reflect sustained media attention to the same ongoing drought consequence rather than a larger number of independent physical impact events. Because
510 news coverage is shaped by editorial priorities, institutional context, public attention, event novelty, perceived severity, and uneven spatial coverage, low reporting frequencies should not necessarily be interpreted as the absence of drought impacts. Rather, media-derived impact data identify when and where drought became socially salient, problematic, or publicly visible, making them useful for relating climate-based drought indicators to observed societal consequences. Recent research has demonstrated that media-based data sets can record drought effects at relatively high spatiotemporal resolution (Madruga de
515 Brito et al., 2020; Wang et al., 2025), although they entail reporting biases and changes in media practices (Stahl et al., 2015; Serrano-Acebedo et al., 2026; Pita Costa et al., 2024).

The findings support the growing view that drought impacts in Spain emerge from the coupled interaction of climatic variability, hydrogeological structure, land management, and anthropogenic water use (Junquera et al., 2025; Sánchez and
520 Cantos, 2025). Recent basin-scale analyses have shown that hydrological deficits across the Iberian Peninsula are strongly conditioned by groundwater exchange, irrigation pressure, permeability, and reservoir regulation, producing substantial spatial heterogeneity in effective water availability (e.g., Segura-Méndez et al., 2026). Within this context, the spatial variability of drought–impact sensitivity coefficients identified in this study likely reflects not only differences in meteorological drought severity but also the varying capacity of socio-hydrological systems to buffer, amplify, or redistribute drought stress. These
525 factors provide plausible physical and management contexts for the regional differences observed here, but the media-based analysis cannot separate their individual contributions from differences in exposure or reporting. Accordingly, spatial variation in the sensitivity coefficient (β) can be interpreted as variation in the drought–reporting relationship rather than as a direct map of physical vulnerability.

530 This study advances understanding of drought-impact relationships by providing a comprehensive multiscalar and nonlinear framework that links climatic drivers to societal responses under changing environmental conditions. The combination of climate indices and impact data provides a good basis for further improvement of the assessment, attribution and prediction of drought impacts, thus facilitating more effective risk management and adaptation efforts in drought-prone regions.

5. Conclusions

535 This work provides a detailed assessment of the multiscale and nonlinear relationships between drought severity and media-reported hydrological and agricultural impacts in peninsular Spain during 1976–2023. We explored relationships between standardised drought indices (SPI and SPEI) and impact data from newspaper records. The results indicate that media-reported impact frequency is more strongly associated with persistent moisture deficits than with short-term climatic variability. The most robust drought-impact relationships are identified at medium-to-long accumulation timescales, reflecting the integration of moisture deficits over longer climatic windows. These results indicate that the widespread impact reporting in peninsular Spain is more strongly associated with persistent drought conditions than with isolated precipitation deficits.

The results also suggest a clear sectoral differentiation in dominant accumulation timescales. Hydrological reporting is mainly associated with longer accumulation timescales, following the integrative nature of water storage systems, whereas agricultural reporting shows stronger associations with short- to medium-term accumulation timescales, due to their dependence on soil moisture and seasonal water availability. Despite these differences, both sectors exhibit a systematic increase in dominant timescales with increasing drought severity, suggesting that longer deficits are increasingly associated with reporting dynamics across both sectors.

550 A major finding of this study is the strong association of atmospheric evaporative demand with media-reported drought impacts. The consistently stronger relationships obtained with SPEI, compared to SPI, underline the importance of temperature-driven processes, especially for moderate to extreme drought conditions and at longer accumulation timescales. The result highlights the increasing role of warming in drought dynamics and suggests that precipitation-based indices alone may underestimate drought severity and related impacts in a changing climate. The analysis also indicates that reporting sensitivity to drought severity is largely nonlinear, increasing disproportionately for severe and extreme conditions. This behaviour reflects a threshold-like increase in reporting sensitivity and should not be interpreted as a direct measure of physical damage thresholds.

Spatial analysis indicates a dominant large-scale drought signal and large regional variability in reporting response. Although a large proportion of reporting variability is associated with coherent climatic forcing over large areas of peninsular Spain, regional differences in sensitivity and dominant timescales suggest the importance of local hydro-climatic conditions, water management and socio-economic factors. These results highlight the importance of accounting for both regional characteristics and large-scale drivers in the assessment of drought impacts.

565 This study contributes to the understanding of drought-impact relationships by assembling a unified framework of multiscale drought metrics, nonlinear sensitivity analysis and impact-based observations. The results have important implications for

drought monitoring and early warning systems, underscoring the importance of multiscale approaches and the inclusion of temperature-sensitive indices such as SPEI. The inclusion of media-reported impacts provides useful insight into how drought manifests itself in society, beyond the traditional climate-based indicators. This framework supports improved assessment, attribution, and prediction of drought impacts in the context of ongoing climate change and ultimately supports more effective risk management and adaptation strategies.

Data availability

Data will be available upon request through direct contact with the corresponding author.

Author contributions

A.M.E. and S.M.V. were responsible for the conceptualization and development of the research idea. A.M.E., F.D.C., and A.H. developed the methodology, carried out the analysis and visualization, and wrote the original draft of the manuscript. S.B., J.V., M.A., B.T., and M.F. assisted with data collection, manuscript editing, and literature enhancement, and contributed to project administration and coordination. A.M.E., S.M.V., and F.D.C. contributed to draft writing. All authors contributed to the manuscript by reviewing and editing the original draft.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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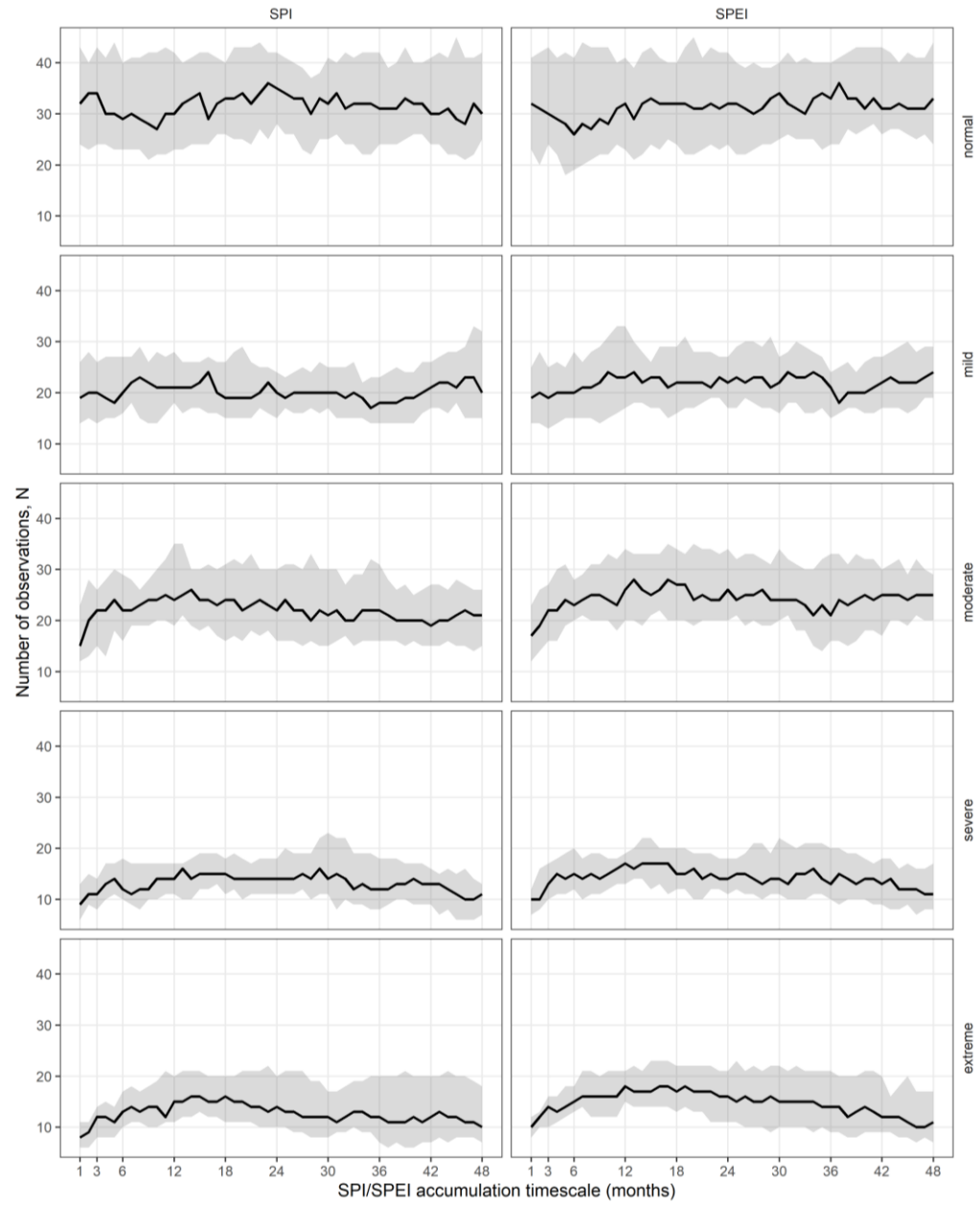
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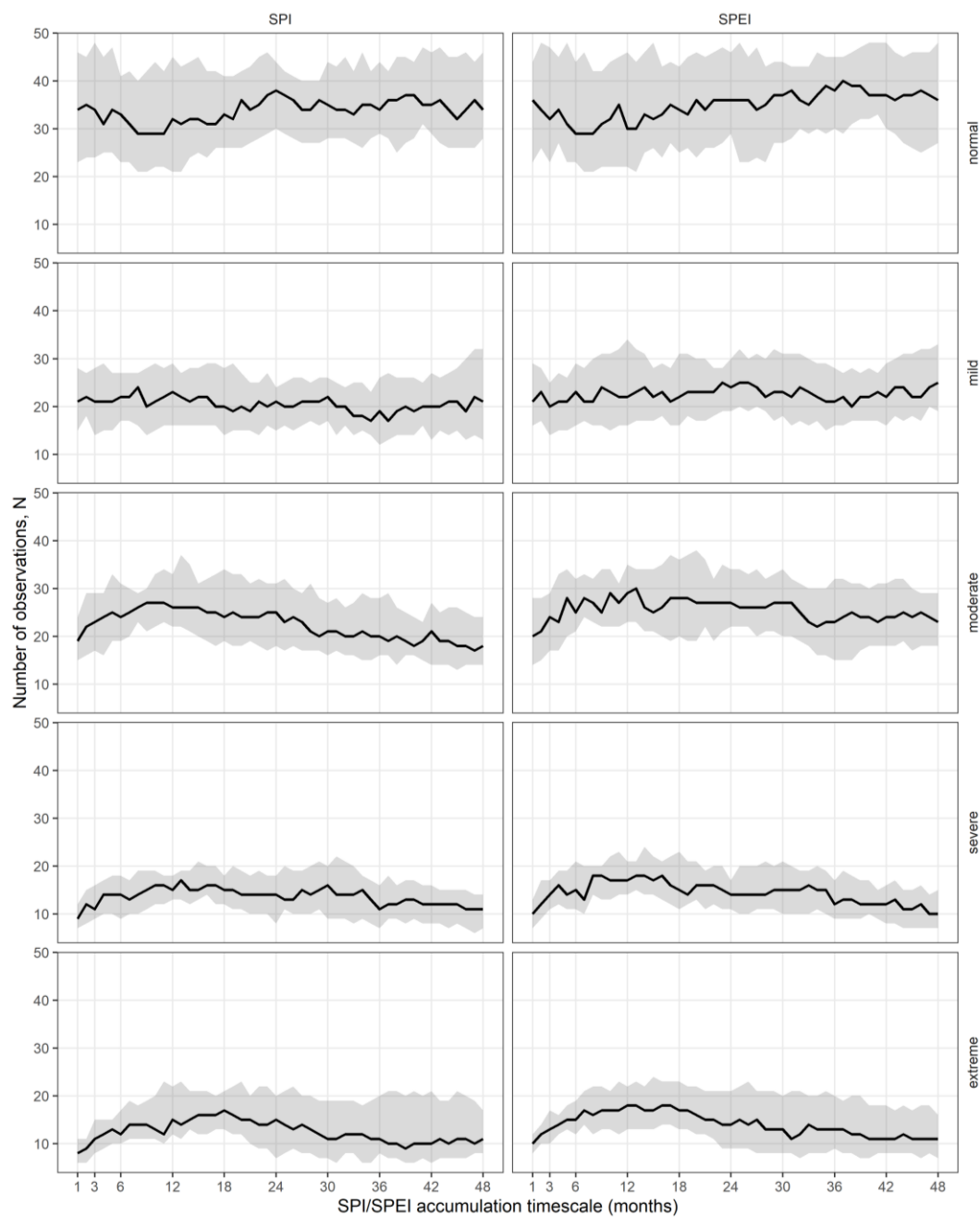
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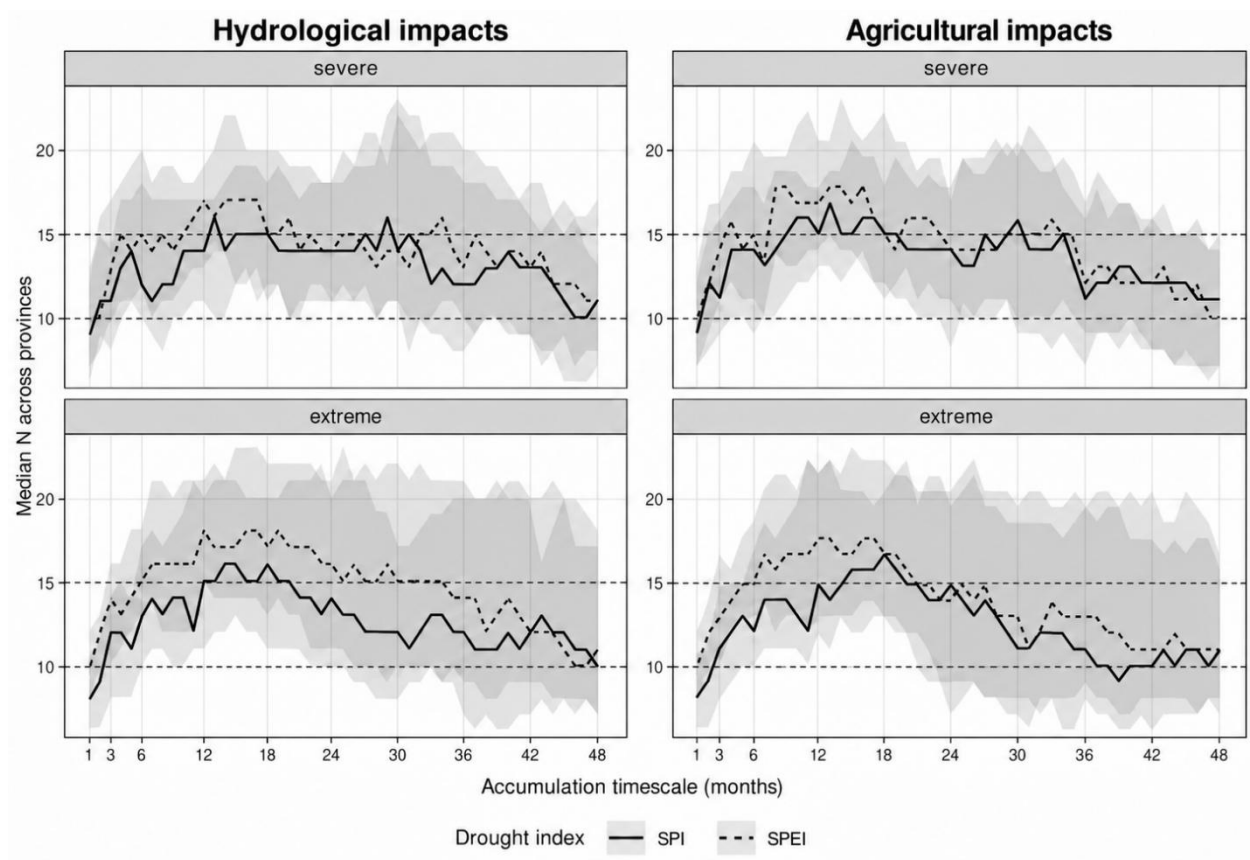
Supplementary Figures



Supplementary Fig. 1. Regression sample size across SPI (left panels) and SPEI (right panels) accumulation timescales (1–48 months) for five drought-severity classes corresponding to hydrological impacts. The black line shows the median number of paired observations (N) across 48 provinces, and the grey ribbon indicates the interquartile range (25th–75th percentiles).



Supplementary Fig. 2. Regression sample size across SPI (left panels) and SPEI (right panels) accumulation timescales (1–48 months) for five drought-severity classes corresponding to agricultural impacts. The black line shows the median number of paired observations (N) across 48 provinces, and the grey ribbon indicates the interquartile range (25th–75th percentiles).



Supplementary Fig. 3. Sample-size support for severe and extreme drought regressions across accumulation timescales (1–48 months). Lines show the median number of observations (N) across 48 provinces for SPI and SPEI, with grey shading indicating the interquartile range. Horizontal dashed lines mark reference sample sizes of N=10 and N=15.