

Optimal distribution functions for drought characterization across Europe's climatic gradient

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ABSTRACT

Study region: This study focuses on pan-European climatic regimes, evaluating drought characterization at the Nomenclature of Territorial Units for Statistics level (NUTS-3).

Study focus: Accurate statistical characterization of drought events is essential for effective water resources management and disaster risk reduction, yet the selection of appropriate probability distributions remains uncertain under regional climatic diversity. This study develops a rigorous methodological framework for optimizing drought characterization through systematic probability distribution function (PDF) selection. Eight candidate PDFs were evaluated for characterizing meteorological and hydrological drought. We calculated the standardized precipitation index (SPI-3), standardized precipitation evapotranspiration index (SPEI-3), and standardized streamflow index (SSI-3) at 3-month timescale using L-moments for parameter estimation. A two-stage selection process was then applied, using the Anderson-Darling test and corrected Akaike Information Criterion.

New hydrological insights for the region: Results show optimal PDF selection is climate-dependent, indicator-specific, and seasonally variable. For SPI-3, the Gamma (GAM) distribution dominates across most European climate zones, validating conventional approaches for precipitation-based indices. SPEI-3 exhibits spatial heterogeneity, with the Pearson Type III being recommended for central and western European climates, and the Normal distribution for Scandinavia and Mediterranean regions. SSI-3 is the most spatially variable, with LN3 recommended across central and western Europe, GAM for northern Scandinavia and parts of the Mediterranean, and GEV in the Baltic region and scattered coastal and southern regions.

1. Introduction

Drought is one of the most complex and devastating natural hazards significantly affecting multiple climate-dependent sectors and natural ecosystems (Buras et al., 2020; Shyrokaya et al., 2023; Stahl et al., 2016). As a dynamic phenomenon, drought develops gradually and can persist for extended periods, making it particularly challenging to monitor, predict and manage effectively (Biella et al., 2025; Hao et al., 2018; Van Loon et al., 2024). Understanding the statistical characteristics of droughts has become increasingly important for effective water resources management, agricultural planning, and climate change adaptation strategies (Omer et al.,

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2020; Rad et al., 2017), and recent syntheses underscore that addressing the multifaceted impacts of drought requires research that explicitly connects drought characterization to risk, governance and decision-making (Wens et al., 2026). A comprehensive analysis of drought patterns requires statistical approaches to capture their temporal and spatial variability, duration, intensity, and frequency, which are fundamental for developing early warning systems, implementing mitigation measures, and enhancing regional resilience to drought conditions (Raziei et al., 2009; Santos et al., 2010; Shyrokaya et al., 2024). Particularly under climate change, drought severity and spatio-temporal patterns are projected to be altered (Gudmundsson and Seneviratne, 2016; Stagge et al., 2017), highlighting the need for robust and capable methods to analyse drought characteristics. Accurate statistical characterization is essential for developing reliable drought monitoring systems and implementing effective water resources management strategies that can adapt to varying drought conditions. It is therefore important to select appropriate statistical approaches (e.g., probability distribution functions (PDFs)) that can effectively capture and characterize drought events based on historical data (Stagge et al., 2015; Yimer et al., 2022).

In Europe, recent decades have seen an increasing frequency and severity of drought events, causing substantial economic losses, agricultural disruption and environmental degradation (García-Herrera et al., 2019; Moravec et al., 2021). The analysis of drought patterns in European regions holds particular significance due to the continent's diverse climatic zones, complex agricultural systems, and interconnected economies (Buras et al., 2020; Hänsel et al., 2019; Peña-Angulo et al., 2022). Without adaptation measures, yearly drought damages across the European Union (EU) and United Kingdom are expected to reach €65 billion by 2100 under a global 4 °C warming (Naumann et al., 2021). The continent's unique geographical characteristics, including its varied topography and the influence of multiple climate systems, create distinct drought vulnerability patterns that require specialized analysis approaches (García-Herrera et al., 2019; Peña-Angulo et al., 2022).

The selection of an appropriate PDF directly influences the accuracy of drought frequency, intensity and duration analysis (Zhao et al., 2020), since candidate distributions differ in their ability to reproduce the characteristics of hydrometeorological variables (Vicente-Serrano et al., 2025). Identifying the most suitable distribution for a given region and drought type therefore improves the reliability of drought monitoring and of the water resources management and risk reduction decisions that depend on it (Song et al., 2021; Svensson et al., 2017).

Despite significant advances in drought analysis, several critical challenges persist in the selection and application of PDFs for characterizing drought events. A primary limitation lies in the inherent complexity of identifying a single "best-fit" distribution that consistently outperforms across different temporal and spatial scales (Guenang et al., 2019; Monish and Rehana, 2019), particularly in domains with diverse hydroclimatic conditions, such as Europe. Recent studies have attempted to identify appropriate PDFs for specific regional contexts (Mathlouthi and Lebdi, 2021; Nasirudeen et al., 2021; Tosunoglu and Kisi, 2016), yet the non-stationary nature of climate patterns and interdependencies between different drought types (meteorological and hydrological) introduce additional uncertainties (Feng et al., 2023; Yang et al., 2017). Continental-scale assessments do exist for individual indices: Stagge et al. (2015) evaluated candidate distributions for standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) across Europe using gridded data and found the Gamma distribution broadly adequate for most climatic conditions, while Tjeldeman et al. (2020) conducted a large-sample comparison of distributions for standardized streamflow index (SSI) across European catchments. However, these efforts addressed meteorological and hydrological drought separately, were not organised around an explicit climatic stratification, and did not quantify how much characterization accuracy is lost when a single distribution is generalised across a region. The translation of distribution-selection findings into a unified, climate-conditioned and transferable guideline that simultaneously spans precipitation-, water-balance- and streamflow-based drought across a heterogeneous continental domain therefore remains a critical gap. This study advances beyond previous individual-index comparisons by treating SPI, SPEI and SSI within a single internally consistent framework forced by one reanalysis-driven model, organising optimal-distribution selection according to Köppen-Geiger climate class, and resolving the analysis at the NUTS-3 administrative level. It further distinguishes genuine distributional preference from statistical near-equivalence through a corrected Akaike Information Criterion (AICc).

We systematically evaluate the performance of various PDFs for characterizing different drought types across Europe's diverse hydroclimatic regions. We use hydrometeorological reanalysis data from the E-HYPE (European Hydrological Predictions for the Environment) model to identify the optimal PDF for each drought indicator at the NUTS-3 scale, and employing the Anderson-Darling (AD) test (Anderson and Darling, 1954) to assess goodness-of-fit and AICc (Hurvich and Tsai, 1989) to select the best-fitting distribution among candidate PDFs. Our analysis is guided by the following scientific questions that advance understanding of drought characterization in heterogeneous climatic regions: (1) *Which PDFs provide the best fit for different drought indicators (meteorological and hydrological) across Europe?* (2) *How does the performance of PDFs vary across Europe's hydroclimatic gradient, and what regional patterns emerge?* and (3) *Can we identify climate-specific optimal PDFs that improve drought frequency analysis at regional scales?*

2. Study area and data

2.1. Domain of interest and historical reanalysis data

The investigation is conducted across the pan-European domain, which is subject to large hydroclimatic heterogeneity. Historical hydrometeorological data simulated by the E-HYPE hydrological model forced with reanalysis data (HydroGFD) are used to provide comprehensive spatial coverage across the pan-European domain, including areas with sparse monitoring networks and overcoming point-based or localized data analysis. The choice of HydroGFD as meteorological forcing reflects an operational requirement: HydroGFD is a global gridded reanalysis product, developed at the Swedish Meteorological and Hydrological Institute (SMHI) and updated in near-real time, which enables the same forcing chain to be used consistently for long historical simulations and for the

initialisation of the operational E-HYPE and World-Wide HYPE medium-range and seasonal forecasting services, thereby ensuring that the distribution recommendations derived here are directly transferable to the operational forecasting and drought-monitoring chain. E-HYPE is a process-based model that represents as a large-scale hydrological modelling framework specifically designed for simulating water balance components across Europe (Hundecha et al., 2016). It operates at a high spatial resolution, dividing the European continent into 35,408 sub-catchments with an average size of 215 km². The model simulates hydrological processes including snow accumulation and melting, soil moisture dynamics, groundwater fluctuations, and river routing, while accounting for human influences such as irrigation and reservoir operations. E-HYPE's ability to simulate multiple hydrometeorological variables minimizes inconsistencies that might arise when using disparate data sources for different drought indicators. Moreover, this model-based analysis can capture the complex spatiotemporal interactions between meteorological forcing and hydrological response, enabling a realistic representation of drought propagation from meteorological to hydrological systems. E-HYPE uses daily precipitation and air temperature from the HydroGFD reanalysis, together with several static physiographic descriptors of the catchments (including land use, soil type and elevation), as input data, and simulates a range of hydrological variables. Among these variables, (corrected) precipitation, potential evapotranspiration and streamflow spanning 1960–2022 were used in the present study to calculate the SPI, SPEI and SSI indicators, respectively; potential evapotranspiration is computed internally using the modified Jensen-Haise/McGuinness method.

2.2. Spatial data aggregation for regional assessment

Nomenclature of Territorial Units for Statistics (NUTS) is the EU's standardized hierarchical system for dividing each member state into three levels of regions for statistical purposes (Eurostat, 2024, 2020). It provides a hierarchical framework for analysing major socio-economic regions (NUTS-1), basic regions for the application of regional policies (NUTS-2), and small regions for specific diagnoses (NUTS-3) (Espinosa et al., 2014; Sokołowski et al., 2015). Here, we utilized NUTS-3 level boundaries from 2021, obtained from the official EU website (<https://ec.europa.eu/eurostat/web/main/home>), to aggregate hydroclimatic data from E-HYPE's catchment-level outputs. Therefore NUTS-3 spatial resolution is adopted for this drought analysis in the current study; through this spatial overlay and area-weighted averaging procedure, hydrometeorological data from E-HYPE's sub-catchments were aggregated into 1481 NUTS-3 administrative regions across the pan-European domain.

3. Methodology

3.1. Framework design

We introduce a systematic three-phase approach for selecting optimal probability distributions for drought characterization across Europe: Phase 1 (spatial and temporal data harmonization), Phase 2 (meteorological and hydrological drought investigation), and Phase 3 (drought characterization and regional analysis) (Fig. 1). Phase 1 addresses the fundamental challenge of reconciling E-HYPE model outputs into administrative boundaries. This phase begins with hydrometeorological data at the catchment scale, which are then spatially integrated at the NUTS-3 administrative regions through a precise overlay procedure. Through area-weighted averaging

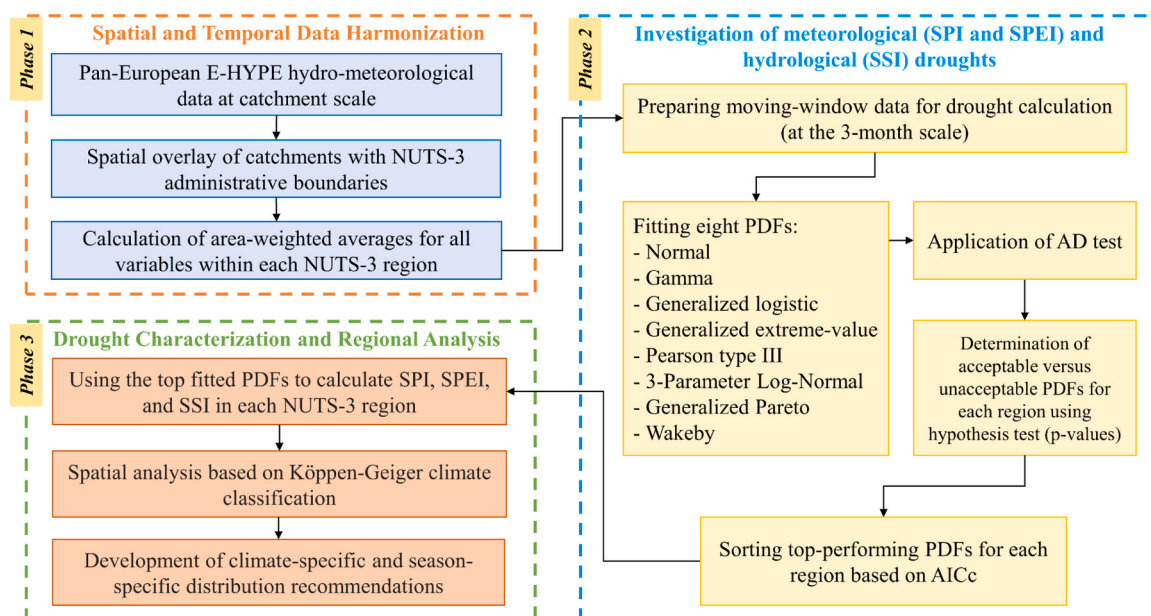


Fig. 1. Methodological framework for pan-European drought analysis and the optimal PDFs selection for each region.

techniques, the E-HYPE model outputs (including simulated hydrometeorological variables) are transformed into administratively meaningful units, while preserving the hydrometeorological signals and creating a spatially harmonized dataset that serves as the foundation for subsequent drought analysis across Europe's diverse climatic regions. For each NUTS-3 region, daily time series data of precipitation, potential evapotranspiration, and streamflow were aggregated from the underlying E-HYPE catchment resolution based on the proportion of catchment area within each NUTS-3 boundary.

Phase 2 employs a rigorous statistical approach to evaluate multiple probability distributions for drought characterization. This phase begins by preparing moving window data at a 3-month scale to capture both rapid-onset and seasonal drought development patterns. Eight candidate probability distributions were systematically fitted to the monthly aggregated data for each NUTS-3 region, including the Normal (NOR), Gamma (GAM), Generalized Logistic (GLO), Generalized Extreme-Value (GEV), Pearson Type III (PE3), 3-Parameter Log-Normal (LN3), Generalized Pareto (GPA), and Wakeby (WAK) distributions (Asquith, 2011; Hosking, 1990; Hosking and Wallis, 1997). These distributions range from simple two-parameter functions to complex five-parameter alternatives, providing comprehensive coverage of potential distribution shapes relevant to hydrometeorological variables.

The distribution selection process follows a two-stage statistical framework. First, the Anderson-Darling (AD) goodness-of-fit test (Anderson and Darling, 1952) was applied to assess whether each candidate distribution adequately represents the empirical data, with distributions failing to achieve p-values greater than 0.05 being excluded from further consideration. For the remaining acceptable distributions, the corrected Akaike Information Criterion (AICc) (Hurvich and Tsai, 1989) was employed as the final selection metric. The AICc extends the standard Akaike Information Criterion (AIC) (Akaike, 1974, 1998) by incorporating a correction term that accounts for small sample sizes (Burnham and Anderson, 2003; Hurvich and Tsai, 1989):

$$\text{AICc} = -2\ln(L) + 2k + [2k(k+1)/(n-k-1)] \quad (1)$$

where L is the maximum likelihood, k is the number of distribution parameters, and n is the sample size. The AICc penalizes model complexity more heavily than AIC in small samples, thereby reducing the risk of overfitting and favouring parsimonious distributions that balance goodness-of-fit with model simplicity. The distribution with the minimum AICc value was selected as optimal for each region-month combination. This selection process was performed independently for each calendar month, recognizing that different months may exhibit distinct distributional characteristics due to seasonal climate variations.

Phase 3 implements these statistically optimal distributions to calculate multiple standardized drought indices across all NUTS-3 regions. This implementation phase applies the optimal distributions identified for each drought indicator. By analysing the drought indices for each Köppen-Geiger class (Kottek et al., 2006; Peel et al., 2007), the framework enables a systematic analysis of distribution performance across different climatic regimes. Each NUTS-3 administrative unit was associated with its corresponding Köppen-Geiger climate classification through a spatial overlay analysis. The Köppen-Geiger raster dataset was systematically cropped and masked to the boundaries of each individual NUTS-3 region, and pixel frequencies were then analysed within each unit to calculate the percentage coverage of all climate classes present. The dominant classification, defined as the Köppen-Geiger type with the highest percentage coverage within a given NUTS-3 unit, was assigned to represent the climatic conditions of that region, ensuring that each unit is characterized by its most prevalent climate. The representation of the adjacent NUTS-3 regions as Köppen-Geiger climate zones aims to identify relationships between climate characteristics and distribution performance, culminating in the development of climate-specific and season-specific recommendations that enhance drought characterization accuracy across Europe's diverse climatic gradient.

3.2. Drought indicators

Three standardized drought indicators were employed to characterize different types of drought conditions across pan-European catchments at the 3-month time scales. We considered the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) for addressing meteorological droughts, and the standardized streamflow index (SSI) for hydrological droughts. The general calculation procedure for all three standardized indices follows these steps:

- 1) Aggregate the input data (precipitation, potential evapotranspiration, and streamflow) at the desired time scale (3-month in this study)
- 2) Fitting various PDFs and selecting the optimal PDF to the aggregated data
- 3) Equiprobability transformation of the optimal distribution cumulative probability to the inverse of the standard normal distribution, expressing the standardized index as:

$$Z = \phi^{-1}(F(X)) \quad (2)$$

where Z represents the standardized drought index (i.e., SPI, SPEI and SSI) value, ϕ^{-1} is the inverse standard normal cumulative distribution function, $F(X)$ is the optimal cumulative probability of observed hydrometeorological variable of interest (X). The indices are computed using a moving accumulation window, the value reported for a given calendar month integrates that month and the two preceding ones; accordingly, the four months presented throughout the analysis correspond to the four standard climatological seasons, with May representing spring (March–April–May), August summer (June–July–August), November autumn (September–October–November) and February winter (December–January–February).

The SPI (McKee et al., 1993) quantifies meteorological drought conditions based solely on precipitation data. It uses distribution-transformed precipitation as the input variable (instead of X in Eq. 2), where aggregated precipitation values are first fitted to an optimal probability distribution (determined through the selection process described in Section 3.3) and the resulting

cumulative probability is then transformed to the standard normal distribution through the inverse normal cumulative distribution function (Eq. 2). This transformation effectively standardizes precipitation deficits and excesses, enabling identification of dry and wet periods at different time scales across diverse climatic regimes with differing precipitation magnitudes and variability. The SPEI (Vicente-Serrano et al., 2010) incorporates both precipitation and potential evapotranspiration to capture the influence of evaporative demand on water availability. It uses the climatic water balance (climatic water balance = precipitation - potential evapotranspiration) as the input variable (instead of X in Eq. 2). SPEI provides a more comprehensive assessment of drought conditions by considering both water supply and atmospheric water demand. The SSI (Nalbantis, 2008; Nalbantis and Tsakiris, 2009; Vicente-Serrano et al., 2012) characterizes hydrological drought conditions based on streamflow data. It uses streamflow volume as the input variable (instead of X in Eq. 2), capturing the effect of catchment processes on water availability in river systems.

For consistent interpretation across all three indicators, the standard classification scheme proposed by McKee et al. (1993) was adopted, as shown in Table 1. This classification system enables the comparison of drought severity across different regions and drought types.

3.3. Fitting and selection of distribution functions

This study evaluated a set of widely-used PDFs (listed in Table 2) for their ability to characterize drought conditions. Eight applied distributions were selected based on their proven applicability in hydrological studies and their ability to capture different aspects of drought behaviour. Each distribution offers unique characteristics that make them suitable for modelling various types of drought conditions. The L-moments approach was used to compute the parameters of each distribution function (Asquith, 2011; Elamir and Seheult, 2003; Hosking, 1990). Details about these distributions are provided in the documentation of the lmomco package for R (Asquith, 2024).

The AD test (Anderson and Darling, 1954, 1952), distinguished by its sensitivity to tail distributions compared to other goodness-of-fit tests (Farrell and Rogers-Stewart, 2006; Razali and Wah, 2011), offers a rigorous statistical framework for evaluating the suitability of different probability distributions in characterizing drought events. The AD test was applied to assess the goodness-of-fit of each fitted PDF, with H_0 assuming that the sample data follows the specified theoretical distribution and H_1 assuming that the data does not follow that distribution. A p-value greater than 0.05 indicates failure to reject H_0 , meaning that the distribution provides an acceptable fit to the observed data. Conversely, a p-value less than or equal to 0.05 indicates a rejection of H_0 , suggesting that the distribution does not adequately represent the data. Following this framework, only distributions with p-values greater than 0.05 were retained as acceptable candidates. Among the acceptable distributions, the top-performing PDFs temporally (i.e., in each season) and spatially (i.e., in each region) were then selected based on the minimum AICc value, ensuring both statistical adequacy and parsimony in drought characterization.

4. Results

4.1. Optimal PDFs at NUTS-3 resolution across Europe

Fig. 2 presents the spatial distribution of optimal PDFs for the three drought indicators (SPI-3, SPEI-3 and SSI-3) across European NUTS-3 regions throughout the four seasons. Due to the 3-month moving window aggregation, May represents spring (March–April–May), August represents summer (June–July–August), November represents autumn (September–October–November), and February represents winter (December–January–February). The maps reveal distinct spatial patterns in distribution selection, with each region coloured according to its optimal PDF as determined through the two-stage selection process (AD test followed by AICc minimization). The three drought indices exhibit markedly different levels of spatial heterogeneity in their optimal distribution selections, reflecting the increasing complexity of the underlying hydrometeorological processes. For SPI-3, the GAM distribution dominates across the vast majority of European regions in all seasons, accounting for (approximately) 50–77% of regions depending on the season, with the NOR distribution accounting for most of the remaining area in spring, summer and winter (28.0%, 32.5% and 46.2% respectively) and for a smaller share in autumn (11%). Together, GAM and NOR account for (approximately) 87–95% of all regions in every season. In contrast, SPEI-3 is dominated by the NOR distribution, reflecting the reduced skewness of the climatic water balance relative to precipitation alone. The Mediterranean regions frequently require more flexible, 3-parameter distributions (e.g., GLO, GEV, PE3) to

Table 1

Classification scheme for the standardized drought indicators (SPI, SPEI and SSI).

Index value	Drought category
≥ 2.00	Extremely wet
1.50–1.99	Severely wet
1.00–1.49	Moderately wet
0.00–0.99	Near normal (mild wet)
-0.99–0.00	Near normal (mild drought)
-1.49 to -1.00	Moderate drought
-1.99 to -1.50	Severe drought
≤ -2.00	Extreme drought

Table 2

Summary of PDFs evaluated including their parameters.

Distribution function name	Abbreviation	Parameters (and their symbols)	Statistical properties and selection rationale
Normal	NOR	Arithmetic mean (μ) and standard deviation (σ) parameters	Simple symmetric distribution
Gamma	GAM	Shape parameter (α) and scale parameter (β)	Handles positive-only values; flexible shape for right-skewed data
Generalized Logistic	GLO	Location (ξ), scale (α) and shape (κ) parameters	Accommodates heavy tails and extreme values; flexible for both positive and negative skewness
Generalized Extreme Value	GEV	Location (ξ), scale (α) and shape (κ) parameters	Suitable for extreme value modelling; captures different extreme value types
Pearson Type III	PE3	Mean (μ), standard deviation (σ) and skew (γ) parameters	Handles moderate skewness; traditional choice in hydrology and widely accepted in water resources
3-Parameter Log-Normal	LN3	Lower bounds (ζ), location (μ_{Log}) and scale (σ_{Log}) parameters	Bounded below by threshold; captures multiplicative processes common in hydrology
Generalized Pareto	GPA	Location (ξ), scale (α) and shape (κ) parameters	Model exceedances over high thresholds; suitable for peak-over-threshold approach
Wakeby	WAK	Location parameter (ξ), two scale parameters (α and β) and two shape (γ and δ) parameters	Highly flexible with 5 parameters; can model complex distributional shapes including heavy tails

adequately capture the combined precipitation - potential evapotranspiration deficit dynamics represented by SPEI. SSI-3 exhibits the highest degree of spatial heterogeneity, with all eight distributions appearing across the European domain in every season and with strong regional clustering patterns. GAM remains the most frequently selected distribution in all four seasons, but its share varies more than threefold, from 76.8% in spring and 61.9% in winter to 40.1% in summer and 30.0% in autumn. In the summer and autumn windows the majority of regions therefore require an alternative distribution, whereas in spring and winter GAM alone covers most of the domain.

Seasonal variations in optimal distribution selection are evident across all three indices, though the magnitude of seasonal influence varies by index type. For SPI-3, the set of leading distributions is stable year-round, GAM and NOR together accounting for (approximately) 87–95% of regions in every season, but their relative shares shift substantially: autumn shows the strongest GAM concentration, whereas in winter GAM and NOR are almost equally represented. SPEI-3 and SSI-3 demonstrate more pronounced seasonal shifts. For SSI-3 the diversity of selected distributions increases markedly in summer and autumn: in autumn GAM is selected in only 30% of regions and is effectively tied with LN3 (29%), with PE3 accounting for a further 21.5%, so that three distributions share approximately 80% of the domain and no single distribution can be regarded as dominant. This near-parity between a two-parameter and a lower-bounded three-parameter form reflects the complex interplay between low-flow conditions, evapotranspiration stress, and regional water management practices during and after the peak water demand period. The optimal approach requires region-specific and potentially season-specific distribution selection, as implemented in this study. The spatial patterns also suggest that climate classification systems may serve as useful predictors of optimal distribution selection. This spatial and temporal variability in optimal distributions underscores the importance of rigorous distribution selection rather than default assumptions, particularly for operational drought monitoring systems serving diverse geographic domains.

To address whether the spatial heterogeneity in optimal distribution selection reflects meaningful hydroclimatic differences or merely weak statistical identifiability among similarly-performing distributions, we quantified the AICc range for each region, calculated as $\text{AICc}_{\text{max}} - \text{AICc}_{\text{min}}$ across all statistically acceptable distributions (those passing the AD test at $p > 0.05$). It measures the spread in support across the accepted set, distinguishing regions where the accepted distributions are not interchangeable (large range) from regions where all accepted candidates perform nearly equivalently (small range, indicating weak discrimination). Fig. 3 reveals distinct patterns across drought indices and seasons. For SPI-3, the AICc range remains below approximately 25 units across most of the continent in all seasons, indicating a limited spread among the accepted distributions; larger ranges are confined to the southern Spain and Italy, the Balkans, Turkey, and parts of Poland and the Baltic states. SPEI-3 displays the most spatially extensive discrimination of the three indicators, with ranges of roughly 40–70 units covering Scandinavia, the British Isles, France, central Europe and the Iberian Peninsula during spring and summer; in autumn and winter the ranges contract markedly and most regions fall below 30 units. SSI-3 exhibits the widest overall spread, although the large majority of regions remain below 50 units; moderate ranges (approximately 50–100 units) occur mainly in summer and autumn and cluster over the central European lowlands (Germany, Czechia, Poland, Austria) and parts of Iberia.

4.2. Optimal PDFs in the Köppen-Geiger climate classes

We investigate the link between optimal PDFs and the regional climatic regime as described by the Köppen-Geiger climate classification at the NUTS-3 resolution. Table 3 quantifies the prevalence of Köppen-Geiger climate classes across the pan-European domain, revealing significant disparities in their representation within NUTS-3 regions. The temperate oceanic climate (Cfb) overwhelmingly dominates the European domain, encompassing 1034 NUTS-3 regions and covering approximately 2.4 million km² (42.96% of the total area). The Mediterranean climate collectively constitutes a substantial portion of the domain, with Csa (hot-summer Mediterranean) covering 887,817 km² (15.85%) across 172 regions. The subarctic climate (Dfc) covers the third-largest area

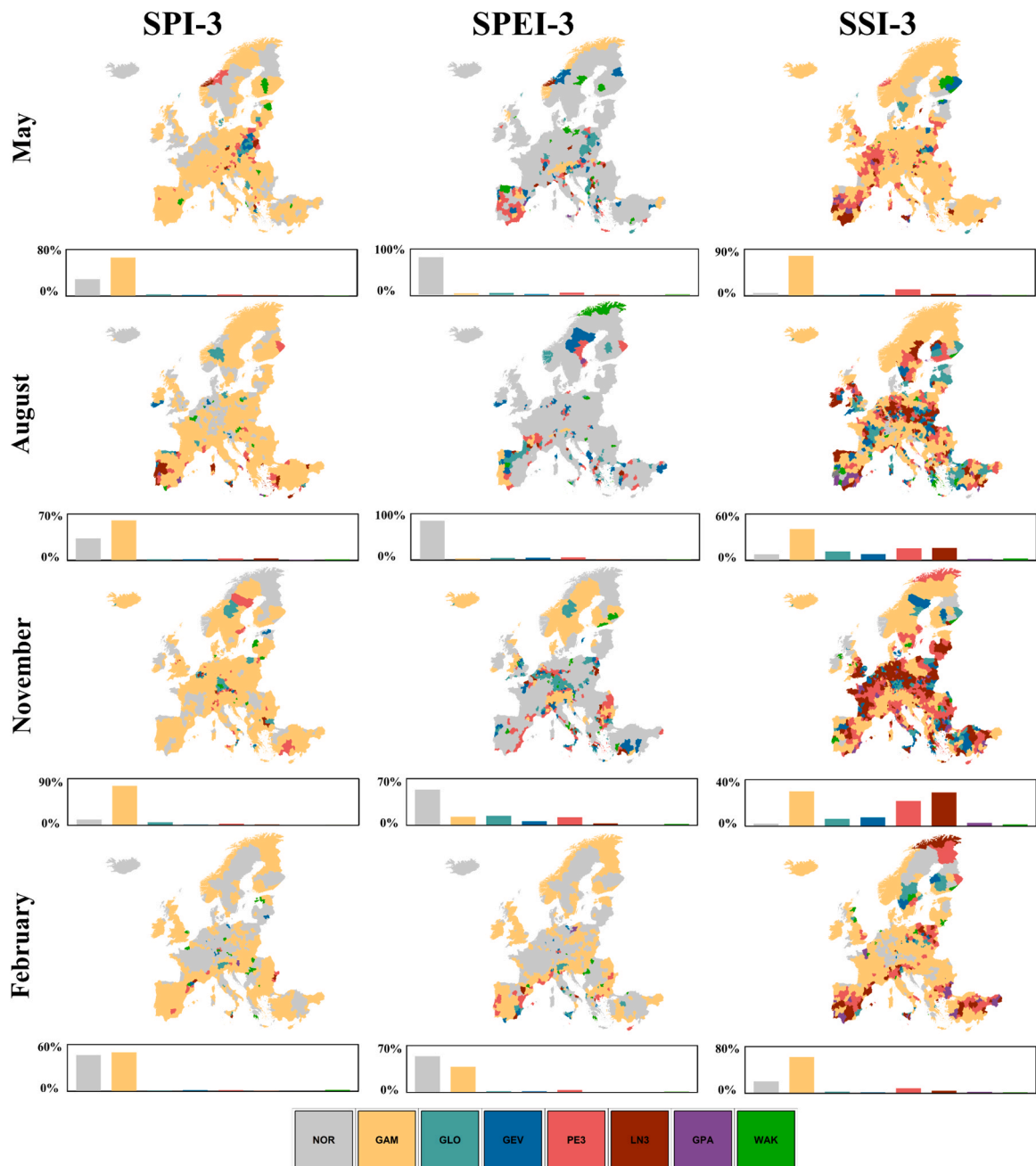


Fig. 2. Spatial distribution of optimal PDFs for SPI-3, SPEI-3 and SSI-3 across European NUTS-3 regions by season. The order of each PDF bar in the plot corresponds to the order of the PDF colours in the legend at the bottom of the figure. Percentages are expressed as the share of NUTS-3 regions for which each distribution was selected as optimal; regions in which no candidate distribution passed the AD test at the 0.05 level are excluded from the corresponding bar chart.

(15.79% of the domain) despite encompassing only 34 NUTS-3 regions, reflecting the large administrative divisions characteristic of Northern Scandinavia. Humid subtropical (Cfa) climate covers 118 NUTS-3 regions which is equal to 7.26% of area. Finally, the Mediterranean-influenced warm-summer humid continental (Dsb) and cold semi-arid (BSk) climates together account for 15 regions and approximately 3.24% of the domain, while the tundra climate (ET) covers 9 NUTS-3 regions (2.38% of the domain). We note that the subpolar oceanic climate (Cfc) is here represented by just a single NUTS-3 region covering 1029 km² (0.02%) and therefore excluded from the analysis.

The resulting spatial distribution of the dominant Köppen-Geiger classification across the European NUTS-3 units, derived through the overlay procedure described in [Section 3.1](#), is shown in [Fig. 4](#).

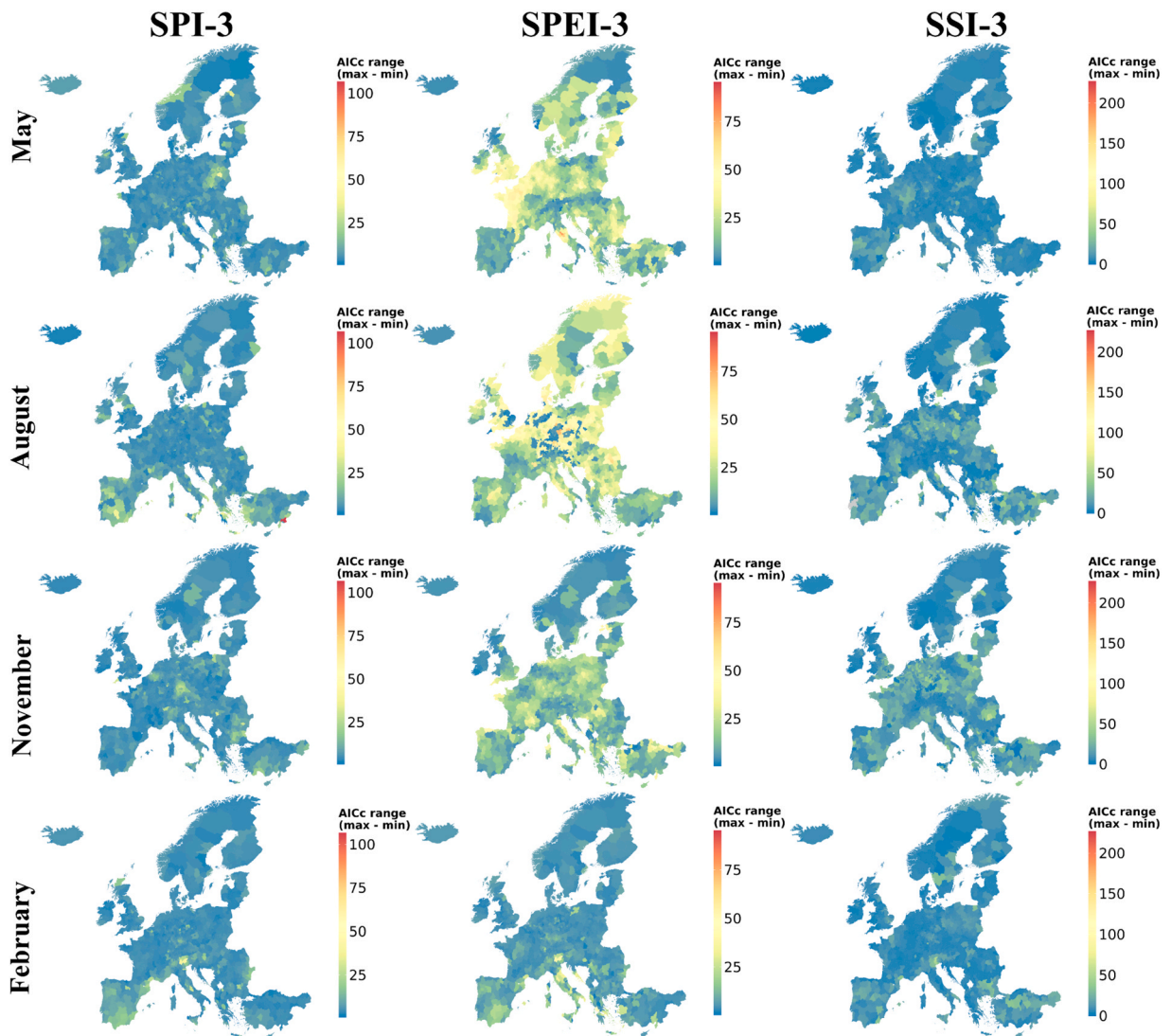


Fig. 3. AICc range (AICc_max – AICc_min) among the statistically acceptable distributions. The colour scale is common to all seasons within each indicator but differs between indicators (values should therefore be compared using the legends rather than the colours).

Table 3

Distribution of Köppen-Geiger climate classes across the European NUTS-3 regions. The representation of each climate class is shown in terms of number of administrative regions, total area coverage (km²), and percentage of total study area.

Köppen-Geiger class	Climate class	Number of NUTS (level 3)	Total Area Coverage (km ²)	Total Study Area (%)
Cfb	Temperate oceanic	1034	2405782	42.96
Csa	Hot-summer Mediterranean	172	887817.4	15.85
Cfa	Humid subtropical	118	406539.6	7.26
Dfb	Humid continental	51	391035.4	6.98
Csb	Warm-summer Mediterranean	47	309210.7	5.52
Dfc	Subarctic	34	884371.1	15.79
ET	Tundra	9	133460	2.38
BSk	Cold semi-arid	8	92179.69	1.65
Dsb	Mediterranean-influenced warm-summer humid continental	7	88804.9	1.59

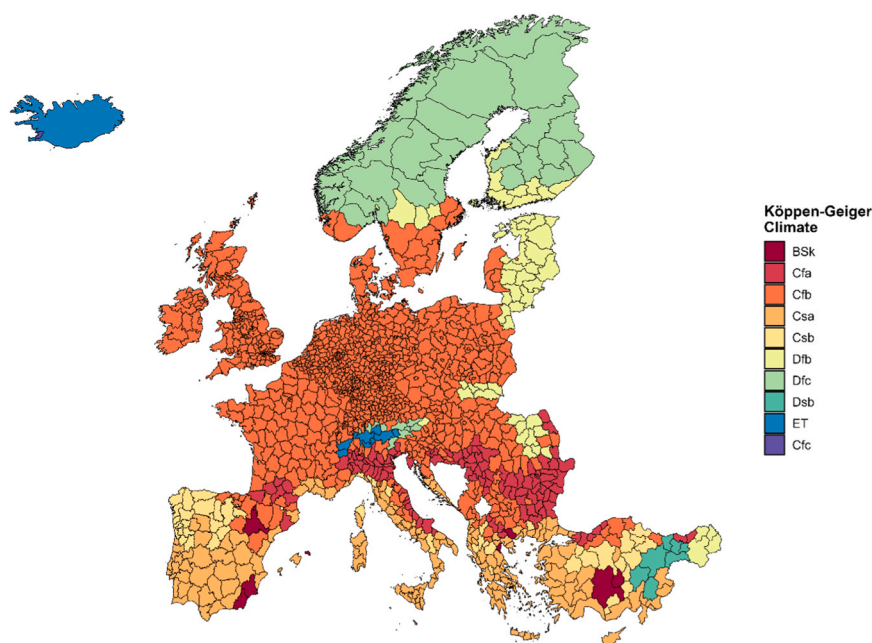


Fig. 4. Spatial distribution of Köppen-Geiger climate classifications across European NUTS-3 administrative units.

An analysis of the optimal PDFs for drought characterization across Köppen-Geiger climate classifications in Europe is further presented in Fig. 5, comparing the three drought indicators (SPI-3, SPEI-3 and SSI-3) across the four seasons. For SPI-3, the GAM distribution demonstrates overwhelming dominance across nearly all climate classes and seasons (except ET in winter, where NOR becomes the most frequent selection), typically accounting for most of optimal selections in most climate classes. This dominance is particularly pronounced in the cold semi-arid (BSk) climate, where GAM accounts for approximately 87.5–100% of selections across all seasons, reflecting the well-documented suitability of the GAM distribution for representing precipitation in water-limited environments. The Cfb (temperate oceanic) in summer and Csa (hot-summer Mediterranean) in spring and summer show the greatest diversity for SPI-3. The Cfa (humid subtropical) display slight increases in distribution diversity during autumn, while the BSk and ET (Tundra) climates show comparatively consistent optimal PDF selection, with no more than three distributions in any season.

SPEI-3 exhibits substantially greater distributional complexity compared to SPI-3, reflecting the additional influence of potential evapotranspiration on drought characterization and the resulting asymmetries introduced by the precipitation-minus-evapotranspiration calculation. The climate-specific patterns are particularly striking. In BSk climates, the NOR distribution gains prominence (approximately 50–75% of selections depending on season), likely because the subtraction of relatively stable evapotranspiration from highly variable precipitation results in more symmetric distributions of climatic water balance. The Cfb display remarkable diversity, with eight distributions with notable NOR distribution presence (approximately 53–89%). Mediterranean climates (Csa, Csb) show distinctive seasonal patterns, with spring requiring greater distributional diversity (eight PDFs for Csa and seven PDFs for Csb), when NOR and PE3 distributions dominate.

SSI-3 demonstrates the highest degree of spatiotemporal heterogeneity, with all eight candidate distributions appearing in substantial proportions across various climate-season combinations, underscoring the complex hydrological processes governing streamflow generation and routing. In BSk climates, GAM is the most frequent selection in spring, summer and winter (approximately 62.5–87.5%), whereas in autumn GEV becomes the dominant choice (50%); GLO, PE3 and GPA also appear in individual regions. The humid subtropical climate (Cfa) exhibits exceptional diversity, with summer showing the strongest heterogeneity (eight different PDFs) and autumn showing a marked shift in which PE3 replaces GAM as the most frequent selection (50.8%), reflecting the varied hydrological response to convective precipitation, high evapotranspiration, and diverse catchment characteristics in these regions. The Mediterranean climates (Csa, Csb) exhibit the most pronounced seasonal variations in SSI-3. Spring and winter show moderate diversity, with the GAM distribution accounting for most of the PDF selections. In contrast, summer and autumn display extreme heterogeneity. In summer, a small number of regions were not adequately represented by any of the eight candidate distributions at the 0.05 level (shown as the dark grey segment in Fig. 5). This may reflect regulated catchments, where abstraction and reservoir operation alter natural flow patterns. The oceanic climate (Cfb) shows consistently high diversity across all seasons, with GAM, NOR, and PE3 appearing in approximately 28–80%, 2–25% and 6–19% of regions respectively, and with LN3 becoming the most frequent selection in autumn (34.1%). The Dsb display strong seasonal patterns with spring showing increased GAM dominance (approximately 85.7%), while summer exhibits maximum diversity (four distributions present, with GLO the most frequent at 42.9%) reflecting the complex interplay of snowmelt, rainfall-runoff, and catchment storage dynamics during the active hydrological season.

The analysis of optimal PDFs across Köppen-Geiger climate classes (Fig. 5) reveals three fundamental patterns that inform our operational recommendations and advance understanding of drought characterization requirements across Europe's climatic gradient.

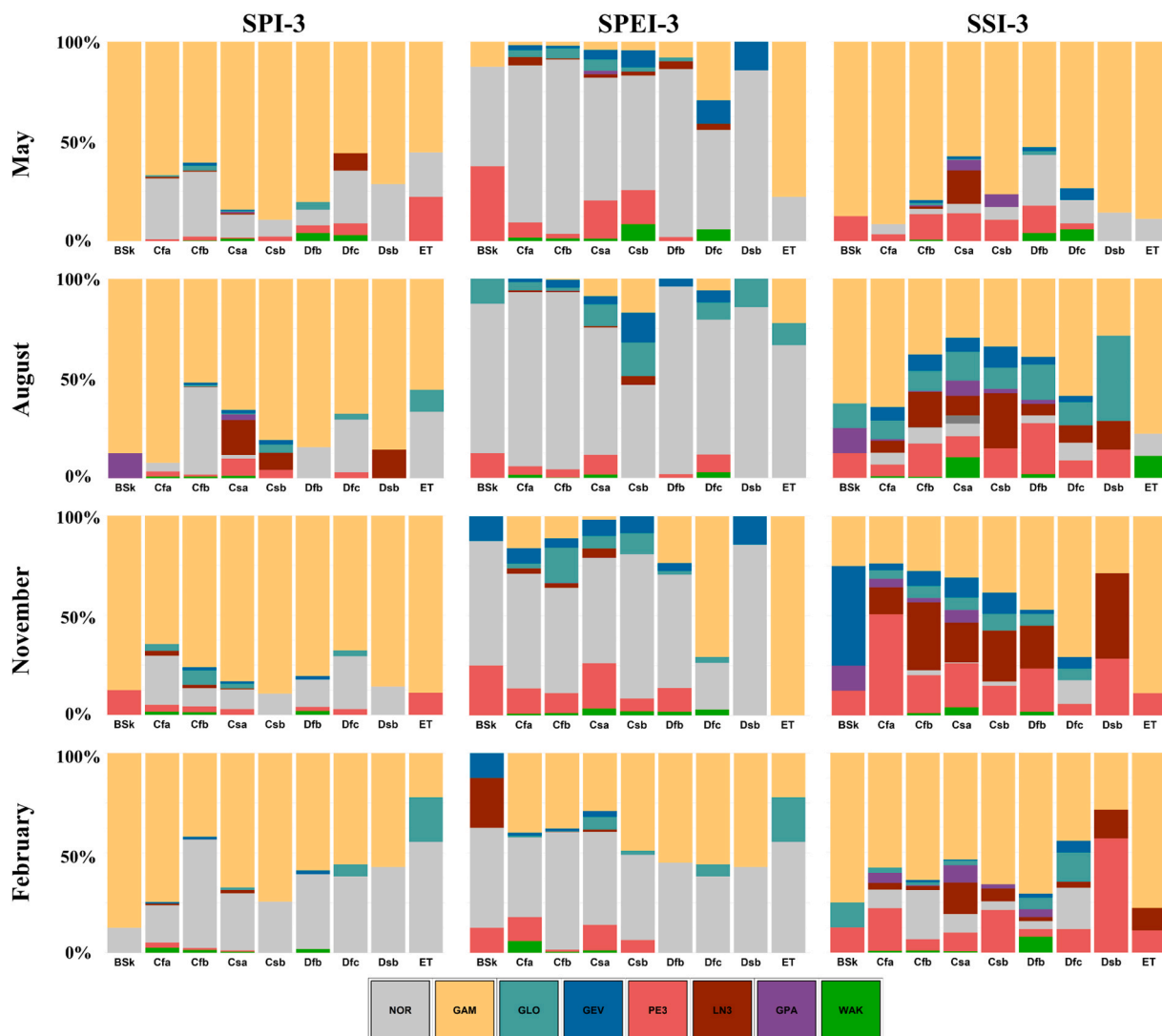


Fig. 5. Seasonal and climate-specific distribution of optimal PDFs for drought characterization (SPI-3, SPEI-3 and SSI-3) across the Köppen-Geiger climate classes. The Cfc was excluded from the analysis due to its negligible spatial representation, being limited to just one NUTS-3 region. Dark grey segments indicate regions in which no candidate distribution passed the AD test at the 0.05 significance level. Due to the 3-month moving window aggregation, May represents spring (March–April–May), August represents summer (June–July–August), November represents autumn (September–October–November), and February represents winter (December–January–February).

The systematic progression in distributional complexity from SPI-3 through SPEI-3 to SSI-3 reflects the cascading effects of hydrological processes on drought characteristics. SPI-3 exhibits remarkable homogeneity, with Gamma distribution dominating across nearly all climate classes and seasons, validating the widespread operational practice of using Gamma-based SPI calculations. SPEI-3 displays intermediate complexity, with 4–6 distributions appearing in substantial proportions across most climate classes, as the inclusion of evapotranspiration introduces asymmetries and seasonal dependencies not present in precipitation-only indices. SSI-3 demonstrates maximum heterogeneity, with 5–8 distributions required to characterize different regions within individual climate classes. This increased complexity for SSI-3 reflects the additional land-surface, subsurface and anthropogenic processes governing streamflow generation. Soil moisture memory, groundwater storage and recession behaviour, snowmelt timing and catchment routing filter and delay the meteorological signal, producing streamflow series whose skewness and tail behaviour differ substantially from those of the forcing precipitation (Svensson et al., 2017; Tjeldeman et al., 2020; Van Loon et al., 2024). The emergence of NOR as optimal for SPEI-3 across the majority of European regions contrasts with the positive skewness typically associated with precipitation. This reflects the subtraction inherent in the climatic water balance: when a relatively stable, low-variance variable (potential evapotranspiration) is subtracted from a more variable, positively skewed variable (precipitation), the resulting distribution exhibits reduced skewness and may approximate normality, particularly where potential evapotranspiration is large relative to precipitation variability. For SSI-3, the GEV occurrences concentrated in parts of Scandinavia and Eastern Europe correspond to

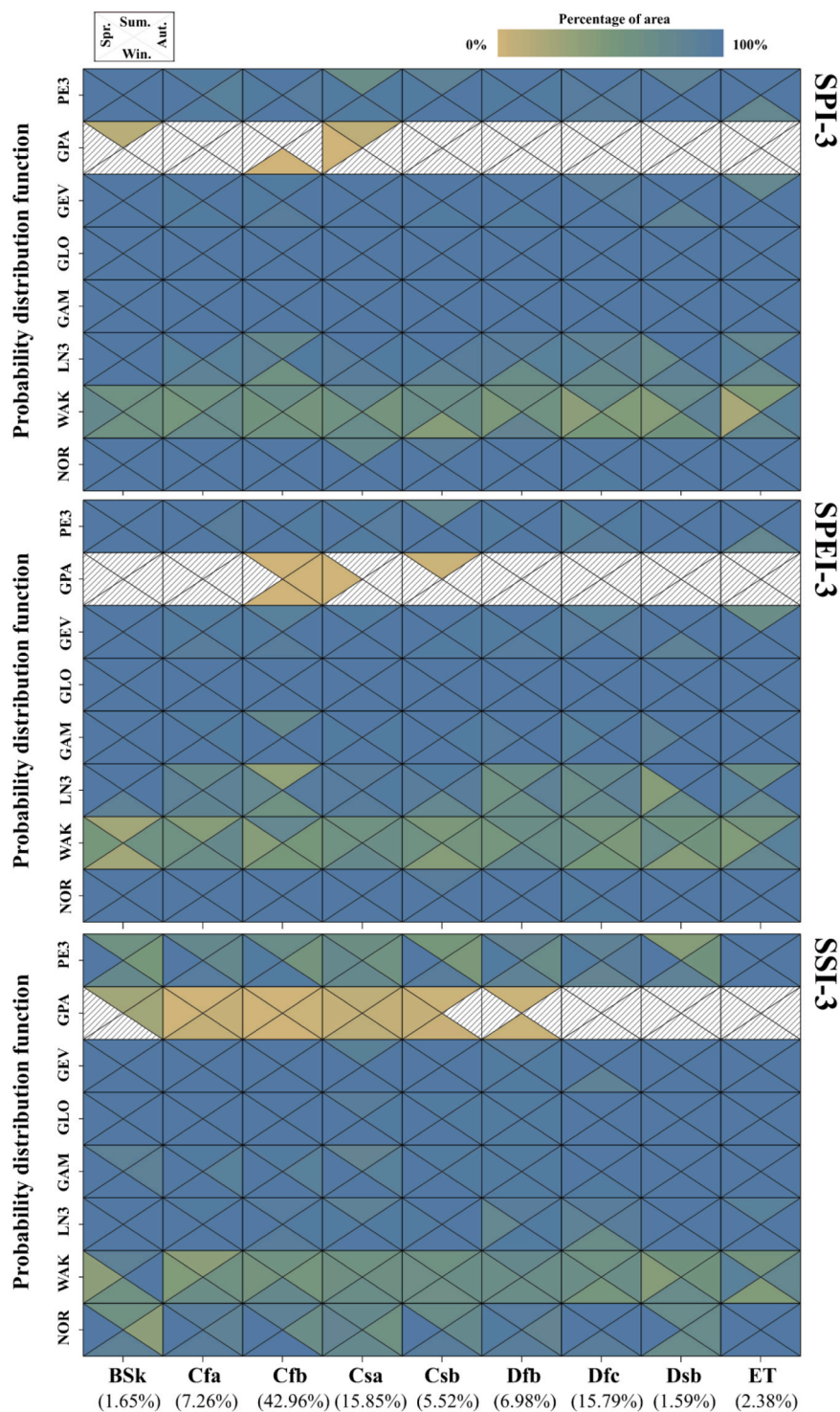


Fig. 6. Recommended PDFs for the three drought indices (SPI-3, SPEI-3 and SSI-3) across climate classes and seasons based on the AD test. Hatched areas represent lack of fit or rejection at the 0.05 significance level, indicating statistically unsuitable distributions for those climate-season combinations. Also, 0 and 100 indicate percentage of area covered by PDFs in each climate class and each season. The Cfb was excluded from the analysis due to its negligible spatial representation (just one NUTS-3 region, covering 0.02% of study area).

snowmelt-dominated or mixed rainfall–snowmelt regimes, in which the annual hydrograph is organised around a single, strongly bounded melt peak and low-flow periods are constrained by frozen-ground and storage conditions. This produces a truncated, bounded low-flow tail that an extreme-value form represents better than the GAM. In contrast, the scattered GLO selections in southeastern Europe, Turkey and northern Spain coincide with intermittent and heavily regulated river systems, where abstraction and reservoir operation generate heavier low-flow tails than the unregulated case; the strongly diverse and occasionally unfittable Csa summer regions noted in Section 4.1 are the extreme expression of this control. The extensive LN3 selections over the central European lowlands in summer and autumn correspond to catchments in which sustained recession from soil and groundwater storage produces strictly positive, strongly right-skewed low-flow samples that a lower-bounded, multiplicative form represents better than GAM. In addition, climate classes differ in how the optimal distribution varies between seasons, particularly for SPEI-3 and SSI-3. This indicates that distribution selection requires season-specific rather than year-round parameterisation.

4.3. Recommending appropriate PDFs for different climate-season combinations

Furthermore, we aim to identify statistically acceptable distribution functions for each climate-season combination so that we can go beyond region-specific and generalize our recommendations. This is done using the AD test results with p-values greater than 0.05 indicating acceptable statistical fits. Fig. 6 presents a comprehensive heatmap evaluation of PDFs for SPI-3, SPEI-3 and SSI-3 across the different Köppen-Geiger climate classifications and seasons. For the meteorological drought indices (SPI-3 and SPEI-3), PE3, GEV, GLO, GAM and NOR demonstrate statistical acceptability across most climate regions, though with varying degrees of suitability. For the hydrological drought (SSI-3), GEV, GLO, GAM and LN3 distributions emerge as particularly robust candidates with acceptable performance across diverse climate classes. Notably, the GEV, GLO and GAM distributions demonstrate statistical acceptability across both meteorological and hydrological drought types in most European climate regimes, suggesting that these distributions perform acceptably across most regions. This cross-applicability makes GEV, GLO and GAM particularly valuable for operational drought monitoring systems that simultaneously track multiple drought indicators, as it enables consistent distributional frameworks across drought types while maintaining statistical rigor. While the WAK consistently appears among the statistically acceptable candidates across all seasons and drought types, its regional applicability appears more limited compared to GEV, GLO and GAM distributions, suggesting that its five-parameter flexibility may provide optimal statistical fit in specific regional contexts rather than universally across all climate zones.

The GPA distribution consistently exhibits statistical unsuitability for both SPI-3 and SPEI-3, indicating failure to meet the minimum p-value threshold (0.05) in the AD test. The LN3 distribution demonstrates moderate performance for certain climate classes in meteorological droughts (particularly for SPEI-3), qualifying as suitable in more regions than GPA but fewer than GEV, GLO, GAM and NOR for SPI-3 and SPEI-3. The WAK distribution, despite its five-parameter flexibility, exhibits notably limited applicability across European climate regimes, indicating that its additional complexity does not translate to systematic performance advantages across climatologically meaningful spatial domains. Significant differences emerge when comparing the three indices, with SSI-3 displaying a more heterogeneous distribution of suitable PDFs across climate classifications. While the WAK distribution maintains marginal performance for the hydrological drought index, the PE3 and NOR distributions exhibit markedly reduced regional coverages for SSI-3 compared to their performance for meteorological indices. By contrast, the regional coverage of LN3 increases for SSI-3 relative to the meteorological indices. The GPA distribution performs poorly across all three drought indices examined, failing to achieve statistical acceptability in the majority of European regions for both meteorological and hydrological drought characterization. While GPA exhibits marginally less severe failure rates for SSI-3 compared to its rejection for SPI-3 and SPEI-3, it remains among the worst-performing distributions for streamflow-based drought assessment and is not recommended for operational implementation.

The recommended PDF selection for drought characterization in Europe was determined through a dominant area approach in Köppen-Geiger climate class coverage. For each drought index (SPI-3, SPEI-3, and SSI-3), PDFs were systematically evaluated across all

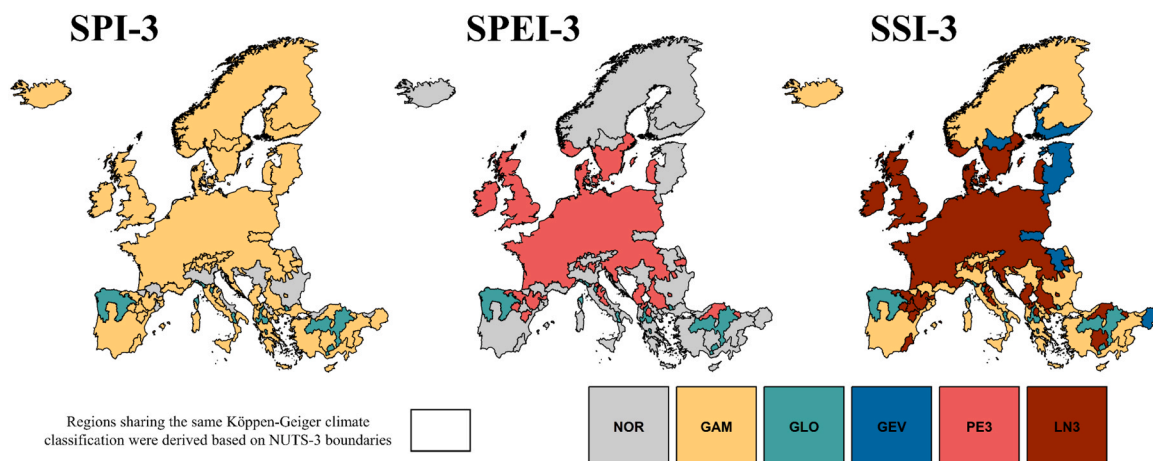


Fig. 7. Spatial distribution of recommended PDFs for SPI-3, SPEI-3 and SSI-3 across European Köppen-Geiger climate classes.

seasonal datasets within each Köppen-Geiger climate class. Distributions that exhibited failure rates in regions covering more than 5% of the total area within a given climate class were excluded from further consideration, ensuring that selected PDFs reliably represent the dominant spatial patterns of each class. The remaining candidate distributions were ranked according to goodness-of-fit criteria, and for each climate class, the recommended distribution was identified based on the climate region with the largest geographical area coverage. The result of this approach is shown in Fig. 7, where we can identify that recommended distribution selection exhibits significant spatial heterogeneity across European climate regions. The recommended distributions shown represent the most frequently selected optimal PDFs within each climate class across all seasons, effectively capturing the dominant distributional characteristics while acknowledging that seasonal or sub-regional variations may exist. It should be emphasised that the recommended distribution is the candidate that remains statistically acceptable across most parts of a climate class, which need not coincide with the distribution selected most frequently as optimal at the individual region level (e.g., Fig. 2). The six distributions appearing in the recommendations (GAM, GEV, GLO, LN3, NOR and PE3) represent a subset of the eight candidate distributions, indicating that two distributions (GPA and WAK) were not dominant in any climate class when aggregated across regions and seasons.

The spatial patterns reveal distinct index-specific characteristics in distribution requirements across Europe's climatic gradient. For SPI-3, the GAM distribution dominates overwhelmingly across the continent, encompassing nearly all climate zones from the Mediterranean through temperate oceanic and continental climates to subarctic regions, with only limited areas (Northern Spain, and parts of Greece, Italy, and Turkey, Romania, Serbia, Croatia, and Bulgaria) requiring the GLO and NOR. This near-universal GAM dominance for precipitation-based drought indices confirms the nature of precipitation distributions across diverse climate classes and validates the widespread use of GAM-based SPI calculations in operational systems. In contrast, SPEI-3 exhibits substantial spatial heterogeneity, with three distributions displaying clear climate-dependent spatial patterns: PE3 dominates across central and western Europe, encompassing the British Isles, Benelux countries, Germany, Poland, Denmark, south of Sweden and south of Norway, and most of France. NOR distribution heavily appears in Scandinavia, parts of Turkey and Spain, and parts of the Mediterranean. GLO emerges in

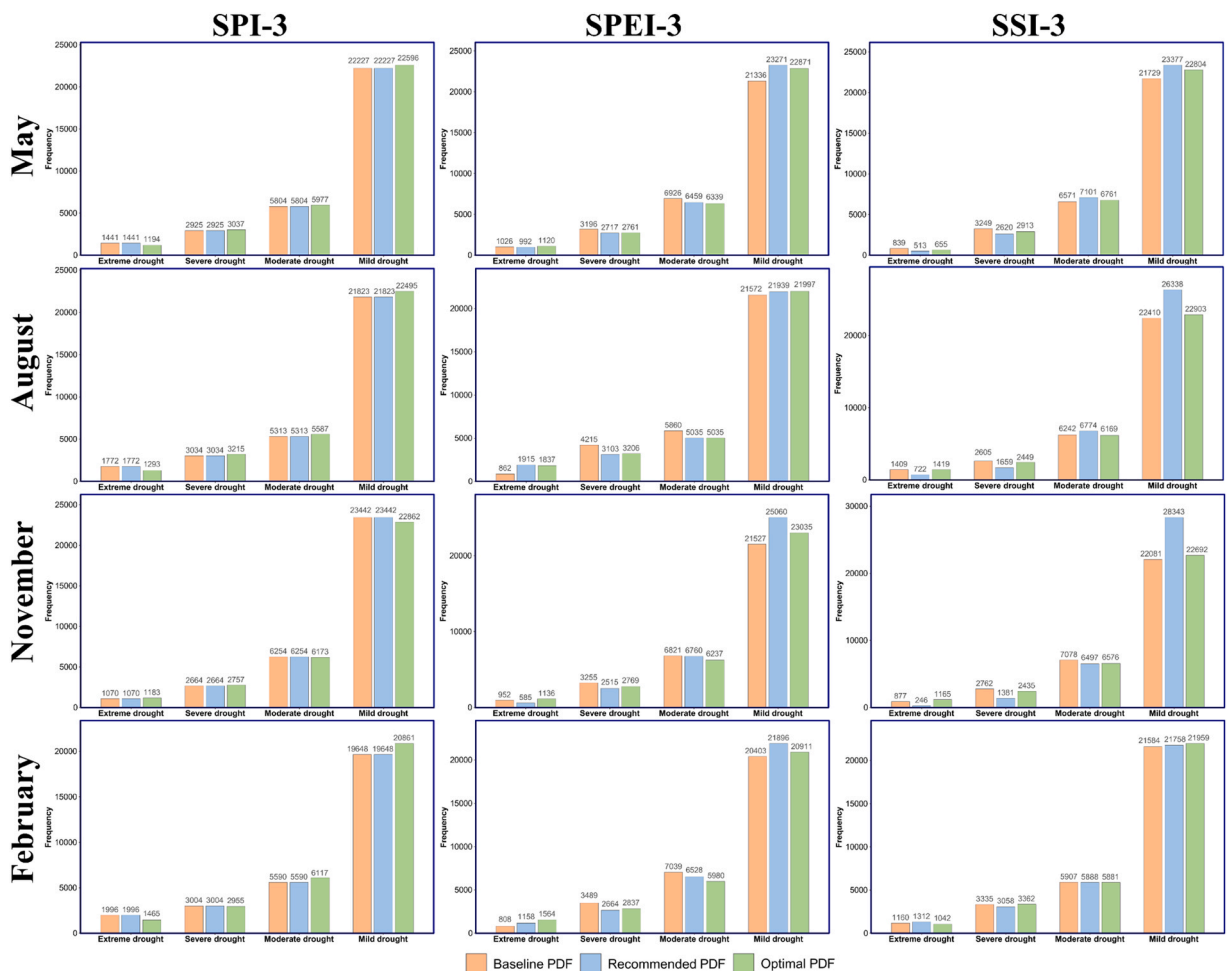


Fig. 8. Frequency of drought events by severity category for the Cfb climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Orange, blue, and green bars represent the baseline, recommended, and optimal PDF approaches, respectively. Numbers above each bar indicate the event count.

scattered southeastern European regions, particularly in parts of Turkey and Italy and Greece, and Northern Spain.

SSI-3 displays a markedly different pattern from both meteorological indices. LN3 is recommended across central and western Europe, encompassing the British Isles, France, the Benelux countries, Germany, Poland, Czechia, Austria, Denmark and southern Scandinavia, corresponding to the temperate oceanic regime in which sustained recession from catchment storage produces strictly positive, strongly right-skewed low-flow samples. GAM is retained across northern Scandinavia and Iceland and throughout the Mediterranean and the lowlands of southeastern Europe, including most of Iberia, Italy, Greece and coastal Turkey. GEV emerges in the Baltic states, southern Finland, central Sweden and parts of Romania and eastern Turkey, corresponding to snowmelt-dominated and mixed rainfall–snowmelt regimes, while GLO occurrences persist in northwestern Iberia and in parts of Turkey and Greece.

The findings demonstrate that while SPI-3 can reasonably employ a nearly universal GAM distribution approach with minimal loss of accuracy (except some areas), SPEI-3 requires spatially explicit distribution selection strategies aligned with climate zones to ensure accurate drought characterization. SSI-3 similarly necessitates climate-informed distribution selection, and the climate-regime-based framework yields a distinct set of recommendations. LN3 is recommended across central and western Europe, whereas GAM is recommended for northern Scandinavia and parts of the Mediterranean, and GEV for the Baltic region and scattered coastal and southern regions. These recommended PDFs can be applied within their respective climate zones, as they remain statistically acceptable across more than 95% of the area of their climate class, supporting their implementation as a climate-aware distribution selection framework across European regions. However, statistical acceptability at the class level does not guarantee accurate reproduction of the extreme tail; as shown in Fig. 8, results obtained with the locally optimal PDF can differ from those obtained with the class-recommended PDF across drought severity categories.

Fig. 8 presents the frequency distribution of drought events classified by severity for the Cfb climate type, which covers approximately 43% of the study area, making it the most spatially dominant climate class across Europe. In each panel, drought indicator values are categorised into four severity levels (mild drought (> -1.00 to < 0), moderate drought (> -1.50 to ≤ -1.00), severe drought (> -2.00 to ≤ -1.50), and extreme drought (≤ -2.00)) and the frequency of occurrence is compared across three PDF approaches: the baseline PDF (orange), which applies a single literature-standard distribution to all regions (GAM for SPI-3, GLO for SPEI-3, and GEV for SSI-3); the recommended PDF (blue), which assigns one distribution per Köppen-Geiger climate type using recommended PDFs in Fig. 7; and the optimal PDF (green), where each individual NUTS-3 region uses its own best-fitting distribution determined by the methodology proposed by the current study (as its results are shown in Fig. 2). Across all four representative 3-month aggregation periods, the three approaches behave differently depending on the indicator. For SPI-3 the baseline and recommended approaches are identical, since GAM is both the literature-standard and the climate-class recommendation for the Cfb class, and only the optimal approach differs; its effect is a modest redistribution between severity categories, with fewer extreme and more mild events in spring, summer and winter and the opposite in autumn. For SPEI-3 the three approaches diverge moderately and in a season-dependent manner: relative to the baseline, the recommended distribution yields more extreme events in summer and winter and fewer in autumn, while the optimal approach lies closer to the recommended one than to the baseline in most severity categories. The largest differences occur for SSI-3, where the recommended distribution systematically identifies fewer extreme and severe droughts than either the baseline or the optimal approach, and correspondingly more mild events, with the divergence being most pronounced in summer and autumn. This reflects the greater flexibility of region-specific PDF fitting, which captures local hydrological and climatic characteristics that a single climate-wide distribution cannot fully represent. The corresponding drought frequency distributions for the remaining eight Köppen-Geiger climate types (BSk, Cfa, Csa, Csb, Dfb, Dfc, Dsb, and ET) are provided in Figures A1–A8 in the Appendix. These figures follow the same structure and colour scheme as Fig. 8 and enable a climate-specific assessment of how the three PDF approaches influence drought severity classification across all European climate zones.

While existing studies have successfully identified optimal distributions for specific geographic regions, their findings remain site-specific or lack a systematic linkage to climatic regimes, limiting their transferability to ungauged or data-sparse regions with similar climate characteristics. For meteorological drought, the GAM and GEV distributions have been recommended for SPI and SPEI across Europe (Stagge et al., 2015), while the log-logistic, GAM and PE3 distributions were proposed in the original SPEI formulation based on global test sites (Vicente-Serrano et al., 2010), and the exponentiated Weibull was advanced as a candidate SPI distribution from an analysis focused on six global regions (Pieper et al., 2020). For hydrological drought, the Tweedie distribution performed favourably for SSI across European regions (Tijdeman et al., 2020). Building on these approaches to distribution comparison for standardized drought indices, our framework extends beyond site-specific optimisation by linking distribution selection to Köppen-Geiger climate classes across nine climate regimes spanning the European continent, and by jointly resolving meteorological and hydrological drought within a single consistent dataset. This enables practitioners to select distributions on the basis of climate regime rather than through extensive site-specific optimisation.

Placing these results against previous European work clarifies both where they confirm existing practice and where they depart from it. Our SPI-3 findings are consistent with Stagge et al. (2015), who found GAM broadly adequate for SPI across Europe. In our analysis GAM is the most frequently selected distribution in every season. The identifiability metric qualifies this agreement in an operationally useful way. As Fig. 3 shows, the AICc range among accepted candidates for SPI-3 remains below approximately 25 units across most of the continent, indicating that the accepted distributions are close to statistically equivalent. For SPEI, NOR is the most frequently selected distribution at the region level across the four seasons, and the class-level recommendation is PE3 for central and western Europe and NOR for Scandinavia and parts of the Mediterranean. Both depart from the GAM and GEV recommendation of Stagge et al. (2015) and from the log-logistic form adopted in the original SPEI formulation (Vicente-Serrano et al., 2010). The identifiability metric indicates that this departure is meaningful rather than an artefact of weak discrimination: SPEI-3 exhibits the most spatially extensive AICc ranges of the three indicators, reaching roughly 40–70 units over Scandinavia, the British Isles, France, central Europe and Iberia in spring and summer, precisely the regions for which a distribution other than GAM is recommended.

For SSI, the region-level results are markedly more heterogeneous than for either meteorological index, and the autumn window is the clearest illustration. The contribution of the present analysis is that a climatic grouping nevertheless recovers a compact recommendation set, LN3 for the temperate oceanic regime, GAM for Mediterranean, subarctic and humid-subtropical regimes and GEV where snowmelt dominates. Climate therefore accounts for a substantial share of the observed variation, but not all of it: the loss of tail fidelity documented in Fig. 8 is larger for SSI-3 than for the meteorological indices, indicating that part of the site-level diversity in streamflow distributions is governed by catchment controls rather than by climate. This is consistent with the spatially complex and diverse hydrological drought patterns reported across Europe by Peña-Angulo et al. (2022).

5. Discussion

5.1. Practical applications and implementations

The temporal evolution of drought occurrence and severity across European regions from 1960 to 2022 reveals distinct patterns of widespread drought events at both short and longer time scales (Figure A9 in the Appendix). Historical analysis demonstrates that meteorological drought indices (SPI and SPEI) exhibit greater spatial coherence during major drought events compared to hydrological drought indices (SSI). The findings of this study provide a methodological framework that can be directly implemented in operational drought monitoring systems across Europe to enhance the accuracy of drought characterization. The framework is intended as methodological guidance for continental- and regional-scale assessment of drought variability and for regional drought forecasting applications, including at ungauged and data-sparse locations. Where long and high-quality observed discharge records are available, detailed operational drought assessment at the national level should continue to be based on those records; the recommendations derived here are intended to complement such analyses and to extend comparable guidance to the substantial portion of the European river network for which suitable observations do not exist. Water resource managers and policymakers can utilize the climate-specific and season-specific distribution recommendations to select suitable and even optimal PDFs for their specific regions, thereby improving the statistical reliability of drought indices. This implementation can be achieved through integration with existing drought monitoring platforms such as the European Drought Observatory (EDO) operating under the Copernicus Emergency Management Service or national hydrological services, where the recommended distribution functions can replace the conventional one-size-fits-all approach. A specific caution applies to SPEI in this context. The climatic water balance is statistically distinct from precipitation alone, so distributional requirements for SPEI differ fundamentally from those of SPI, and operational drought monitoring systems should not automatically transfer SPI distribution recommendations to SPEI calculations.

Beyond improving the statistical reliability of drought indices, the practical value of climate-informed distribution selection ultimately depends on whether it improves the detection of decision-relevant drought events, those with documented societal, agricultural or environmental consequences. Recent syntheses emphasise that drought risk is co-determined by hazard, exposure and vulnerability, and that monitoring systems deliver value only when index-based hazard characterization can be linked to observed impacts and management decisions (Shyrokaya et al., 2024; Wens et al., 2026). Our framework contributes to this chain at the hazard-characterization stage: by reducing tail-fitting bias for extreme events, climate-tailored distributions can sharpen the timing and severity estimates that downstream impact-based and early-warning systems rely on (Shyrokaya et al., 2023). A natural and high-value next step, building directly on Fig. 8, is to test whether drought events flagged by locally optimal distributions but missed by conventional baseline distributions coincide with historically documented impact events; demonstrating such correspondence would convert the statistical gains reported here into quantified operational benefit. By adopting these regionally optimized distributions, early warning systems can more accurately detect drought onset, persistence, duration and severity, particularly for extreme events that occur in the tails of the probability distributions. The framework also provides flexibility for operational implementation at various administrative levels (NUTS-3 or aggregated to larger administrative units), allowing for customization based on specific management requirements and computational resources. In addition, while the proposed framework employs AICc to account for model complexity through parameter penalization, our results demonstrate that five-parameter distributions such as WAK do not provide sufficient performance advantages to justify their additional complexity in operational drought monitoring contexts. Despite WAK's theoretical flexibility, simpler distributions (2–3 parameters) consistently achieve comparable or superior performance when evaluated using AICc, indicating that parsimony should be prioritized in operational implementation. The spatial and seasonal variability in the number of acceptable PDFs across NUTS-3 regions for SPI-3, SPEI-3 and SSI-3 (Figures A10–A13 in the Appendix) demonstrates that distribution selection is context-dependent, with most regions exhibiting 5–7 acceptable distributions but rarely all eight, indicating that no single distribution universally outperforms others across all climatic zones and temporal scales. Thus, while multiple distributions may be statistically acceptable at NUTS-3 scales, proposed climate-informed framework successfully identifies distributions that perform reliably across entire climate regimes, providing practitioners with clear, implementable guidance rather than requiring exhaustive region-by-region selection among numerous acceptable alternatives.

The practical implementation of this research extends to impact-based drought assessment systems, where accurate statistical characterization serves as the foundation for correlating drought indices with sectoral impacts. Implementing these findings within impact assessment frameworks involves creating transition matrices that link drought severity levels (based on optimized distribution functions) with historically observed impacts in various sectors such as agriculture, water supply, and ecosystem health. Water management agencies can implement seasonal distribution adjustment protocols that automatically shift the statistical approach as the year progresses, ensuring that drought characterization maintains optimal accuracy throughout different seasonal regimes. As climate change intensifies, implementation should include periodic reassessment protocols that evaluate distribution performance against recent data, potentially adjusting the recommended distributions as climate patterns evolve. This adaptive implementation approach

would involve establishing regular (e.g., decadal) statistical evaluation cycles to ensure that distribution selections remain optimal under changing (climate and/or land use) conditions. Furthermore, cross-border water management authorities can utilize these climate-specific distribution recommendations to develop harmonized drought monitoring frameworks that maintain statistical rigor while respecting regional climatic differences, thereby improving the coherence of transboundary drought assessments.

5.2. Climatic appropriateness of temporal aggregation scales

While our framework provides statistically rigorous distribution recommendations for 3-month drought indices, the climatic meaningfulness of fixed temporal aggregation windows varies across Europe's hydroclimatic gradient. In some regions (e.g., Mediterranean climates), it is possible that summer precipitation may be climatologically minimal or absent, meaning that a 3-month SPI or SPEI during June–August may reflect normal seasonal aridity rather than anomalous drought conditions. Longer aggregation windows (e.g., 6–12 months) may better capture meteorological drought as persistent, multi-seasonal precipitation deficits that deviate from expected annual water budgets. Our climate-specific distribution recommendations are most operationally relevant when the chosen temporal scale aligns with regional hydrological memory and drought propagation time scales. Practitioners should therefore consider whether 3-month indices appropriately represent water scarcity dynamics in their region, potentially adapting aggregation windows to match climate-specific drought development patterns. Future extensions of this framework could systematically evaluate optimal temporal scales alongside optimal distributions across climate regimes, further enhancing the decision relevance of standardized drought monitoring approaches. We therefore recommend that future research applies the present framework to longer accumulation periods (e.g., 6-, 9- and 12-month indices), which are more representative of multi-seasonal precipitation deficits and water-supply-relevant water scarcity, in order to establish whether the climate-conditioned distribution recommendations reported here for the 3-month scale remain valid as the aggregation window lengthens and the influence of catchment storage memory increases. The methodology proposed in this study is scale-agnostic and can be transferred to any accumulation window, so that such an extension would yield a complete, multi-scale and climate-informed guideline for operational drought monitoring across Europe.

5.3. Model Limitations and Uncertainties

A limitation of the current study is the reliance on a single hydrological model (E-HYPE) for SPI, SPEI, and SSI characterizations, which introduces potential model-dependent uncertainty into PDF recommendations. While E-HYPE has been extensively validated across European river basins and provides spatially consistent continental-scale simulations essential for the current study analysis, different hydrological models employ varying process representations, parameterization schemes, and calibration strategies that can influence simulated hydro-meteorological characteristics. Model structural uncertainty may affect the skewness, kurtosis, and tail behaviour of simulated hydro-meteorological distributions, potentially influencing which PDF achieve optimal statistical fit. Future research should evaluate the robustness of the proposed climate-regime-based distribution recommendations by comparing results across multiple hydrological models to quantify the sensitivity of distribution selection.

In addition, the reliance on E-HYPE simulated variables (e.g., streamflow) rather than observed data introduces model structural uncertainty that may propagate into drought indicator distribution selection, particularly affecting the characterization of extreme values, which are critical for drought analysis. Model biases in representing baseflow recession, groundwater contributions, and anthropogenic water management could systematically influence distribution tail behaviour and skewness, potentially affecting which probability distributions achieve optimal statistical fit. Future validation of drought indicator recommendations against observed data (e.g., streamflow records) would quantify the sensitivity of distribution selection to model choice and strengthen operational confidence. A further consideration concerns the explanatory variables used to stratify distribution selection. Köppen-Geiger classes provide a physically interpretable climatic stratification, but the markedly stronger spatial heterogeneity observed for SSI-3 relative to SPI-3 and SPEI-3 suggests that catchment-scale hydrological controls (soil moisture memory, baseflow and recession behaviour, snowmelt timing, storage and human regulation) play a larger role in shaping streamflow distributions than climate alone. These same controls are known to organise European river systems into coherent hydrological regimes and to govern streamflow predictability across the continent's hydroclimatic gradient (Pechlivanidis et al., 2020). A promising extension of the present framework would therefore replace or augment the climatic stratification with a hydrologically meaningful one, derived from catchment descriptors and hydrological signatures (e.g., baseflow index, flow-duration characteristics, runoff ratio, snow fraction) through a clustering approach. Such a hydrology-informed classification could yield a more physically grounded explanation of the observed SSI distribution patterns and potentially tighter, more transferable recommendations for hydrological drought, and we identify it as a priority for future work.

The selection of the 0.05 significance level as the acceptance threshold for the AD test represents a methodological choice. However, we acknowledge that this threshold is a pragmatic convention rather than an absolute criterion for distribution acceptability. The number of acceptable distributions per region reported here (Figures A10–A13) would change under more stringent or more relaxed thresholds, and a sensitivity analysis of this choice would be a useful extension. Finally, as illustrated in Fig. 8, our climate-class recommendations trade a portion of site-specific fitting accuracy for transferability, most markedly for hydrological drought, and therefore complement rather than replace local optimisation where extreme-tail precision is critical.

6. Conclusions

This study developed and applied a framework for selecting optimal probability distributions for drought characterization across Europe's climatic gradient, evaluating eight candidate PDFs for SPI, SPEI and SSI at the 3-month time scales using L-moment parameter estimation, AD screening and AICc-based ranking, and organising the resulting recommendations by Köppen-Geiger climate class. Its principal contribution is the transformation of site-specific statistical findings into transferable, climate-informed guidance applicable to ungauged and data-sparse regions sharing the same climatic regime.

Three main conclusions emerge. First, optimal distribution selection is indicator-specific, climate-dependent and seasonally variable, and the required complexity increases from SPI-3 to SPEI-3 to SSI-3. SPI-3 is dominated by GAM across nearly all European climates, confirming current operational practice (although in winter GAM and NOR are almost equally represented). SPEI-3 requires spatially explicit selection, with PE3 recommended for central and western Europe and NOR for Scandinavian and Mediterranean regions. SSI-3 exhibits the greatest region-level heterogeneity, reflecting the catchment processes that transform meteorological forcing into streamflow. Second, this diversity nevertheless converges on a compact set of six distributions: GAM, GEV, GLO, LN3, NOR and PE3. For SPI-3, GAM dominates; for SSI-3, LN3 is recommended for the oceanic climate, which covers the largest share of the European domain. This convergence is the key practical result of the study, indicating that relatively simple distribution frameworks can serve operational monitoring of both meteorological and hydrological drought, although the appropriate PDF differs between meteorological and hydrological drought. Third, seasonal dependence is strongest for SPEI-3 and SSI-3 in Mediterranean and continental climates, where summer and autumn show the greatest distributional diversity.

The Köppen-Geiger stratification therefore offers a practical middle ground between exhaustive region-by-region optimisation and a uniform, one-size-fits-all assumption, and the recommendations are directly usable within continental-scale monitoring and seasonal forecasting services, although for hydrological drought the associated loss of tail fidelity means that region-specific fitting remains preferable where extreme-event thresholds drive water-management decisions. Because the procedure is transparent and scale-agnostic, it can be reapplied to updated datasets and to longer accumulation periods, enabling periodic reassessment of optimal distributions as hydroclimatic conditions evolve; extending it to non-stationary distribution approaches is a natural direction for future work. Future research should explore how these distribution requirements might evolve under changing climatic conditions, potentially incorporating non-stationary distribution approaches to account for shifting hydroclimatic regimes. Extending this framework to finer spatial scales and investigating distribution performance for longer accumulation periods (6–12 months) would further enhance our understanding of appropriate statistical characterization strategies for drought analysis across Europe's diverse landscape.

CRedit authorship contribution statement

Babak Mohammadi: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wei Yang:** Writing – review & editing, Visualization, Validation, Project administration, Methodology, Conceptualization. **Majid Cheraghalizadeh:** Writing – review & editing, Visualization, Validation. **Ilias Pechlivanidis:** Writing – review & editing, Visualization, Validation, Project administration, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

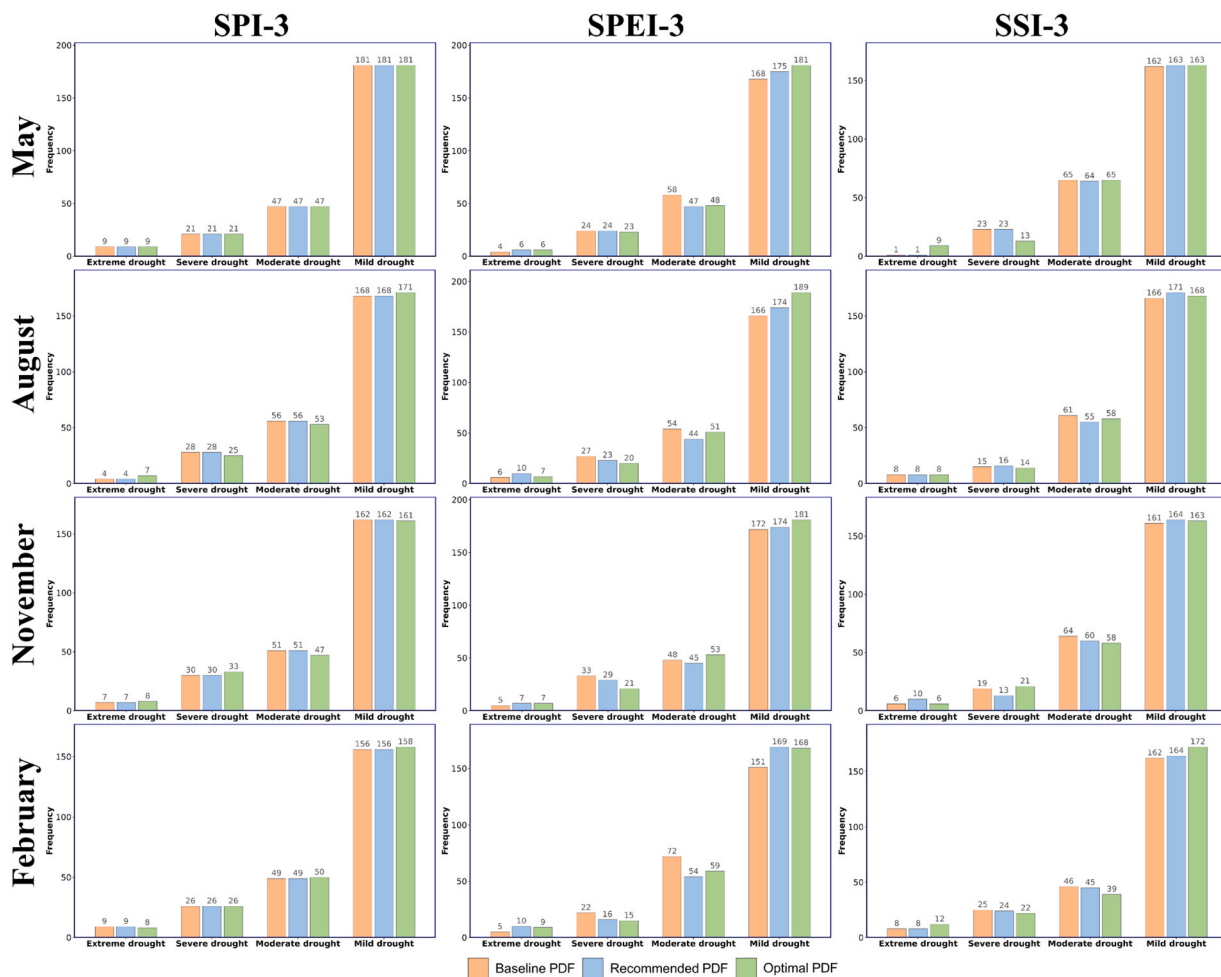


Figure A1. Frequency of drought events by severity category for the BSk climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

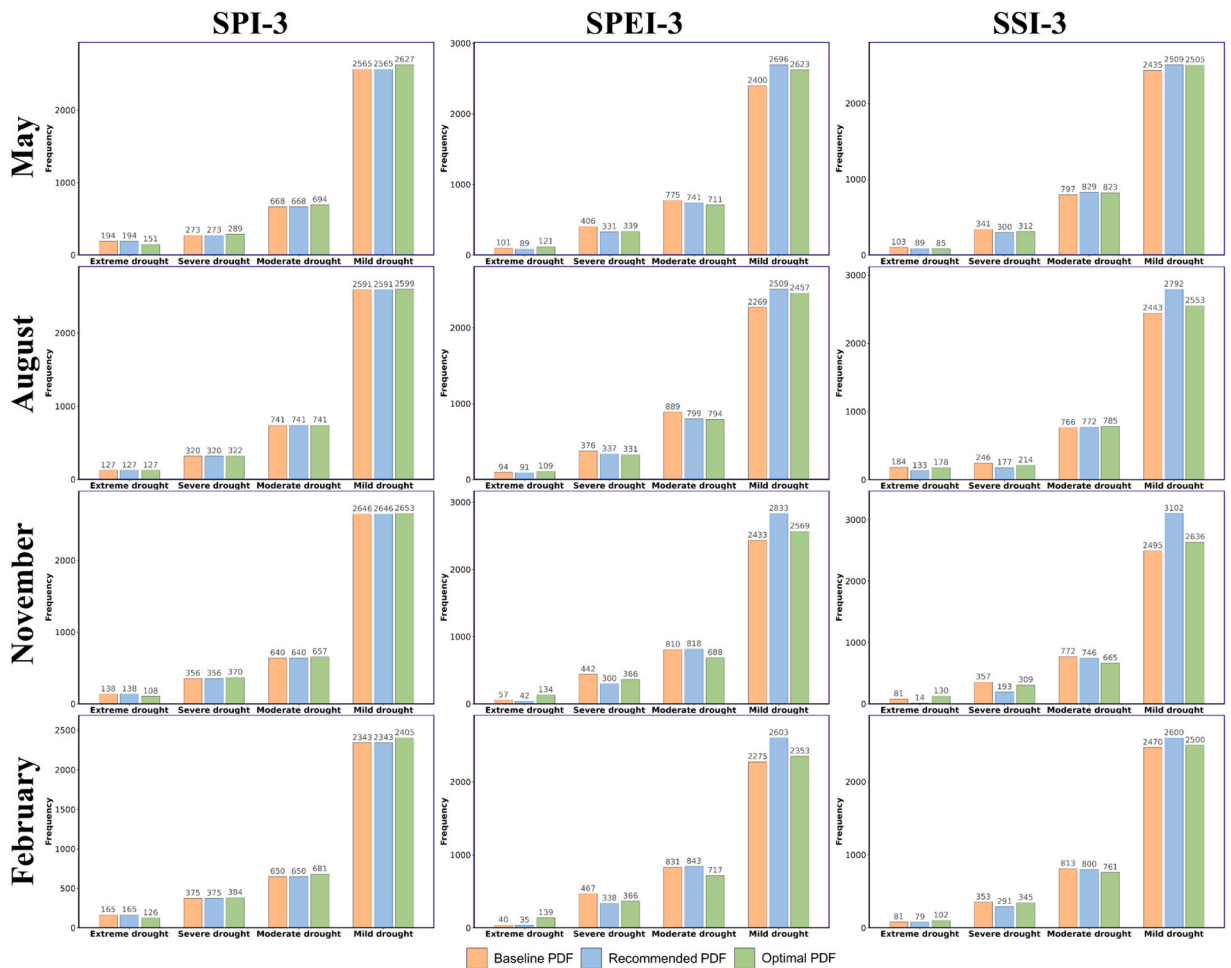


Figure A2. Frequency of drought events by severity category for the Cfa climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

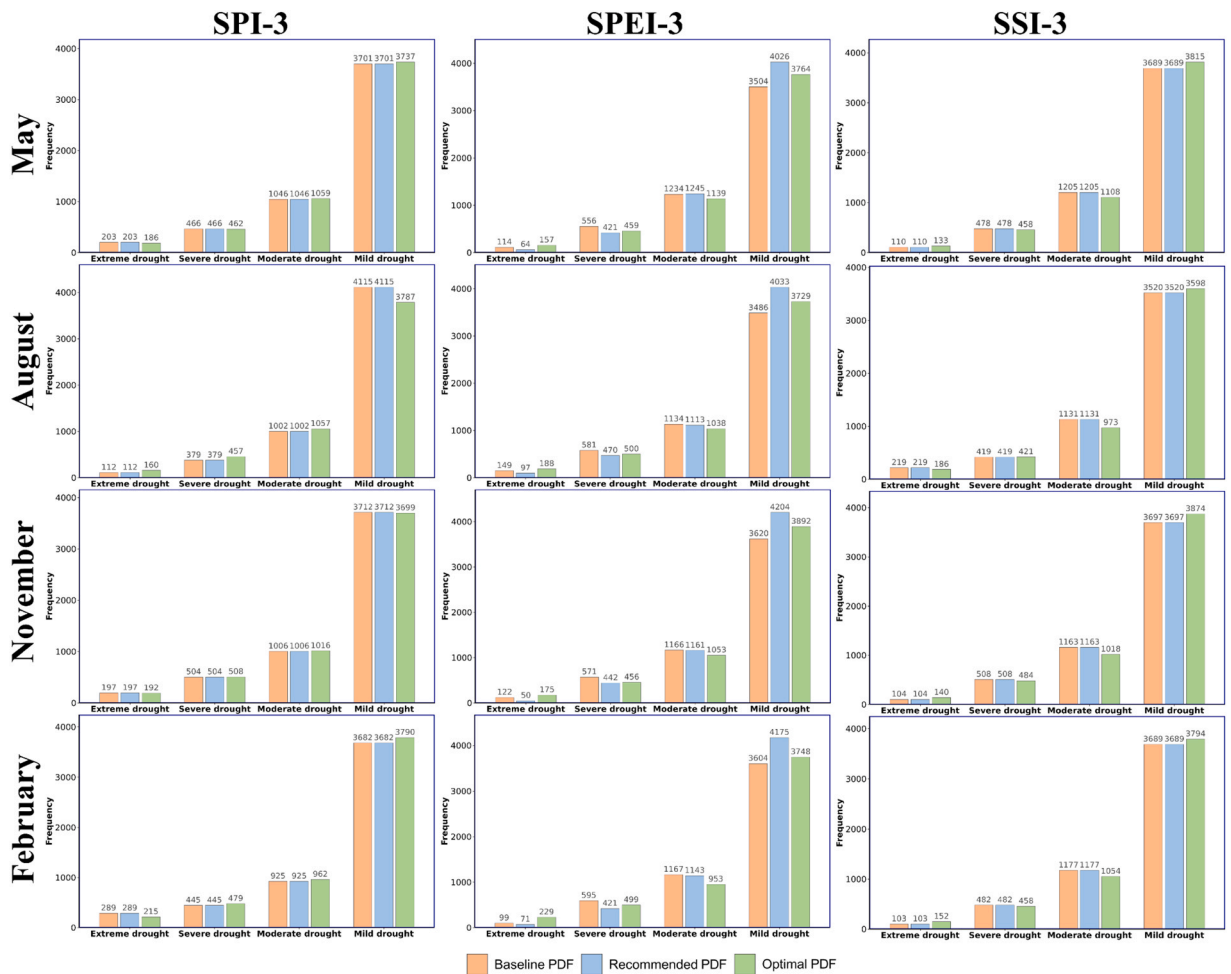


Figure A3. Frequency of drought events by severity category for the Csa climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

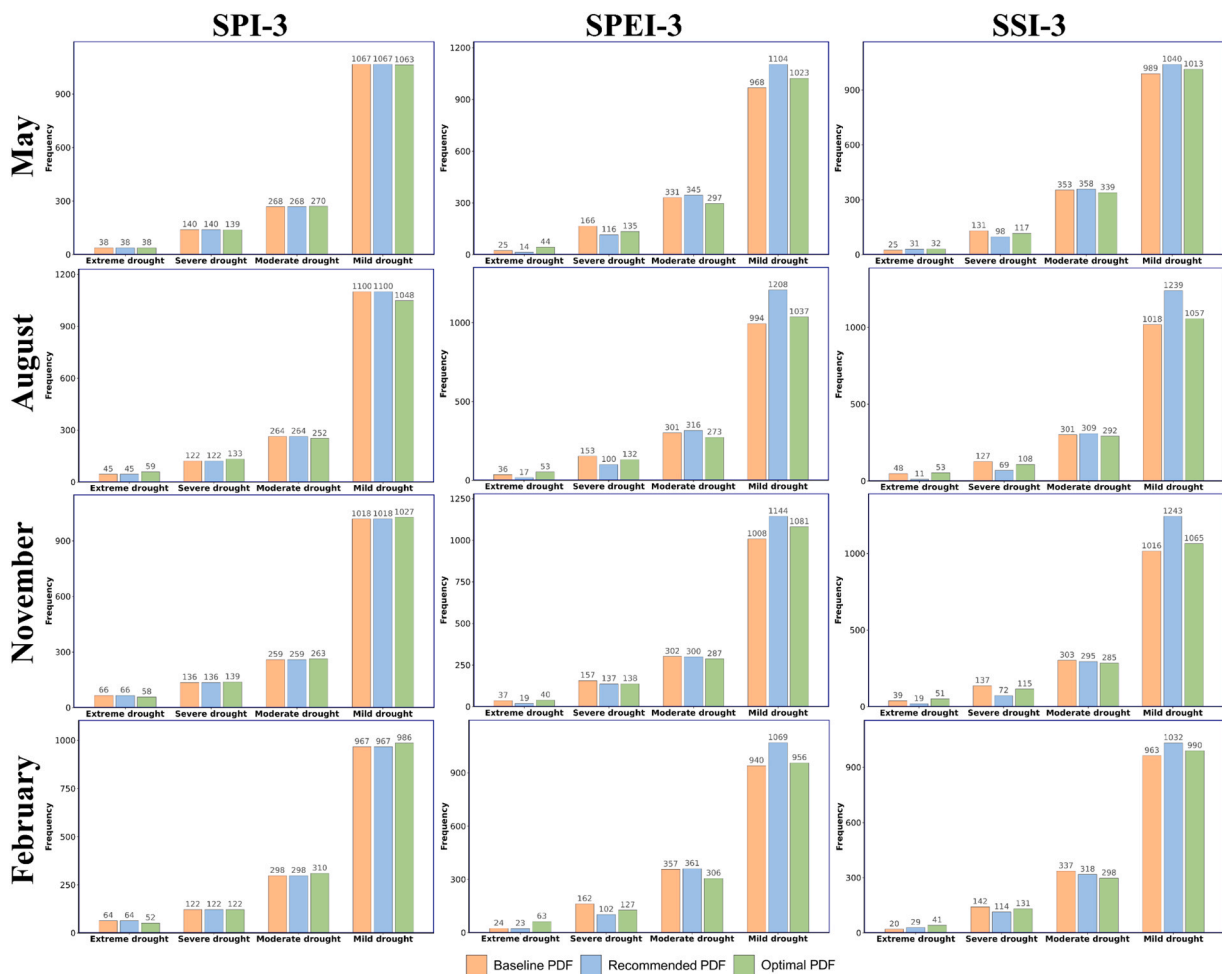


Figure A4. Frequency of drought events by severity category for the Csb climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

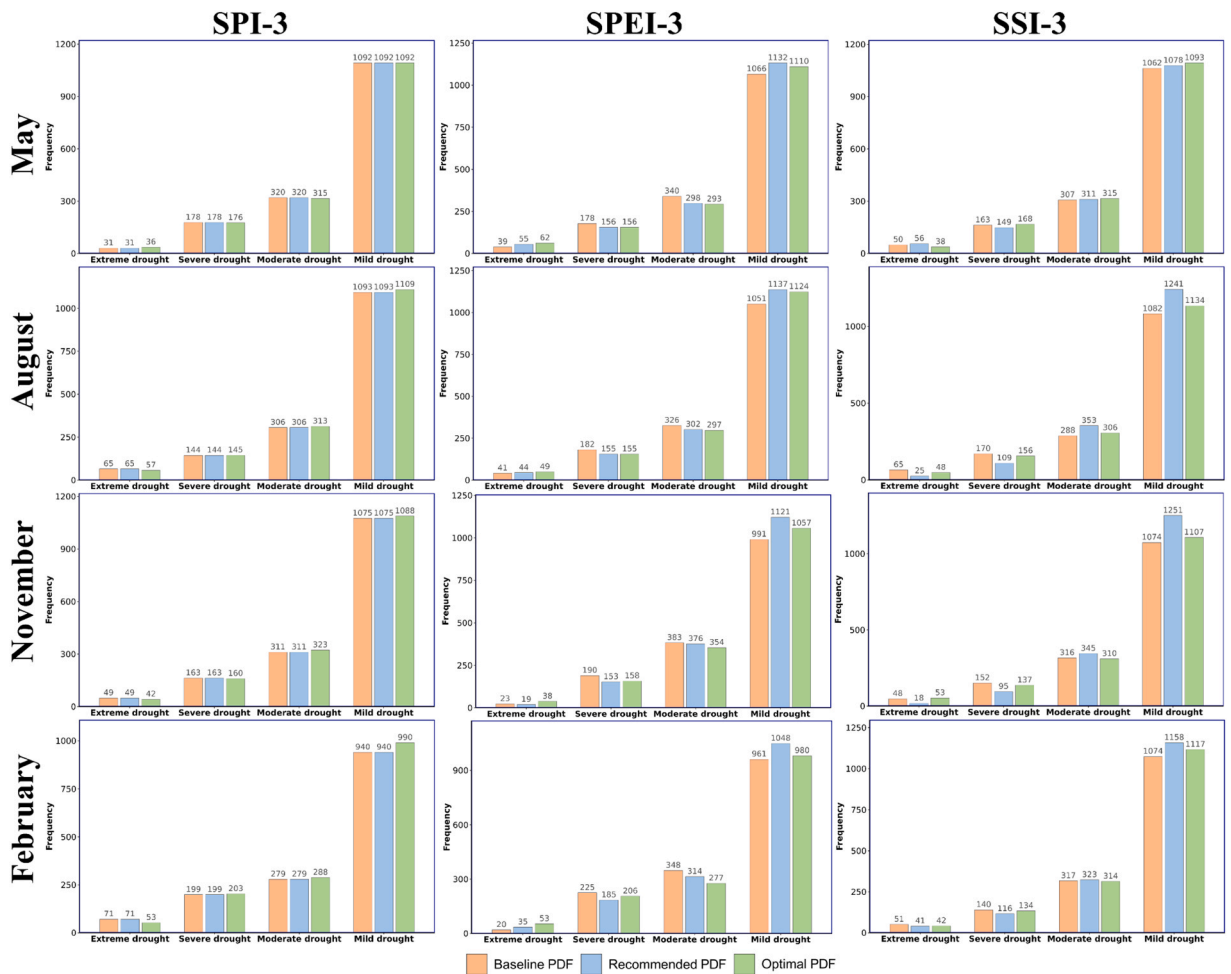


Figure A5. Frequency of drought events by severity category for the Dfb climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

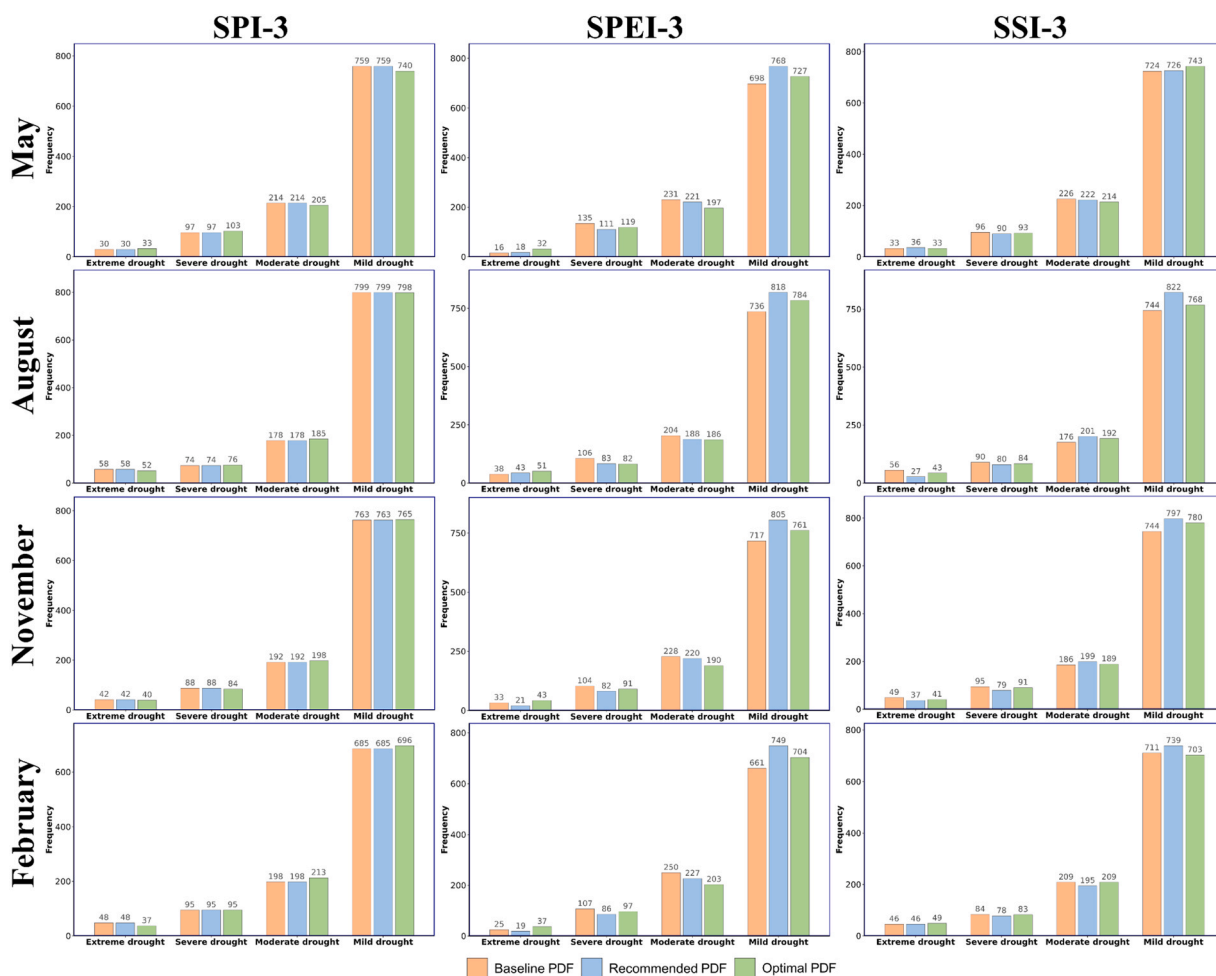


Figure A6. Frequency of drought events by severity category for the Dfc climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

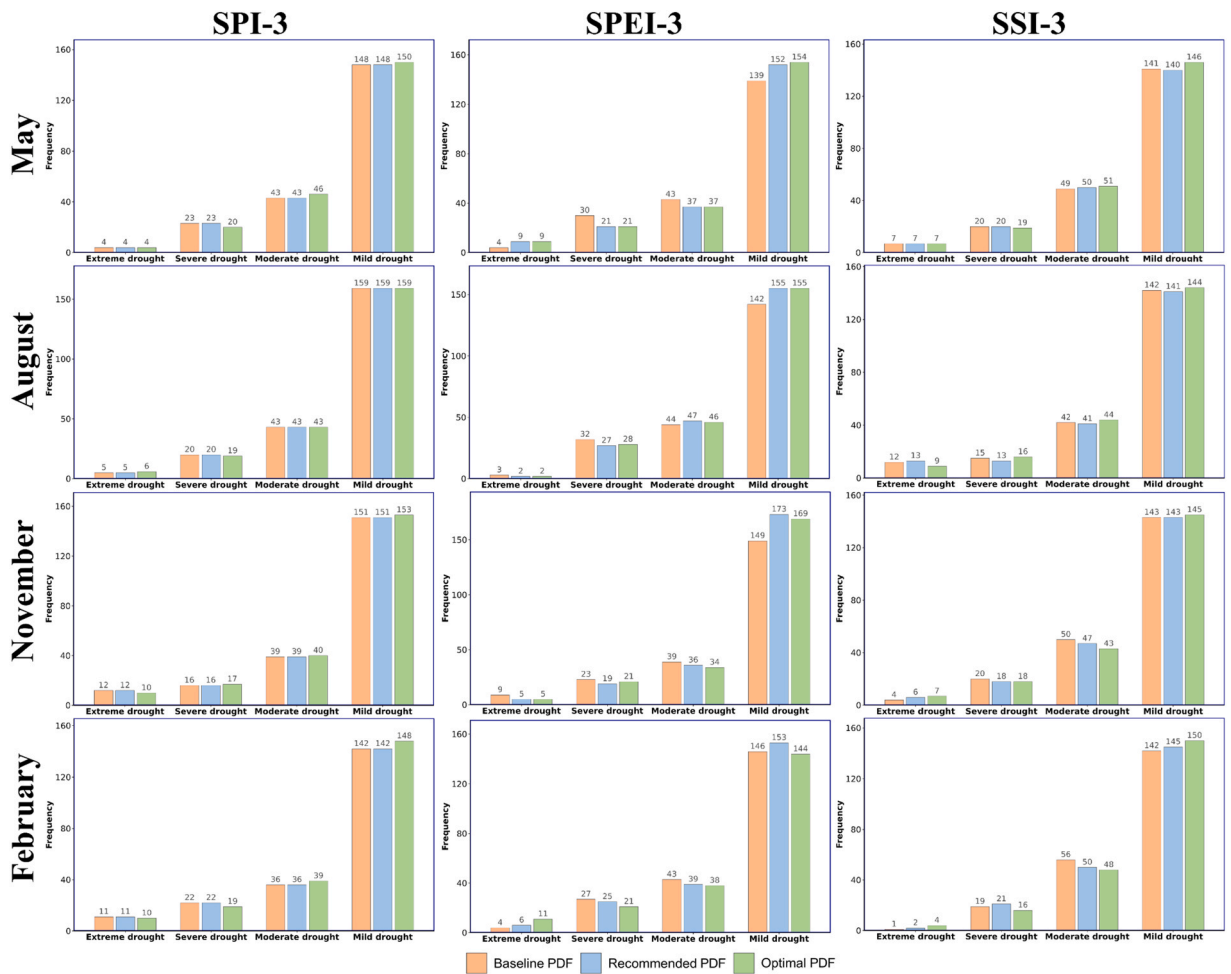


Figure A7. Frequency of drought events by severity category for the Dsb climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

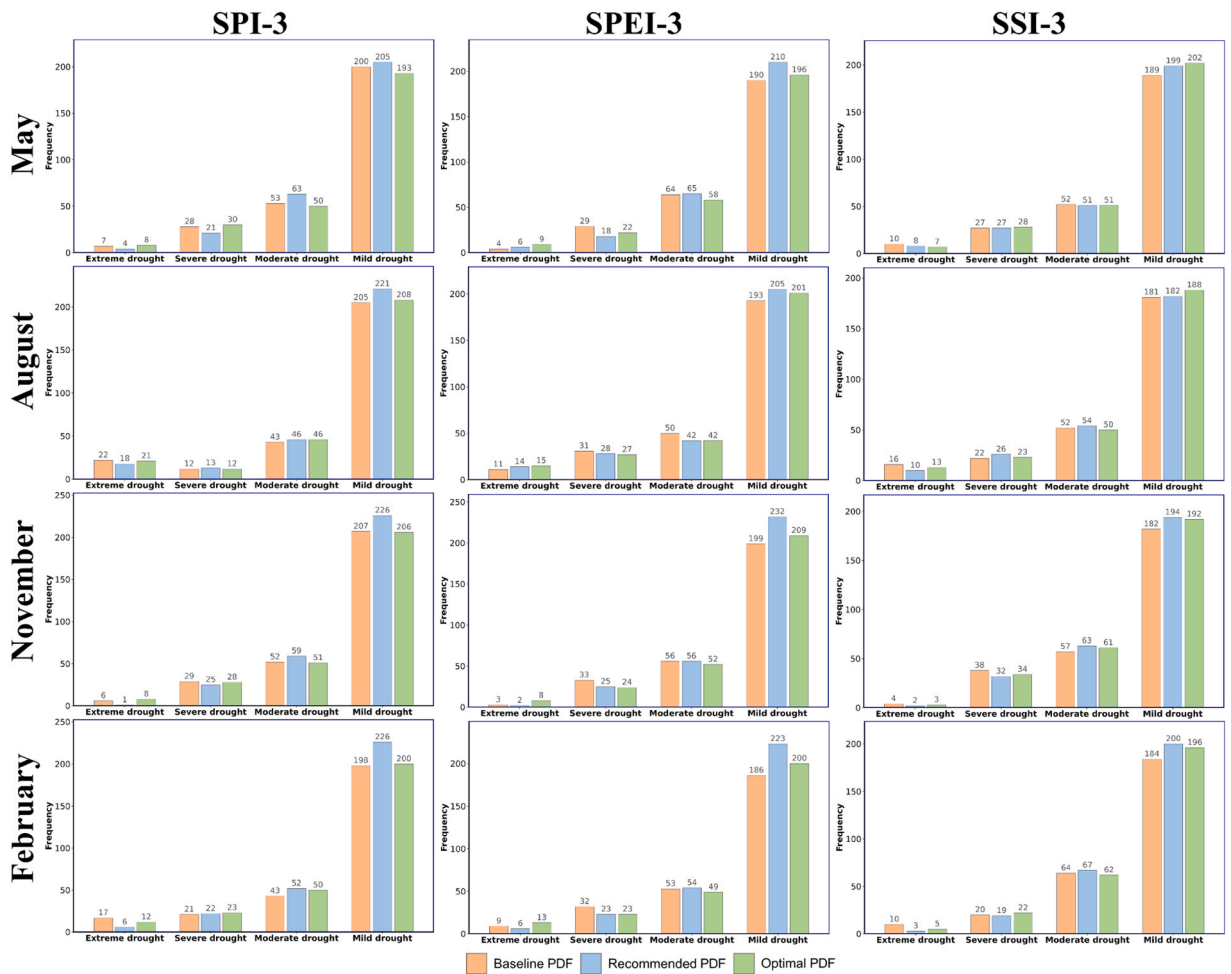


Figure A8. Frequency of drought events by severity category for the ET climate type across four representative months (May, August, November, February) and three drought indicators (SPI-3, SPEI-3, SSI-3). Same structure and colour scheme as Fig. 8

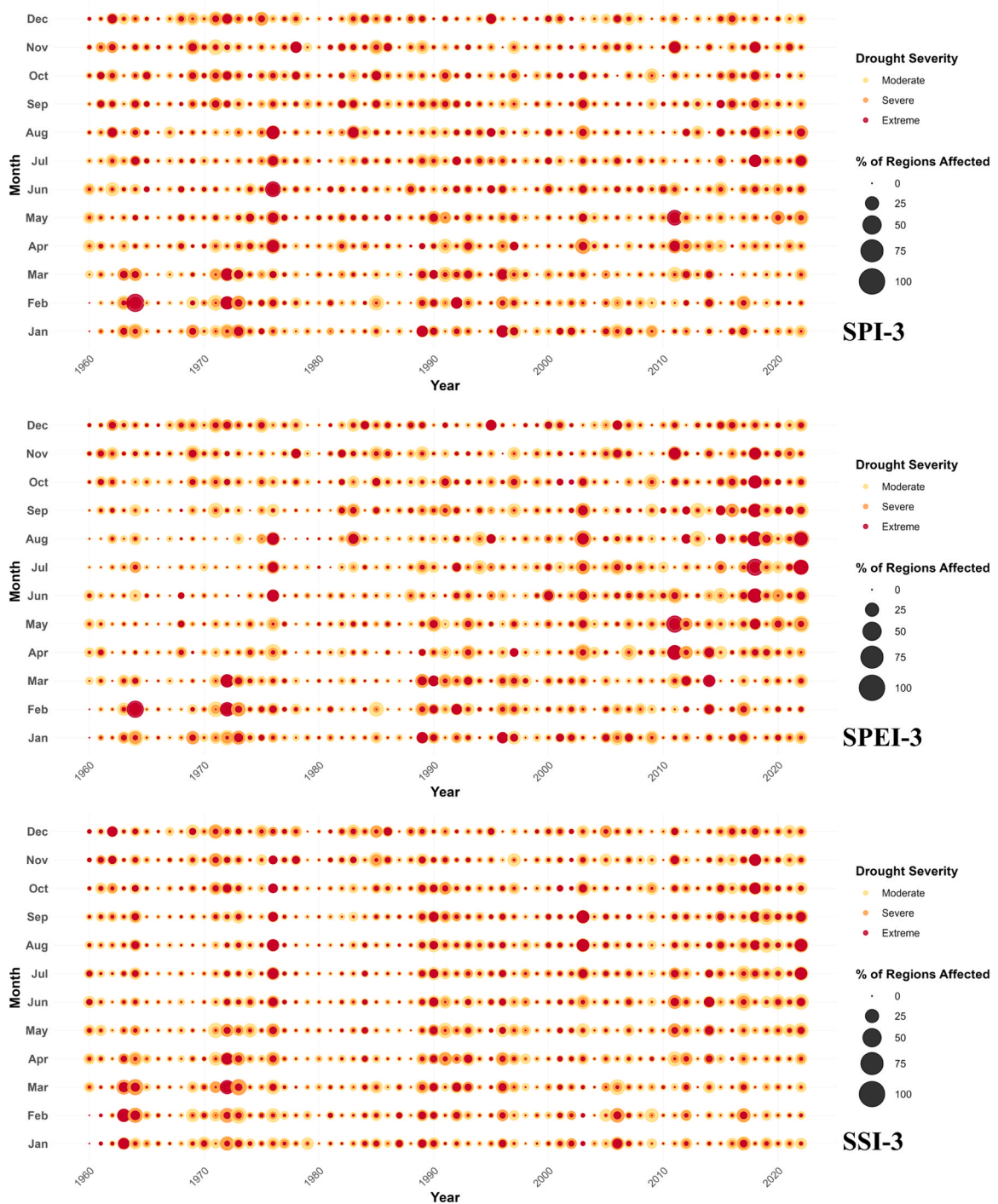


Figure A9. Temporal evolution of drought occurrence and severity across European regions from 1960 to 2022 using the three hydrometeorological drought indices at 3-month scale (i.e., SPI-3, SPEI-3 and SSI-3). Circle size indicates the percentage of European NUTS-3 regions affected by drought conditions, while colour represents drought severity classified as moderate (yellow, $-1.50 < \text{index} \leq -1.00$), severe (orange, $-2.00 < \text{index} \leq -1.50$), and extreme (red, $\text{index} \leq -2.00$)

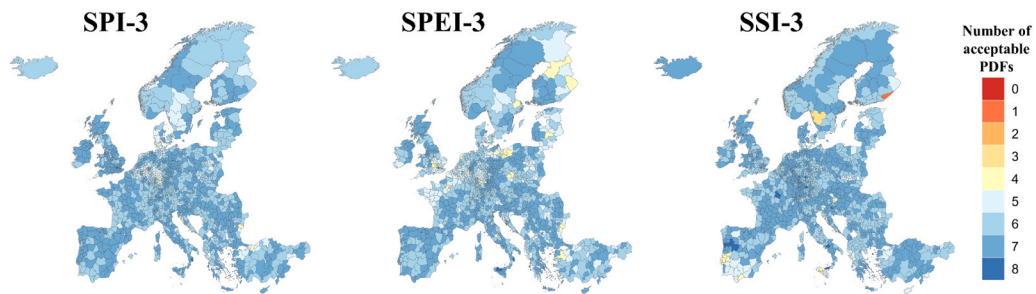


Figure A10. Number of acceptable PDFs for each NUTS-3 region during spring, based on AD test. Colours represent the count of acceptable distributions (0–8), with red indicating no acceptable distributions and blue indicating all eight distributions are acceptable

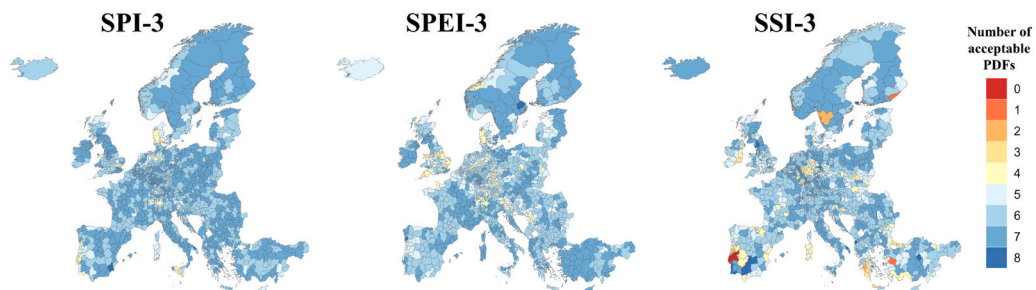


Figure A11. Number of acceptable PDFs for each NUTS-3 region during summer, based on AD test. Colours represent the count of acceptable distributions (0–8), with red indicating no acceptable distributions and blue indicating all eight distributions are acceptable

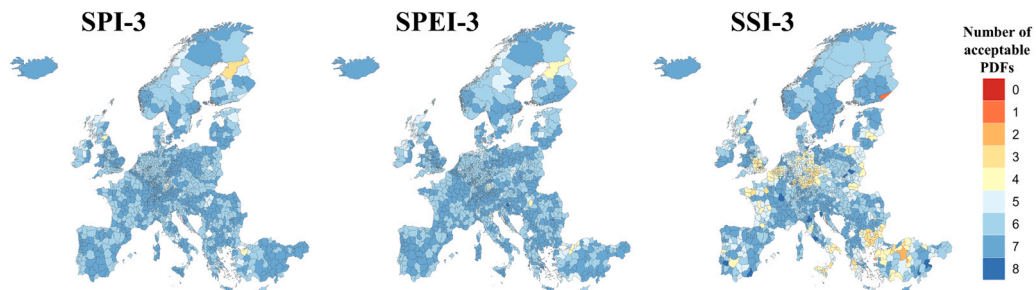


Figure A12. Number of acceptable PDFs for each NUTS-3 region during autumn, based on AD test. Colours represent the count of acceptable distributions (0–8), with red indicating no acceptable distributions and blue indicating all eight distributions are acceptable

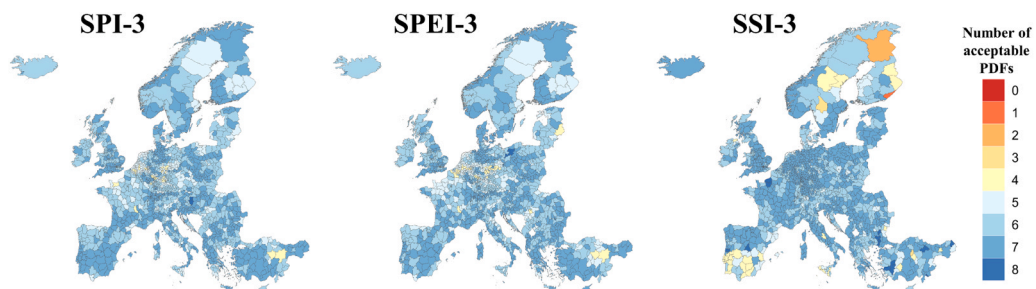


Figure A13. Number of acceptable PDFs for each NUTS-3 region during winter, based on AD test. Colours represent the count of acceptable distributions (0–8), with red indicating no acceptable distributions and blue indicating all eight distributions are acceptable

Data availability

Data will be made available on request.

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