

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

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Abstract. This study assesses the multiscalar and nonlinear relationships between drought severity, characterized 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 standardized monthly frequencies of drought-related newspaper articles at the provincial scale. Results demonstrate robust temporal coherence between drought 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 ($|r| \approx 0.6\text{--}0.8$), 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~~agricultural systems respond more rapidly to short- and intermediate-term drought conditions (3–12 months).~~ However, for both sectors, dominant accumulation timescales lengthen as drought severity increases~~both sectors shift to longer time scales as drought severity increases.~~ Sensitivity analyses reveal pronounced nonlinear responses, with media-reported impact frequency increasing disproportionately with impacts increasing disproportionately~~during severe drought conditions with a peak at 12–36 months.~~ The consistently stronger association of SPEI relative to SPI, especially in case of agricultural impacts, suggesting 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~~drought impacts are governed by the accumulation and nonlinear propagation of moisture deficits modulated by temperature-dependent processes~~ and provide a framework for improved impact-based drought monitoring in a warming climate.

35 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 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).

To monitor and characterize drought severity, researchers use drought indices, which provide objective measures across meteorological, agricultural, and hydrological domains (Keyantash, 2021). The relationship between most drought indexes 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 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. 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 ~~specific time lag of drought accumulation~~ for the link between climate anomalies and impacts. Warm conditions can intensify water stress through increased atmospheric 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.

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 a key to document 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 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 (Dominguez-Castro et al., 2019; Vicente-Serrano et al., 2019; Noguera et al., 2022). Despite extensive use of drought indices, the spatial organization 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

95 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
100 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 did 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
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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.
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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.
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Province extraction was performed to identify the Spanish provinces referenced in drought-related articles and affected by drought and was done separately from extracting impacts. 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
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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 of mainland Spain and for the Balearic Islands for the spatially consistent analysis, but also an overall national SPI and SPEI series. The SPI and SPEI were computed for accumulation periods from 1 to 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

standardized drought indices. We applied the method proposed by Vicente-Serrano et al. (2025). We concentrate on the application of 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 standardized values. This approach preserves the ordinal structure of the original series while accommodating repeated values and months without drought reports. This yields a standardized 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~~ severity 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, making them directly comparable and suitable for multivariate statistical analysis.~~ 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. Moreover, standardization reduces differences in media coverage among provinces and across time. This improves the comparability of temporal drought impact signals. 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 standardized 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.~~ To reduce dimensionality and identify dominant spatial-temporal patterns in drought-related impact signals, we applied Principal Component Analysis (PCA) to the standardized monthly drought impact time series compiled for all provinces of Spain over the period 1976–2023, where rows represented months (n = 576) and columns represented provinces (n = 48). The analysis was conducted separately for hydrological impacts and agricultural impacts, allowing for an independent assessment of the spatiotemporal variability in each sector. The objective was to extract a reduced set of orthogonal components (principal components, PCs) that explain the maximum amount of variance in the dataset while minimizing information redundancy. The decomposition was derived from the covariance matrix, and components were ordered

according to explained variance. We selected only the principal components with eigenvalues greater than 1 and explaining more than 5% of the total variance individually (Kaiser criterion) to consider only statistically meaningful modes of variability for further analysis. This threshold was selected to balance the removal of insignificant patterns against the inclusion of noise-dominated components. The loadings corresponding to each selected component were extracted and analyzed. This enabled quantification of the contribution of each province to the principal component. Spatial patterns were used to visualize the loadings to recognize regions with similar behavior 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–impact 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. To quantify the severity dependence of drought impacts, we calculated a drought impact sensitivity coefficient, which is the regression coefficient based on a log–log relationship between drought indexes (SPI and SPEI) and media-reported impact anomalies. This approach allows for a consistent and scale-independent evaluation of the relationship between drought conditions and reported impacts across sectors, regions, 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 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 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.

Both variables were transformed prior to analysis to ensure that drought conditions and impacts are not linear and heteroscedastic. For the sensitivity analysis, only the months with drought condition (SPI or SPEI < 0) were kept. To ensure that high values representing greater drought severity (i.e., drier conditions) are directly comparable with increasing impact anomalies, the retained SPI and SPEI values were reversed (multiplied by -1). The 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). Both drought

225 magnitude and impact data were transformed using a natural logarithmic transformation (Ln). Observations with zero impact values were removed before logarithmic transformation. The transformation is useful for decreasing skewness, stabilizing variance, and assessing scale-independent links between drought severity and impacts within a log-log framework.

230 To examine whether the reporting-drought association changes across drought severity, monthly observations were stratified 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. 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.

240 Separate analyses were performed for different drought severity classes to capture the nonlinear nature of drought-impact relationships. Monthly observations were classified according to the value of the sign-reversed drought index, distinguishing between normal conditions (≤ 0.5), mild ($0.5-0.84$), moderate ($0.84-1.28$), severe ($1.28-1.65$), and extreme (>1.65) drought, and a combined category including all drought conditions (>0) (Agnew, 2000). Each class time series was subset to contain only the corresponding observations and all subsequent analyses were conducted independently. Using this approach, the evolution of impact sensitivity with an increasing drought severity can be assessed.

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

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

250 where I_t represents the monthly media-reporting count at the impact series at timescale t , D_t is the sign-reversed drought index at timescale 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 impact 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 impact-reporting intensity). This statistic provides a dimensionless measure of drought-reporting sensitivity drought impact sensitivity. As a result, comparisons can be made across (hydrological vs. agricultural), provinces, and timescales (1 to 48). 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 exert the strongest influence on impacts. 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.

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 verify that temporal dependence did not materially invalidate the statistical inference from the fitted models.

To evaluate the role of atmospheric evaporative demand on drought severity and subsequent drought impacts, sensitivity coefficients were calculated independently using SPI and SPEI. Differences between SPEI- and SPI-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.

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. This metric represents the drought duration most strongly linked to observed impacts. In cases where multiple timescales exhibited similar values, the smallest timescale among the maxima was selected to ensure consistency.

3. Results

3.1. Drought impacts track climate variability across timescales

Figure 1 depicts the temporal evolution of standardized drought indices (SPI-12 and SPEI-12) and media-reported drought impacts in Spain from 1976 to 2023. Hydrological ~~reporting impacts~~ closely track multi-year drought variability, with major drought frequency impacts 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 impacts~~. However, some inconsistencies are observed, such as the effect of moderate drought conditions (~ 0.5 to -1) are not always significant, 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

290 ~~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. The dominant relationship between hydrological and~~
~~agricultural impacts ($r = 0.89$, Fig. 1c) reflects coherent cross-sector drought propagation.~~

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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
300 relationships are further modulated by seasonal variability, with higher correlations during months of summer 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 reported impacts are~~
305 ~~primarily controlled by~~ persistent moisture deficits ~~rather than~~ with short-term anomalies.

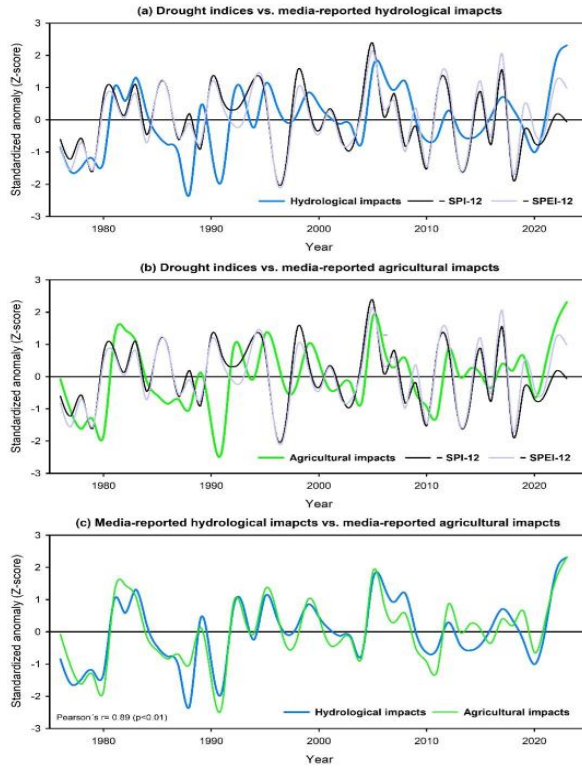


Fig. 1: Temporal evolution of standardized drought indices and media-reported drought impacts in peninsular Spain over the period 1976–2023. (a) Hydrological impacts and (b) agricultural impacts are compared with SPI-12 and SPEI-12, while (c) illustrates the relationship between hydrological and agricultural impacts. All series are expressed as standardized 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 $\uparrow$, impacts $\uparrow$).

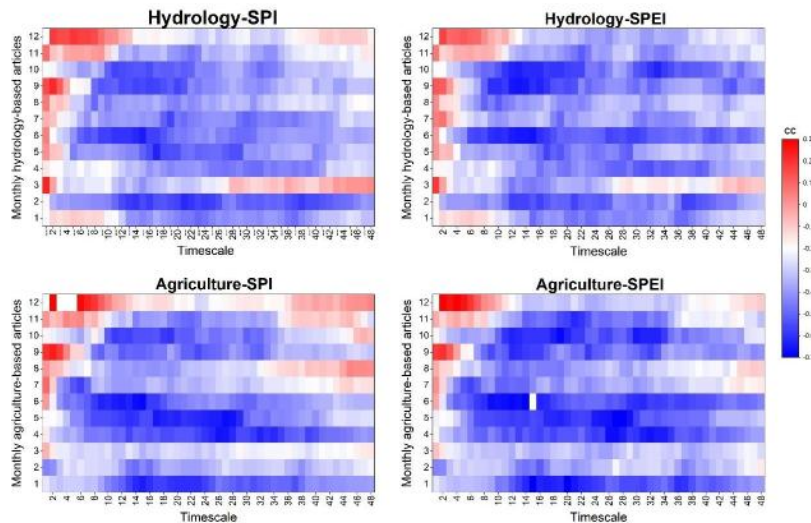


Fig. 2: Correlation matrix (Pearson coefficient) between standardized monthly frequencies of drought-related newspaper impacts and drought indices (SPI and SPEI) computed at accumulation timescales from 1 to 48 months. Absolute values of CC exceeding 0.28 are statistically significant at $p < 0.05$.

3.2. Mechanisms and nonlinear sensitivity of drought–impact relationships

Figure 3 illustrates the drought–~~impact reporting~~ sensitivity coefficient of ~~media-reporting frequency drought impacts~~ to drought severity across accumulation timescales. ~~Reporting impact~~ 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 compared to 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 impacts~~ display 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 impacts~~ to drought severity and the dominant role of sustained moisture deficits.

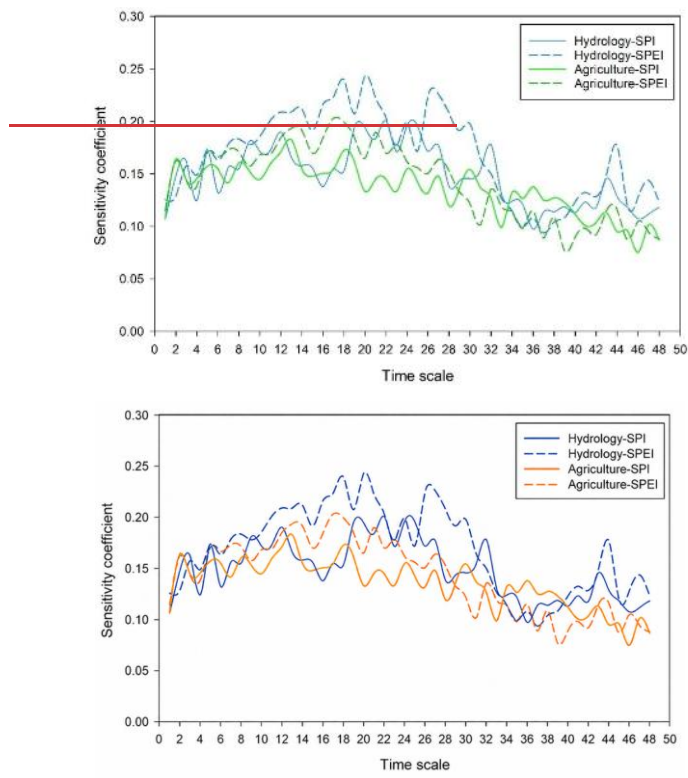


Fig. 3: Drought-impact sensitivity coefficient response curves linking drought indices (SPI and SPEI) with media-reported hydrological and agricultural drought impacts across accumulation timescales from 1 to 48 months. Lines represent mean drought-impact sensitivity coefficient values averaged across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

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 the hydrological (Supplementary Fig. S1) and agricultural impacts (Supplementary Fig S2), 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. 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 artifacts of a single or very small number of sparsely sampled regressions.

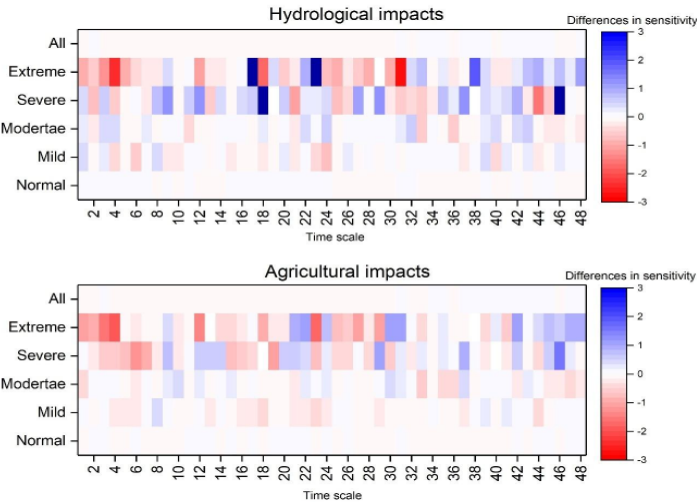


Fig. 4: Differences in national-scale mean drought-impact responses between SPI and SPEI across accumulation timescales (1–48 months). Differences between SPI and SPEI responses indicate the contribution of temperature-driven evaporative demand across drought severity classes.

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.

Figure 5 reveals clear spatial heterogeneity in drought-impact 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, with increasing drought duration.

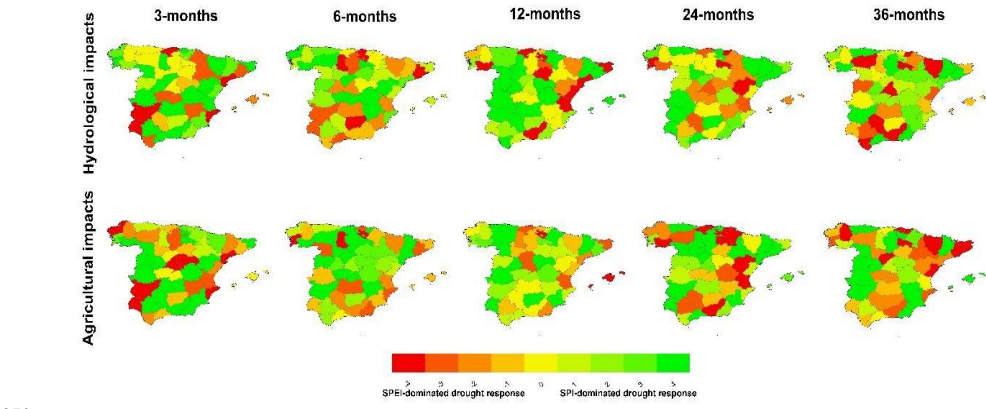


Fig. 5: Spatial differences in drought-impact sensitivity between SPI and SPEI across peninsular Spain at multiple accumulation timescales. The relative dominance of SPEI-driven versus SPI-driven drought responses for hydrological impacts (top row) and agricultural impacts (bottom row) is presented at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

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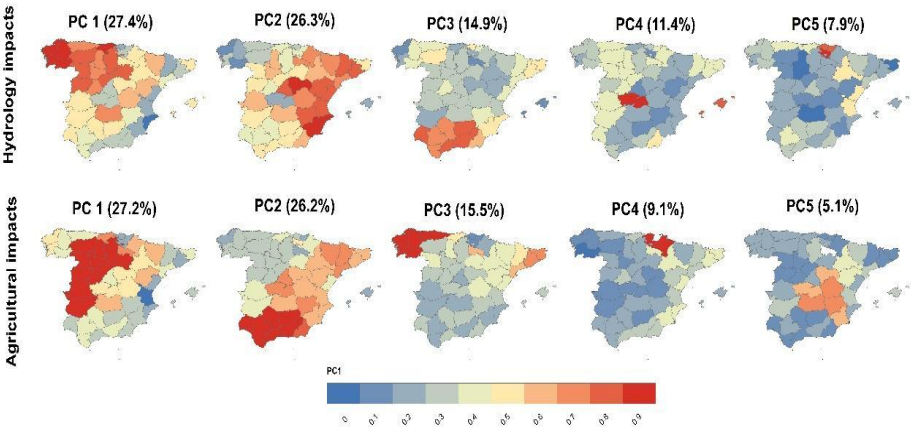


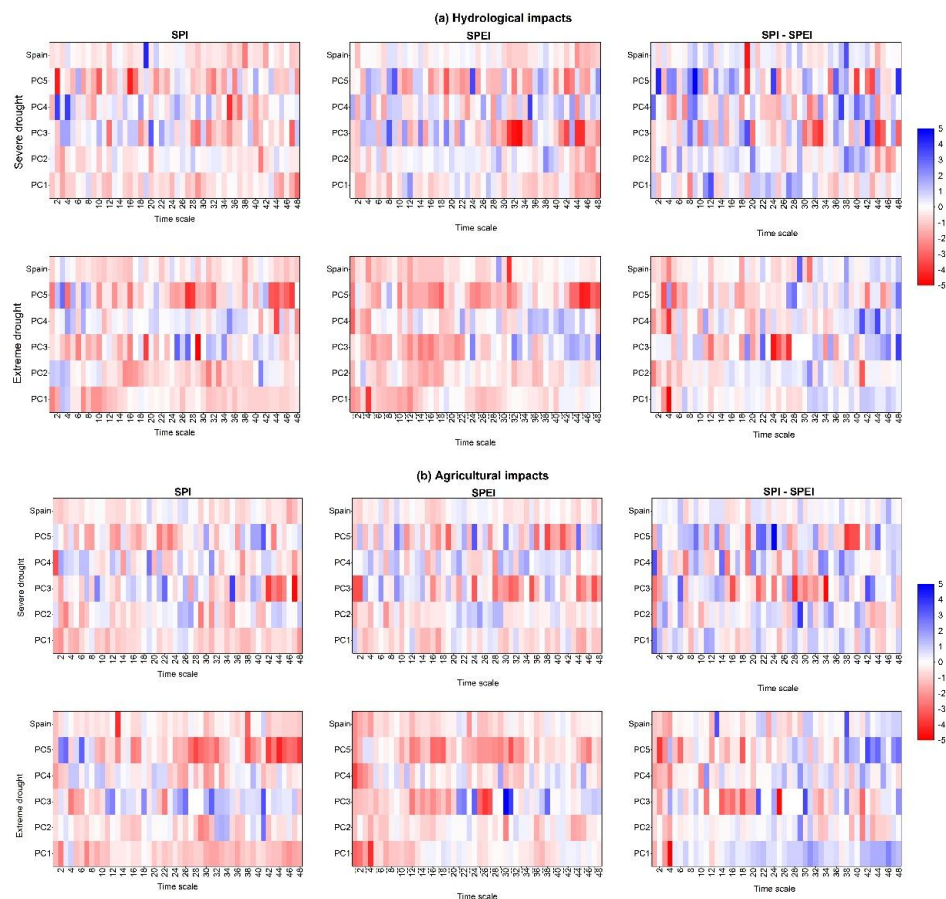
Fig. 6: Spatial loadings of the principal components (PCs) derived from standardized monthly hydrological (upper row) and agricultural (lower row) drought impact time series across Spanish provinces (1976–2023). Numbers in parentheses indicate the percentage of total variance explained by each principal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

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Drought sensitivity coefficient was assessed under different drought severity classes for the different PCs for both 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-impact 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, in agreement with the integrative ~~behavior~~behaviour of large river basins and storage systems. The 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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405 **Fig. 7: Drought-impact sensitivity coefficient 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.**

410 Agricultural impacts-reporting shows higher sensitivity are more sensitive and respond more quickly, 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 agriculture impacts (Fig. 7), there are also marked sub-regional differences. The first principal component (PC1, west and southwest) exhibits high and fast increases in sensitivity at short to intermediate time scales (6 to 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 impact~~~~timescales controlling impacts~~

Figures 8 synthesize the dominant accumulation timescales associated with maximum impact sensitivity. Specifically, the spatial distribution of the dominant drought accumulation timescale associated with maximum drought–impact 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 ~~consistent with rapid responses 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 ~~suggesting that the atmospheric evaporative demand amplifies the persistence and propagation of drought impacts~~. 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 ~~temperature driven stress accelerates the shift towards longer effective drought durations~~.

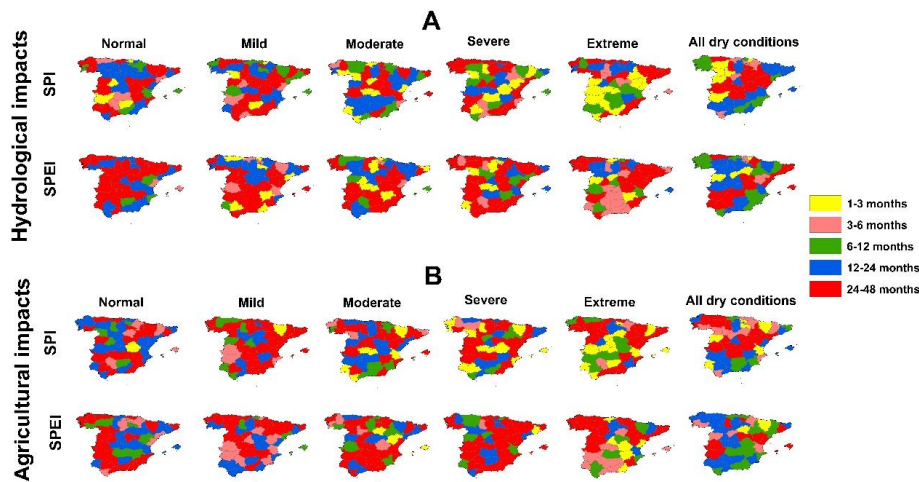


Fig. 8: Spatial distribution of the dominant drought accumulation timescale corresponding to maximum impact sensitivity coefficient between drought indices (SPI and SPEI) and (a) hydrological and (b) agricultural drought impacts across Spanish provinces. Each panel corresponds to a drought severity class (normal, mild, moderate, severe, extreme, and all dry conditions). Colors 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).

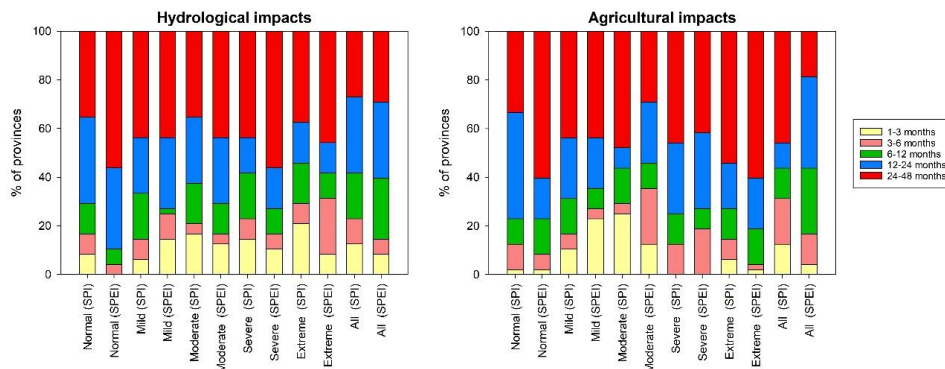


Fig. 9: Percentage of Spanish provinces associated with the dominant drought accumulation timescale derived from the maximum impact sensitivity between drought indices (SPI and SPEI) and reported impacts. Stacked bars show the distribution of provinces across five drought timescale categories, meteorological (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).

455 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–impact sensitivity coefficient between drought indices (SPI and SPEI) and reported impacts for hydrological and agricultural sectors. Figure 9 shows that most provinces fall within the 12–48-month range for agricultural and hydrological impacts. However, agricultural impacts indicate higher concentrations for the 1–6 months 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 shifts the distribution to larger dominant timescales than SPI in all sectors consistently, 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~~~~an effect of atmospheric evaporative demand on drought persistence and propagation~~. The effect is particularly striking for 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).

470 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~~~~confirm that temperature-driven processes consistently increase the effective duration of drought impacts~~. Collectively, these results demonstrate ~~systematic shift from shorter to longer dominant accumulation timescales~~ a systematic shift from short to long-term drought control with increased severity and highlight contrasting temporal sensitivities of hydrological and agricultural impacts.

475 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 standardized 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 insights into ~~drought-reporting relationships across accumulation timescales and sectors~~~~the propagation of drought signals across 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~~~~limited responses to short-term anomalies, whereas medium- and long-term drought conditions exert much stronger controls on both hydrological and~~

~~agricultural impacts~~. 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., 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 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. Our results in Spain also suggest that hydrologic impacts are stronger for long accumulation periods, while agricultural impacts respond faster at intermediate timescales, in line with their dependence on soil moisture and seasonal variability. 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. The analysis confirms that isolated precipitation deficits rarely produce major impacts unless they persist over extended periods

The study demonstrates that SPEI is more strongly associated with media-reported impacts ~~drought impacts~~ than SPI, consistent with an important confirming the dominant role of atmospheric evaporative demand in the determination of drought-reporting relationships ~~drought impacts~~. 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 suggest that future droughts will increasingly reflect the combined effects of precipitation deficits and enhanced atmospheric evaporative associated with regional warming. This finding is particularly

520 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~~~~response of drought impact relationships where sensitivity is disproportionately increased 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 ~~threshold-like increase in reporting sensitivity; however, this should not be interpreted as direct evidence that physical impact magnitude increases at the same rate, the existence of critical thresholds beyond which system resilience is exceeded and impacts rise rapidly~~. 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).
535 Moreover, more 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 drought impacts~~ and underscore the need to incorporate nonlinear dynamics into drought risk assessments.

540 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 as evidenced by 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. Previous studies have linked drought variability in Spain to large scale atmospheric circulation~~

patterns (Vicente-Serrano et al., 2006; Ruoco et al., 2015; Baldo et al., 2022; Neguera et al., 2024). Crucially, local hydro-
climatic conditions, water management practices and socio-economic factors modulate drought responses, as evidenced by
regional differences in sensitivity and dominant timescales (Grau-Saturnas et al., 2016; Urquijo et al., 2015; Estrela et al.,
2016; Iglesias et al., 2021; Junquera et al., 2025). ~~In the meantime, 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 organization of drought impacts. Hydrological
impacts are reporting is predominantly driven by associated with medium to long-term accumulation timescales drought
conditions, while agricultural impacts are reporting is more linked connected to short to medium-term accumulation
timescales variability (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 an increasing control of impact
dynamics by prolonged deficits. 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 indicating that prolonged drought can overcome the normally faster response of agricultural systems. 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 drought impacts are dominated by persistent not transient anomalies.

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 evaporative demand indicates the requirement for integrated temperature-sensitive indicators like the
SPEI in operational monitoring networks. ~~Drought impacts have also been reported by the media and though media reporting
is biased and subject to varied media coverage, this also offers another way (and perhaps a more salient one) to understand
the way in which drought is consumed within society.~~ 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 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. ersistent 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 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 effectively record drought effects at quite high spatio-temporal resolution (Madruga de Brito et al., 2020; Wang et al., 2025), although they entail reporting biases and changes in media practices. Yet, 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 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 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 sensitivity coefficient (β) can be interpreted as variation in the drought–reporting relationship rather than as a direct map of physical vulnerability.

This study advances understanding of drought–impact relationships by providing a comprehensive multiscale 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

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 of standardized drought indices (SPI and SPEI) with impact data from newspaper records. The results indicate that media-reported impact frequency is more strongly associated with drought impacts are primarily controlled by persistent moisture

620 deficits, rather than with short-term climatic variability. The most robust drought-impact relationships are identified at medium-to-long accumulation time scales, reflecting the integration of moisture deficits over longer climatic windows capturing the gradual propagation of drought signals through soil moisture and surface water systems. These results confirm-indicate that the widespread impact reporting s-in peninsular Spain is more strongly associated with are primarily driven-by-the persistent drought conditions than with ,rather than-by-the isolated precipitation deficits-in-precipitation.

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The results also suggest a clear sectoral differentiation in dominant accumulation timescales for the response to drought. Hydrological impacts are reporting is mainly associated with driven-by longer accumulation timescales, following the integrative nature of water storage system timescales, following the integrative nature of water storage systems, whereas agricultural impacts-reporting shows stronger associations respond more quickly to-with short- to medium-term accumulation timescales, variability, 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-increasingly drive impact-dynamics across both systems-sectors.

635 A major finding of this study is the the strong association important-role of atmospheric evaporative demand with media-reported drought impacts-in-exacerbating-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 time scales. 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 the-sensitivity-of-impacts-to-drought-severity is largely nonlinear, with-the-sensitivity-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 threshold-the-existence-of-thresholds-in-natural-and-managed-systems-above-which-buffering-capacities-are-exceeded-and impacts-accelerate.

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Spatial analysis indicates a dominant large-scale drought signal and a-large regional variability in reporting-impact response. Although a large proportion of reporting variability is associated with drought-impacts-is-driven-by-the 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.

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This study contributes to the understanding of drought-impact relationships by assembling a unified framework of multiscalar 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 a useful insight into the way 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 proposing the research idea. A.M.E., F.D.C., and A. H. developed the methodology, carried out analysis and visualization, and wrote the original draft of the manuscript. S.B, J.V., M. A., B.T., and M.F. assisted in data collection, contributed to manuscript editing, and literature enhancement, and contributed to project administration and coordination, A.M.E., and S.M.V., and F.D.C. contributed to draft writing. All authors contributed to the manuscript by reviewing editing the original draft.

Competing interests

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

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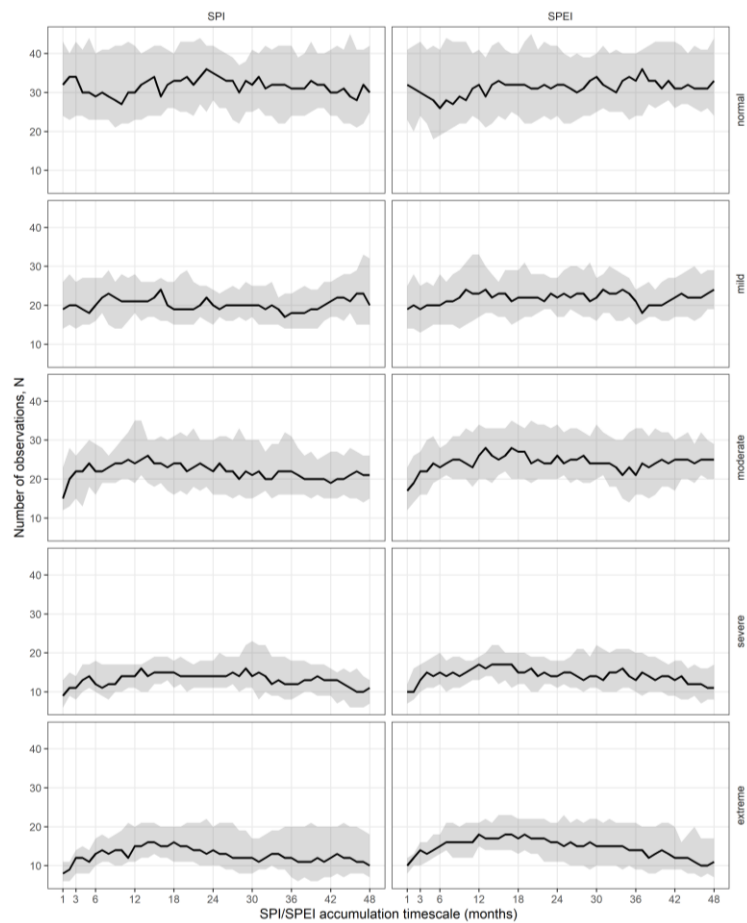
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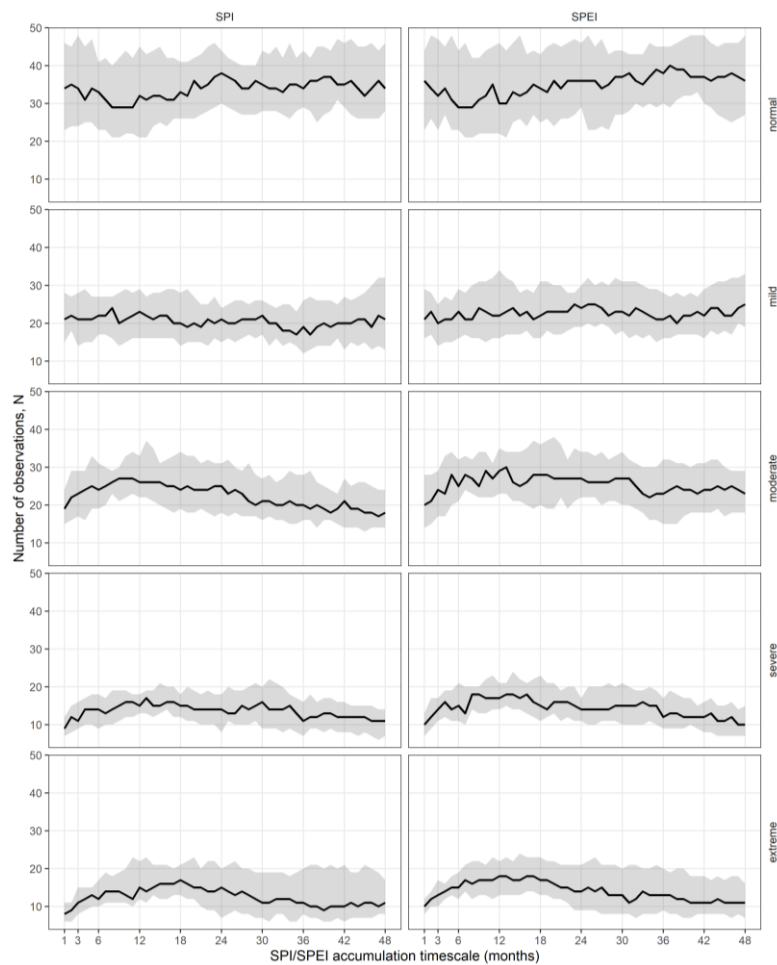
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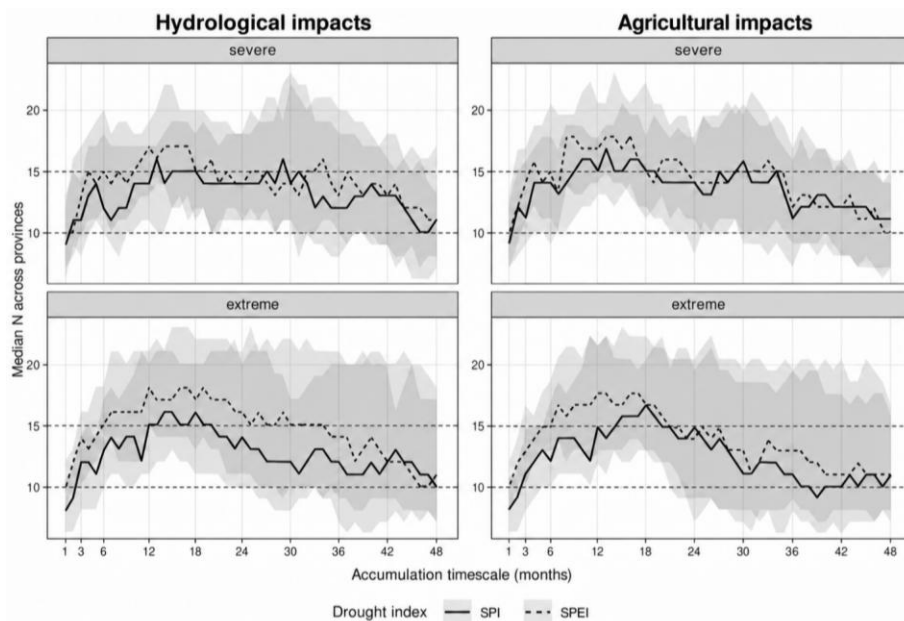
Supplementary Figures



920 **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 gray 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 gray 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 gray shading indicating the interquartile range. Horizontal dashed lines mark reference sample sizes of N=10 and N=15.