

Where drought matters most: A crop calendar-aware index for prioritizing irrigated agricultural drought hotspots in Italy

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ARTICLE INFO

Keywords:

Drought hotspots
Management priority
Italy
Irrigated agriculture
Crop calendars
SPEI

ABSTRACT

Drought increasingly threatens irrigated agriculture in Mediterranean regions, where limited water resources, diverse cropping systems, and growing climate variability require tools that can support timely and spatially targeted water management decisions. However, drought assessments based only on climatic anomalies may overlook where water deficits are most relevant for agriculture, since their impacts depend on whether drought occurs during the crop growing season, how much irrigated land is exposed, and the economic importance of the affected crops. This study introduces PRIME (PRiority Index for crop-season drought ManagemEnt), a crop calendar-aware index designed to rank irrigated agricultural areas according to their drought management priority. PRIME combines drought frequency derived from the Standardized Precipitation Evapotranspiration Index (SPEI) computed over local crop-specific growing seasons with irrigated crop distribution and gross production value. The index was applied to 17 irrigated crops in Italy over 1951 – 2022, covering 1.84 million hectares of irrigated farmland. Results identify priority hotspots where recurrent crop season droughts overlap with strategic irrigated production systems, particularly in the Po River Valley and in the irrigated districts of Emilia-Romagna and Veneto. Additional priority areas appear in central Italy and in perennial crop systems of southern regions such as Apulia, Calabria, and Sicily. At the crop level, maize-growing areas most frequently show high management priority, while localized high value systems, including sugar beet, fruit crops, and olives, are often associated with the highest PRIME classes. By translating crop season drought exposure into a priority ranking, PRIME provides an operational and reproducible screening tool to help water authorities, irrigation agencies, and policymakers identify critical areas for drought preparedness, resource allocation, and targeted adaptation in Mediterranean irrigated agriculture.

1. Introduction

Drought represents one of the most critical climate related hazards for agriculture in the Mediterranean region, where increasing temperatures, altered precipitation regimes, and rising evaporative demand are determining severe agricultural losses (Cammalleri et al., 2020; García-Herrera et al., 2010). The severity of these impacts is underscored by the latest European Climate Risk Assessment, which identifies Southern Europe as a primary hotspot where risks to crop production have already reached critical levels, requiring urgent action (European Environment Agency, 2024). Within this high risk regional context, Italy stands out as a particularly vulnerable focal point, characterized by a widespread reliance on irrigation to sustain agricultural production (Ellena et al.,

2025; Straffellini and Tarolli, 2023). Recent drought events, such as those occurred in 2003, 2017, and 2022, have highlighted the growing exposure of Italian agriculture to water deficits and the need for more effective tools to support drought risk management and prioritization of mitigation efforts (Biella et al., 2025; Coldiretti, 2017, 2022; García-León et al., 2021; Mysiak et al., 2013a; Toreti et al., 2022a, 2022b).

In response to increasing drought pressure, Italy has recently mobilized substantial public investments to strengthen the resilience of agricultural water systems. Under the National Recovery and Resilience Plan, Mission 2 includes specific measures for improving the resilience of the irrigation agro-system through infrastructure modernization, enhanced water use efficiency and monitoring, and the reduction of

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<https://doi.org/10.1016/j.agwat.2026.110688>

Received 27 May 2026; Received in revised form 4 August 2026; Accepted 7 August 2026

Available online 11 August 2026

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distribution losses (Presidency of the Council of Ministers, 2024). While these measures represent a major national effort to improve water management, they also highlight a key operational challenge: when drought risk affects multiple regions, how should mitigation efforts be prioritized across a large and heterogeneous territory such as Italy?

In the Italian legislative framework, the coordination of drought-related management policies is addressed by a national drought steering committee (Italian Republic, 2023). However, when multiple agricultural regions face simultaneous deficits, the legal framework lacks a standardized, objective criterion to rank drought hotspots and guide coordinated management responses.

Recent scientific efforts have addressed this prioritization challenge through the development of multi-criteria sorting models designed to classify regions into criticality levels and ensure transparent water distribution (de Oliveira Castro et al., 2024; de Oliveira Castro and Costa Morais, 2026; Gómez-Limón et al., 2020). Yet, for these tools to be effective in an agricultural context, they must account for the specific timing of water demand, which varies significantly by crop (Cetinkaya and Gunacti, 2018).

To date, the most widely adopted approach for quantifying the drought hazard component within such frameworks remains the use of standardized drought indicators, including the Standardized Precipitation Index (SPI) (McKee et al., 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). While these indices provide valuable information on meteorological drought conditions, they are typically applied using fixed accumulation periods (e.g. 3 or 6 months) (Haro-Montegudo et al., 2018; Hussain et al., 2023; Lindenlaub et al., 2026; Mohammed et al., 2022; Parsons et al., 2019; Stagge et al., 2015), that do not explicitly reflect crop-specific growing seasons. As a result, they may fail to capture the timing and cumulative nature of water deficits that are most relevant for agricultural impacts (Lobell and Field, 2007; Zhang et al., 2019), particularly in countries such as Italy, where diverse cropping systems and contrasting phenological cycles coexist.

Beyond climatic hazard, agricultural drought risk also depends on exposure and vulnerability, which are influenced by the spatial distribution of crops and their economic relevance (Meza et al., 2020). In a country such as Italy, where diverse cropping systems and contrasting phenological cycles coexist, incorporating crop calendars, irrigated area distribution, and crop value within the same spatial framework is therefore essential to support operational drought management. Without this integration, prioritization based only on climatic severity may overlook areas where recurrent drought affects extensive or high value irrigated production systems. To support more balanced and transparent prioritization of water management actions, drought assessments should therefore combine information on climatic hazard with indicators of agricultural exposure and economic relevance. Such an integrated perspective can help identify areas where recurrent drought conditions are likely to translate into the greatest impacts in terms of production and stability.

It is within this context that we introduce PRIME (PRiority Index for crop-season drought ManagemEnt), a crop calendar-aware framework designed to identify and rank irrigated agricultural areas according to their drought management priority. PRIME integrates three components: (i) the frequency of drought events occurring during crop-specific growing seasons, evaluated through the SPEI; (ii) the spatial distribution of irrigated crops; and (iii) their economic value. By explicitly accounting for crop calendars and growing season duration, the index links climatic hazard directly to agricultural production cycles. This enables the identification of drought hotspots that are not only climatically exposed, but also relevant for agricultural water management, where decisions must prioritize limited resources across competing regions, crops, and production systems. Therefore, in water constrained agricultural systems, the key challenge is no longer only detecting drought occurrence but transparently prioritizing where limited water resources matter most for agricultural sustainability. In this sense, PRIME is

conceived as a strategic, ex-ante prioritization tool to support drought preparedness and targeted adaptation planning rather than the real-time management of a specific unfolding drought event.

We apply PRIME to Italy's irrigated agriculture over the period 1951–2022 and address the following research questions: (1) where are the most critical irrigated agricultural drought hotspots when considering recurrent growing-season drought exposure? (2) which crops predominantly drive drought management priority at local and regional scales? and (3) how does the integration of crop specific phenology and economic value modify hotspot identification compared to climate-only indicators? By providing a transparent and reproducible prioritization framework, this study supports drought risk management and water resources planning through a national scale relative ranking that enables consistent comparison among regions and cropping systems.

2. Materials and methods

2.1. Study area

Italy is a Southern European peninsula extending between 35°N–47°N latitude and 6°E–18°E longitude, with a total area of 302068 km². Administratively, the country is divided into 20 regions, as illustrated in Fig. 1. Lowlands are mainly concentrated in the Po River Valley and along coastal areas. Mean annual precipitation ranges from less than 500mm yr⁻¹ in southern coastal and insular regions to more than 2500mm yr⁻¹ in Alpine and pre-Alpine areas, while mean annual temperatures generally vary between 10 and 18 °C (Fratianni and Acquafredda, 2017).

Agriculture plays a central economic, environmental, and cultural role in the country. Italy's pronounced latitudinal extent and complex orography support a wide diversity of cropping systems, ranging from cereals and forage crops in the Po River Valley to vineyards, olive groves, citrus orchards, horticulture, and perennial tree crops in central and southern regions (see Supplementary Figure S1 for crop wise spatial distribution). More than half of the national territory is devoted to agriculture (CREA, 2024), making Italy one of the most productive agricultural systems in Europe (European Commission, 2021). A distinctive feature of Italian agriculture is the exceptional concentration of certified quality products: Italy holds the highest number of Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI) labels in Europe, reflecting not only its economic relevance but also the strong cultural and territorial embeddedness of agricultural practices (ISMEA, Fondazione Qualivita, 2025).

Since 2013, Italy has been the largest contributor to gross agricultural added value in the European Union, accounting for nearly one fifth of the total (€43 billion in 2024; Eurostat, 2026). The country is also a major producer of high value crops such as grapes, olives, rice, wheat, and maize and one of Europe's leading agri-food exporters (Carbone and Henke, 2023; CREA, 2025; Eurostat, 2025). Despite its importance, the sector is increasingly exposed to drought risk. Annual damages from agricultural drought are estimated at €0.55–1.75 billion, corresponding to 0.01–0.10 % of national GDP (García-León et al., 2021). A key structural characteristic of Italian agriculture is its strong reliance on irrigation. Agricultural water withdrawals yearly reach 17 billion m³ (FAO, 2026), and approximately 85% of crops rely on irrigation (ISTAT, 2022). During the 2022 drought, nearly half of all irrigated farmland (49%) experienced severe to extreme drought conditions (The European House - Ambrosetti S.p.A., 2023).

Given its economic weight, export relevance, and cultural value, Italian agriculture represents a strategic sector whose resilience to drought is of both national and European importance. The combination of high agricultural value and growing climatic pressure makes Italy a particularly relevant case study for developing spatially explicit tools to identify agricultural drought hotspots and support targeted water management and adaptation strategies.

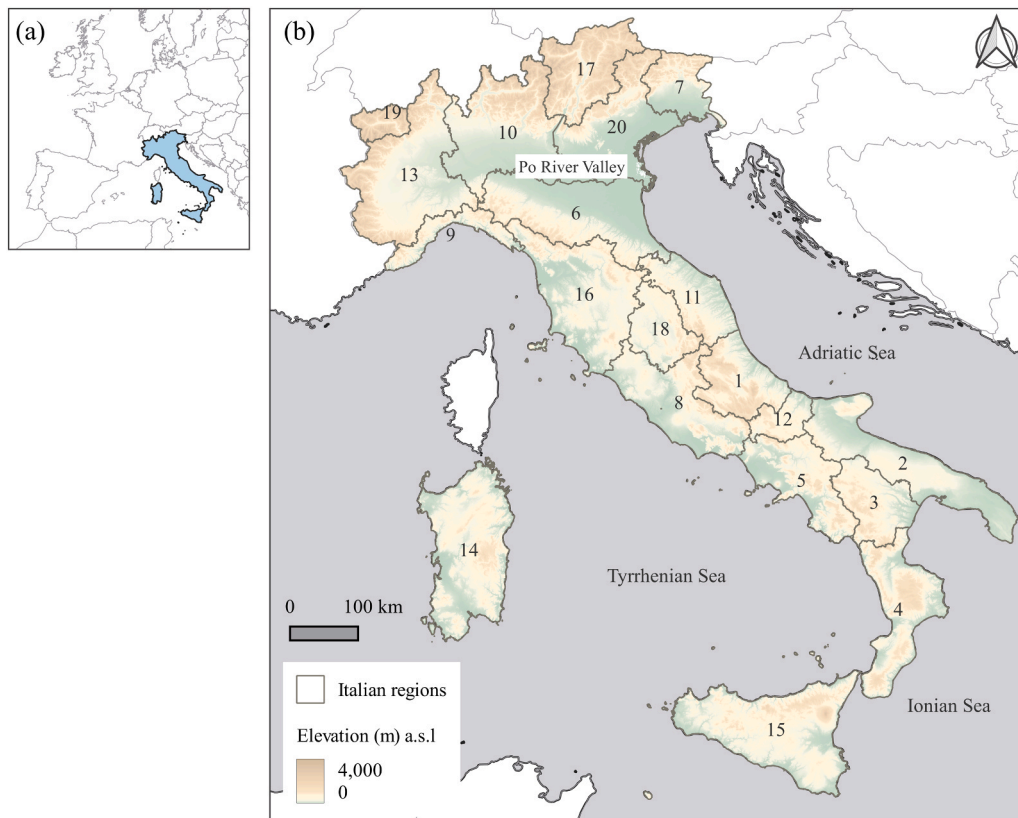


Fig. 1. (a) Study area. (b) Elevation map of Italy (in meters) showing the boundaries of the 20 administrative regions and their corresponding identification numbers: 1 – Abruzzo (ABR); 2 – Apulia (APU); 3 – Basilicata (BAS); 4 – Calabria (CAL); 5 – Campania (CAM); 6 – Emilia-Romagna (EMI); 7 – Friuli Venezia Giulia (FRI); 8 – Lazio (LAZ); 9 – Liguria (LIG); 10 – Lombardy (LOM); 11 – Marche (MAR); 12 – Molise (MOL); 13 – Piedmont (PIE); 14 – Sardinia (SAR); 15 – Sicily (SIC); 16 – Tuscany (TOS); 17 – Trentino-Alto Adige (TRE); 18 – Umbria (UMB); 19 – Aosta Valley (VAL); 20 – Veneto (VEN).

2.2. Data sources

2.2.1. Climate data

As drought conditions in agricultural lands depend on both precipitation and temperature (Tigheelaar et al., 2018; Wang et al., 2021), among all available drought indices, we selected the Standardized Precipitation Evapotranspiration Index, SPEI (Vicente-Serrano, Beguería and López-Moreno, 2010), as it integrates both variables into a simplified water balance. For the 1951–2022 period, the monthly water balance D was computed from monthly cumulated precipitation (P) and monthly reference evapotranspiration (ET_0) as:

$$D = P - ET_0 \quad (1)$$

The D series, accumulated over the selected time scale, is fitted to a three parameter log-logistic distribution, and the resulting cumulative probabilities are transformed into standardized normal values with zero mean and unit variance. This standardization enables the comparison of drought characteristics across timescales and regions regardless of their climatic conditions.

The required input variables such as precipitation, minimum and maximum temperature, dew-point temperature, wind speed, surface pressure, and surface net radiation were obtained from ERA5-Land at a 0.1° spatial resolution (Muñoz-Sabater et al., 2021). We chose this dataset based on its demonstrated ability to accurately reproduce precipitation and evapotranspiration patterns in Italy (De Caro et al., 2023; Moccia et al., 2025; Vanella et al., 2022) and on its provision of all the meteorological variables required to compute reference evapotranspiration.

In this study, both ET_0 and SPEI were computed in R 4.4.0 using the ‘SPEI’ package (Beguería and Vicente-Serrano, 2023). In particular, ET_0

was estimated with the FAO–56 Penman–Monteith formulation (Allen et al., 1998):

$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

where Δ is the slope of the saturation vapour pressure curve, R_n the net surface radiation, G the soil heat flux density, T the mean 2m air temperature, u_2 the 2 m wind speed, e_s and e_a the saturation and actual vapour pressure respectively and γ the psychrometric constant. Δ , G , γ , e_s and e_a were derived from the input variables following Allen et al. (1998).

2.2.2. Irrigated crops and crop calendars

The analysis focuses exclusively on irrigated areas, excluding rainfed farmland. This choice is supported by the fact that, in the Italian context, rainfall is generally sufficient to sustain production for non-irrigated crops (Straffellini and Tarolli, 2023). We obtained irrigated crop-specific harvested areas from Italy’s most recent and exhaustive crop observation dataset AIDA (Galli et al., 2025), having a 0.008° spatial resolution. We considered 17 irrigated crops: barley, citrus, fodder, fruits, maize, oats, olives, potatoes, pulses, rapeseed, rice, rye, sugar beet, sunflower, triticale, vegetables, and vineyards that account for 77% of Italy’s irrigated agricultural land and more than 48% and 52% of human calorie and protein intake respectively (D’Odorico et al., 2014).

AIDA was aggregated to the ERA5-Land grid (0.1° degrees $\approx 9\text{km}$) by summing the irrigated harvested area (ha) for each crop within each ERA5-Land pixel. Consequently, all of the following computations and outputs are produced with a 0.1° grid resolution. Cultivated hectares for each pixel and crop after aggregation are provided in Supplementary

Figure S1.

We derived crop calendars (sowing and harvest months) from MIRCA-OS dataset (Kebede et al., 2025), which provides spatially variable planting/harvesting months at a sub-national scale. Region specific sowing and harvesting months are reported in [Supplementary Tables S1, S2 and S3](#).

2.2.3. Crop economic value

Crop economic relevance was represented using Gross Production Value (GPV) from FAOSTAT (constant 2014–2016 standard local currency) (FAO, 2024), computed as a five-year average over 2018–2022 to smooth interannual anomalies ([Supplementary Figure S2](#)). For aggregated crop categories, such as fruits, vegetables, and citrus, which comprise multiple sub-crops, the representative GPV was calculated as the arithmetic mean of the GPVs of the constituent sub-crops. The complete list of sub-crops and their individual GPV values is provided in [Supplementary Table S4](#).

2.3. Methodology

2.3.1. Crop-season drought hazard

PRIME integrates drought hazard during the local crop-specific growing seasons with exposure and agricultural value, to produce a national management priority score per pixel. Graphical representation of the methodological workflow may be found in [Fig. 2](#).

To accurately reflect agricultural drought impacts, the SPEI was computed for each crop i and pixel p using an accumulation time scale equal to the local growing-season length $L_{i,p}$ and sampled at the harvest month $H_{i,p}$. This approach accounts for spatial shifts in crop calendars across Italy and ensures that drought events are evaluated only when they coincide with the growing season, the period when droughts are most critical to production (Mishra and Cherkauer, 2010; Shiru et al., 2018). By tailoring the index to specific phenological windows, we directly link the climatic hazard to the actual production cycle of each

cropping system.

A drought event is defined when:

$$\text{SPEI}_p(H_{i,p}, L_{i,p}) < \tau \quad (3)$$

where τ is a drought threshold. Here we set $\tau = -1$, corresponding to moderate drought conditions according to the standard SPEI classification used to identify drought events (McKee et al., 1993). This threshold is also consistent with impact based evidence showing that vegetation responses to water stress typically emerge for SPEI values between approximately -0.7 and -1 (Xu et al., 2023).

Accordingly, for each pixel and crop, a given year is classified as a drought year when the SPEI defined above falls below τ . We then computed the crop-season drought frequency as (Sein et al., 2021):

$$\text{DH}_{i,p} = \frac{n_{i,p}}{N} \times 100 \quad (4)$$

where $n_{i,p}$ is the number of drought years during the local crop-specific growing season and N is the number of years (1951–2022). This procedure yielded 17 crop-specific $\text{DH}_{i,p}$ maps, one for each crop.

2.3.2. Agricultural value and exposure

We combined crop economic value and crop exposure (irrigated harvested area) to obtain for each crop i and pixel p , its agricultural value (AG):

$$\text{AG}_{i,p} = \frac{A_{i,p}}{A_i^{\text{tot}}} \text{GPV}_i \quad (5)$$

where GPV_i is the national mean GPV of crop i (2018–2022), $A_{i,p}$ is irrigated harvested area of crop i in pixel p , and A_i^{tot} is total national irrigated harvested area of crop i . This formulation expresses the relative contribution of each pixel to national crop value. By construction, $\text{AG}_{i,p}$ jointly reflects both the economic value of a crop (through GPV_i) and its cultivated extent (through the relative irrigated area $A_{i,p}/A_i^{\text{tot}}$). This

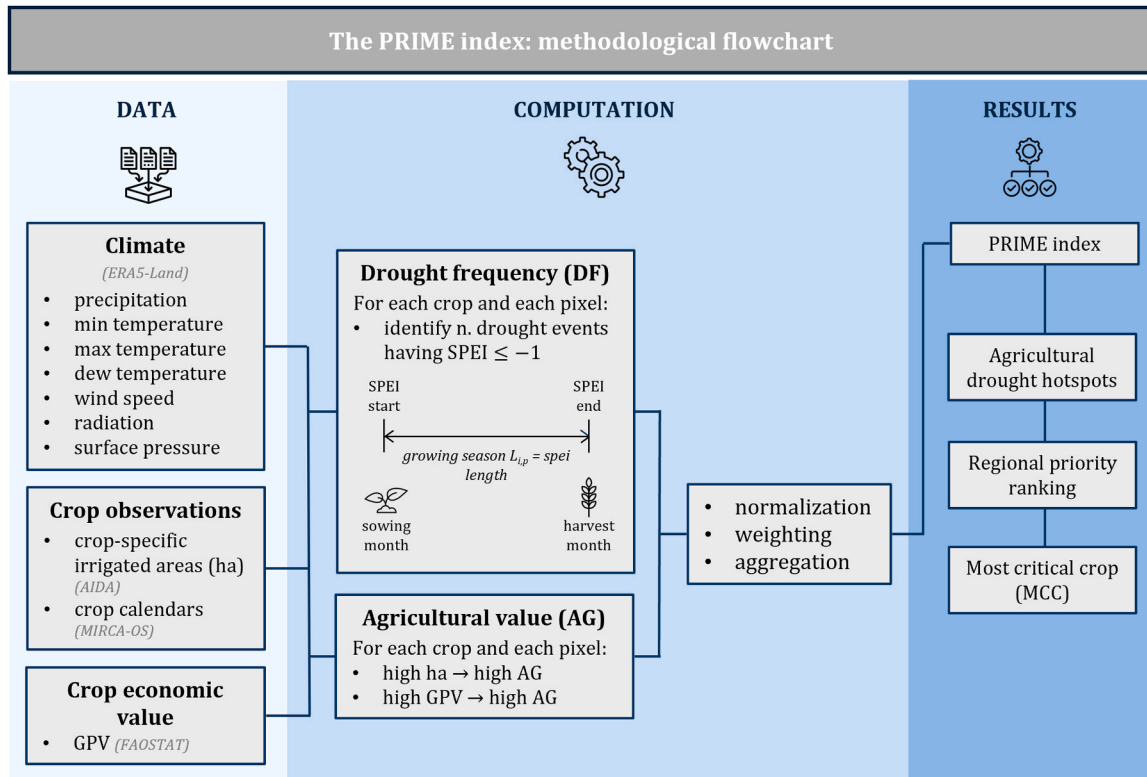


Fig. 2. PRIME methodological flowchart.

design choice allows both high value crops and widely irrigated staple crops to be accounted for. This procedure yielded 17 crop-specific $AG_{i,p}$ maps, one for each crop.

2.3.3. Normalization, aggregation and classification

Since $DH_{i,p}$ and $AG_{i,p}$ have different units, we applied crop-specific min–max normalization across cultivated pixels (Carrão et al., 2016):

$$X'_{i,p} = \frac{X_{i,p} - X_{i,min}}{X_{i,max} - X_{i,min}} \quad (6)$$

with $X \in \{DH_{i,p}, AG_{i,p}\}$.

We then computed crop-specific PRIME values as an equally weighted additive score:

$$PRIME_{i,p} = DH'_{i,p} + AG'_{i,p} \quad (7)$$

This transparent baseline assigns equal importance to drought hazard frequency and agricultural value. Equal weighting was adopted as a neutral assumption in the absence of an a priori preference for either component, allowing both dimensions to contribute symmetrically to the priority ranking. This choice ensures interpretability and comparability at the national scale, while maintaining flexibility for applications in which weights may be adjusted according to specific management objectives.

Pixel-level PRIME sums crop-specific contributions:

$$PRIME_p = \sum_i PRIME_{i,p} \quad (8)$$

and was classified into ten priority classes (1–10) using quantiles of $PRIME_p$ across all Italian cultivated pixels (class 10 = highest priority, class 1 = lowest priority). The crop-specific components $DH_{i,p}$ and $AG_{i,p}$ are available for all 17 crops. Although PRIME is computed at the crop level from $DH_{i,p}$ and $AG_{i,p}$, we additionally derived two aggregated layers, DH^* and AG^* , obtained respectively as the across-crop average of the $DH_{i,p}$ layers and the sum of the $AG_{i,p}$ layers, to appreciate the aggregate contribution of all crops to the drought hazard and agricultural value dimensions of PRIME.

2.3.4. Comparison with a climate-only assessment

The 6-month SPEI (SPEI-6) is commonly used for agricultural drought assessment, as the 6-month accumulation period broadly corresponds to crop growing season timescales (Dahal et al., 2024). Therefore, we compared the priority ranking provided by PRIME with the one provided by the SPEI-6: for each pixel, we computed the SPEI-6 drought frequency as the ratio between the number of months for which $SPEI-6 \leq -1$, over the total number of observation months from 1951 to 2022 (Dahal et al., 2024; Harsányi, 2025; Mohammed et al., 2022; Nikdad et al., 2024). SPEI-6 uses a single fixed accumulation period and does not include crop calendars, irrigated exposure, or economic value. We then normalized and classified it into the same ten priority classes used for PRIME, allowing a pixel-by-pixel comparison between the two classifications.

2.3.5. Sensitivity analysis

To assess the robustness of the priority ranking to the equal weighting design choice, we performed a sensitivity analysis in which the crop-specific PRIME score (Eq. 7) was recomputed using alternative weight combinations for the DH and AG components as follows:

$$PRIME_{i,p} = aDH'_{i,p} + bAG'_{i,p} \quad (9)$$

For the baseline scheme adopted in this study, $a = b = 0.5$, for the AG-oriented scheme $a = 0.25$, $b = 0.75$, while for the DH-oriented scheme $a = 0.75$, $b = 0.25$. For each scheme, the pixel level PRIME was aggregated, normalized, and classified into the same ten priority classes following the procedure described in Section 2.5, so that the

three classifications are directly comparable. The three schemes were selected to span the neutral case and the two extremes of plausible emphasis; intermediate weightings would fall between the cases tested here.

2.3.6. Most critical crop (MCC)

For each pixel, the Most Critical Crop (MCC) was defined as the crop whose crop-specific PRIME value contributed most to the overall priority score at that location:

$$MCC_p = \max_i (PRIME_{i,p}) \quad (10)$$

where MCC indicates the dominant contributor to drought priority locally (not necessarily the crop with maximum national value).

3. Results

3.1. National drought hotspots and regional patterns

PRIME reveals a heterogeneous spatial ranking of agricultural drought management priority across Italy, reflecting the combined interaction of recurrent growing-season drought frequency, crop distribution, and crop economic value. The spatial distribution of PRIME priority classes are shown in Fig. 3(a) where each cultivated pixel is assigned a relative priority score ranging from 1 (lowest priority) to 10 (highest priority).

Across Italy, approximately 1.84 million hectares of irrigated farmland were analysed. The distribution of PRIME values is mostly concentrated within intermediate classes. Indeed, the largest share of cultivated pixels falls within class 6 (32.7%), followed by class 5 (25.4%) and class 7 (19.3%), indicating that most irrigated agricultural systems are characterized by moderate priority. Lower priority classes are comparatively limited, with classes 1–3 together accounting for only 2.6% of the analysed cultivated area. At the upper end of the distribution, classes 8–10 together represent about 170,000 ha, corresponding to 9.3% of total farmland, while the most critical class, 10, accounts for only 0.1% (approximately 1153 ha).

This concentration is even more evident when considering the agricultural value component. Although classes 8–10 represent only 9.3% of total irrigated cropland, they account for 7.2% of the total agricultural value represented in the dataset, with class 8 contributing 4.28%, class 9 2.69%, and class 10 0.2%. More broadly, classes 4–7 account for the majority of both cultivated area and agricultural value, jointly representing 88.1% of the analysed area and 89.3% of total agricultural value, indicating that the most economically relevant production systems are largely concentrated in areas of moderate priority. In contrast, the lowest classes (1–3) account for only 3.5% of total agricultural value, confirming that low priority areas play a comparatively marginal role in the national irrigated production system.

From the climatic perspective, the average drought hazard component DH^* (Fig. 3(b)) highlights recurrent growing-season drought frequency across a north-central belt extending from eastern Piedmont through the Po River Valley towards Veneto and Emilia-Romagna. Elevated drought frequencies are also observed in central regions such as Tuscany and Lazio, as well as in parts of southern Italy including Apulia and northern Calabria. Regarding the total AG^* component (Fig. 3(c)), high value crops such as vineyards, olives, vegetables, and maize exert a dominant influence on PRIME patterns due to their elevated GPV and spatial concentration. As a result, even areas with moderate drought frequency may reach high priority levels when associated with economically important irrigated production, whereas crops with lower economic value or more limited spatial extent contribute less to the cumulative index despite local drought exposure.

The resulting PRIME map highlights three main drought management priority zones: the irrigated plains of northern Italy, agricultural districts in central regions such as Marche and Lazio, and perennial crop

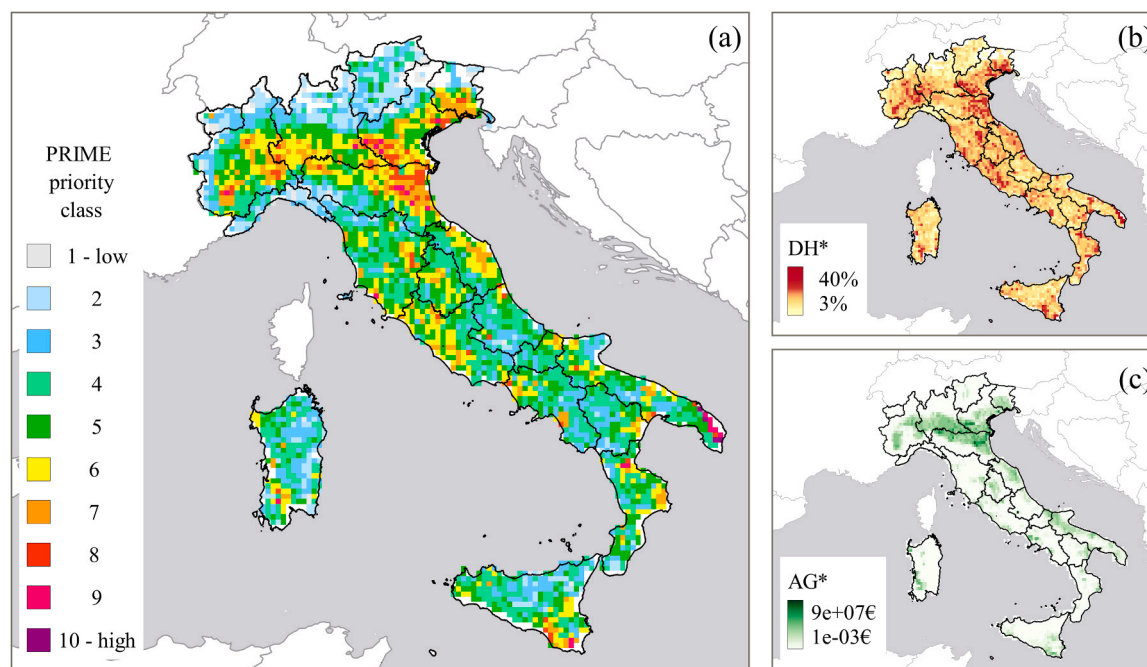


Fig. 3. Spatial distribution of PRIME priority classification across Italy (a) and its two aggregated components (b, c). Panel (b) shows the average drought hazard (DH*) and panel (c) the total agricultural value (AG*) across the 17 crops. The crop-specific maps of DH and AG are reported in [Supplementary Figs. S7 and S8](#).

systems in southern regions including Apulia, Calabria, and Sicily. These areas represent locations where recurrent drought exposure overlaps with economically important irrigated production, generating the highest relative drought management priority at the national scale.

At the regional scale, the distribution of PRIME values allows comparison of how pervasive drought management priority is within each administrative region ([Fig. 4](#) and [Supplementary Figure S3](#)). Using the regional median as a summary metric, regions with median PRIME ≥ 5 are identified as priority regions, indicating that at least half of their cultivated pixels fall within moderate-to-high priority classes. Under this

criterion, Friuli Venezia Giulia, Lazio, Lombardy, Marche, Piedmont, Umbria, Emilia-Romagna, and Veneto emerge as the highest-priority regions. Among these, Emilia-Romagna and Veneto show the highest medians (both equal to 6) together with relatively broad interquartile ranges, indicating that high priority of drought management is not confined to isolated hotspots but is spatially widespread across their irrigated agricultural systems. Other priority regions, such as Lombardy, Lazio, Marche, Piedmont, Umbria, and Friuli Venezia Giulia, display medians around 5, again suggesting pervasive priority conditions across a substantial share of cultivated land.

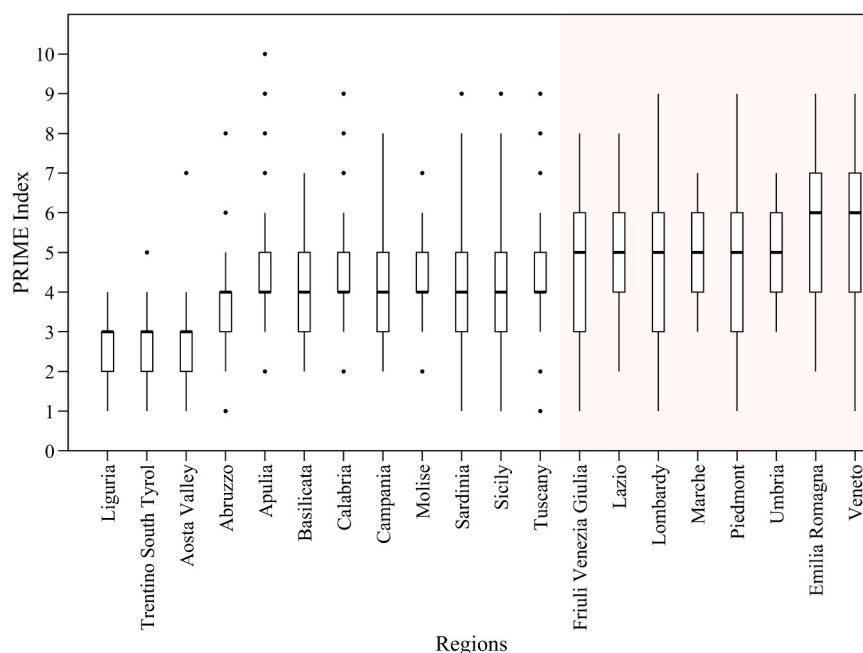


Fig. 4. Distribution of PRIME values across Italian regions, ordered from left to right by increasing median values. The red-shaded area highlights regions with a median PRIME value greater than or equal to 5, identified as priority areas. For each region, the box shows the interquartile range (IQR) with the median as the central line, the whiskers extend to $1.5 \times \text{IQR}$, and the dots denote statistical outliers.

By contrast, regions with median PRIME values below 5 exhibit more heterogeneous distributions, often characterized by lower central values but long upper tails. This indicates that, although they are not priority regions in a median based sense, the presence of statistical outliers in Fig. 4 indicate localized hotspots of very high priority. Apulia is a notable example: despite a regional median of 4, its distribution includes pixels reaching classes 9 – 10, reflecting highly critical but spatially concentrated priority clusters. Similar patterns are visible in Sicily, Sardinia, Tuscany, and Calabria, where extreme values coexist with broader areas of lower or intermediate priority.

To assess the added value of PRIME relative to a conventional climatic assessment, we compared its priority classification with that based on SPEI-6 drought frequency (Supplementary Figures S4). The two rankings differ substantially: only 10.8% of cultivated irrigated pixels retain the same priority class, 31.2% remain within ± 1 class, and 68.8% shift by two or more classes, with a mean absolute shift of 2.7 classes. The class-transition matrix (Supplementary Figure S4(d)) confirms that pixels are widely redistributed rather than reshuffled between adjacent classes, indicating that PRIME does not simply reproduce the drought frequency pattern but reorganizes it. Indeed, PRIME raises the priority of 20.4% of cultivated pixels by at least two classes and lowers that of 48.4%. The pixels whose priority increases are associated with a markedly higher agricultural value than those whose priority decreases (meanAG $\approx 5 \times 10^6\text{€}$ versus $2 \times 10^3\text{€}$), despite experiencing a comparable or even lower SPEI-6 drought frequency (16.4% vs 18%). In other words, PRIME shifts priority towards areas where recurrent growing season drought coincides with economically relevant, extensively irrigated production, and away from frequently dry but marginal or low value cropland. Geographically, the SPEI-6 analysis assigns broadly uniform high frequencies across northern Italy, whereas PRIME concentrates priority on the irrigated districts of the Po River Valley, Emilia-Romagna, and Veneto, and additionally raises the priority of high value perennial and horticultural systems in central and southern Italy that the climate only indicator does not distinguish.

The equal weighting design choice of PRIME's components proved robust to the choice of weights assigned to the DH and AH (Supplementary Figure S5 and Supplementary Table S5). Under the DH oriented scheme, 71.4% of cultivated pixels retained exactly the same priority class as the equal weight baseline scheme, 98.8% remained within ± 1 class, and only 1.2% shifted by two or more classes. The AG oriented scheme, produced a larger redistribution, yet 96.1% of pixels still remained within ± 1 class of the baseline and only 3.9% shifted by two or more classes and 33.7% keeping exactly the same class. In both cases the class transition matrices show that pixel movements are concentrated along the main diagonal (Supplementary Figure S6), confirming that reweighting mostly reshuffles pixels between adjacent classes rather than relocating priority across the country.

3.1.1. Crop-specific contributions to drought management priority

To identify the crop driving drought management priority at the local scale, we determined for each cultivated pixel the Most Critical Crop (MCC), defined as the crop associated with the highest crop-specific PRIME value at that location. The MCC therefore represents the crop contributing most strongly to the overall drought management priority at the pixel level. The spatial distribution of MCC across Italy is shown in Fig. 5, while the regional occurrence of each crop as MCC is summarized in Fig. 6. In Fig. 6 values are expressed as the percentage of total cultivated pixels at the national scale for which a given crop is identified as MCC within a specific region, allowing direct comparison of crop contributions across both space and crop types.

At the national scale, maize emerges as the dominant crop driving priority, accounting for 22.3% of cultivated pixels and appearing as MCC in all 20 Italian regions. Triticale ranks second (16.7%), with a widespread distribution across central and northern regions, while pulses constitute the third most frequent MCC (10%), particularly across cen-

tral and southern Italy. Together, these three crops account for approximately 49% of all MCC occurrences, indicating that a limited number of crops drive nearly half of the national priority pixels.

A second group of crops contributes substantially but more heterogeneously, including vegetables (7.8%), barley (7.3%), and sugar beet (6.7%), followed by fruits (4.9%), fodder crops (4.8%), and rye (4.3%). Crops such as citrus (3.6%), potatoes (3.3%), and sunflower (2.2%) play more localized roles, while rapeseed (1.7%), rice (1.5%), oats (1.1%), olives (1.1%), and vineyards (0.6%) contribute only marginally to the overall MCC distribution due to their limited spatial extent or lower relative contribution to the PRIME index.

The spatial patterns illustrated in Fig. 5 and Fig. 6 reveal strong regional specialization in the crops driving priority. In northern regions such as Lombardy, Emilia-Romagna, and Veneto, MCC patterns are dominated by maize, triticale, and sugar beet. In Piedmont, maize and triticale remain the dominant driver, with additional contributions from pulses. In central regions (Tuscany, Umbria, and Marche), MCC composition is more heterogeneous, with maize, triticale, and pulses contributing comparable shares. In southern regions such as Apulia, Calabria, and Basilicata, pulses emerge as the dominant MCC, often associated with vegetables and barley, while in the islands (Sicily and Sardinia) drought management priority is primarily driven by pulses and vegetables, together with localized contributions from citrus and horticultural systems.

The relationship between MCC occurrence and PRIME intensity further highlights how different crops dominate different levels of priority. Low-priority classes (PRIME 1 – 2) are primarily associated with vegetables, whereas intermediate classes show a progressive dominance of maize and triticale. Specifically, maize dominates classes 3, 5, and 6, while triticale is the most frequent MCC in class 4. At higher priority levels, the contribution shifts towards crops characterized by higher economic value and more spatially concentrated production systems: sugar beet dominates classes 7 and 8, while fruits and olives emerge as the dominant MCC in the highest priority classes (9 – 10).

4. Discussion

There is growing evidence that European agriculture will face increasing drought stress in the coming decades, requiring more proactive and spatially targeted water management strategies (Black et al., 2026). In Italy, drought already represents a structural vulnerability of the agricultural sector (Buttinelli et al., 2026), and future assessments indicate declining resilience and increasing pressure on irrigated systems under climate change (Masia et al., 2018).

Within this context, PRIME provides a simple and operational framework to identify where drought is most likely to become a management priority. Rather than relying on drought frequency alone, PRIME captures the intersection between recurrent drought events occurring during crop-specific growing seasons, the spatial distribution of irrigated agriculture, and the economic value of production systems. Not all droughts matter equally for agricultural management: recurrent deficits become critical when they affect strategically relevant irrigated systems during their growing season. This enables a shift from a purely climatic description of drought to a management-oriented prioritization.

4.1. Drought management priority across regions and crops

The results clearly show that drought management priority is not uniformly distributed across space. Instead, it concentrates in relatively limited portions of the agricultural landscape. High priority classes (PRIME 8 – 10) cover 9.3% of the cultivated area and account for 7.2% of the total agricultural value represented in the dataset. This indicates that the most critical drought hotspots are spatially contained and economically significant, highlighting areas where water scarcity can disproportionately affect high-value and strategically relevant production systems.

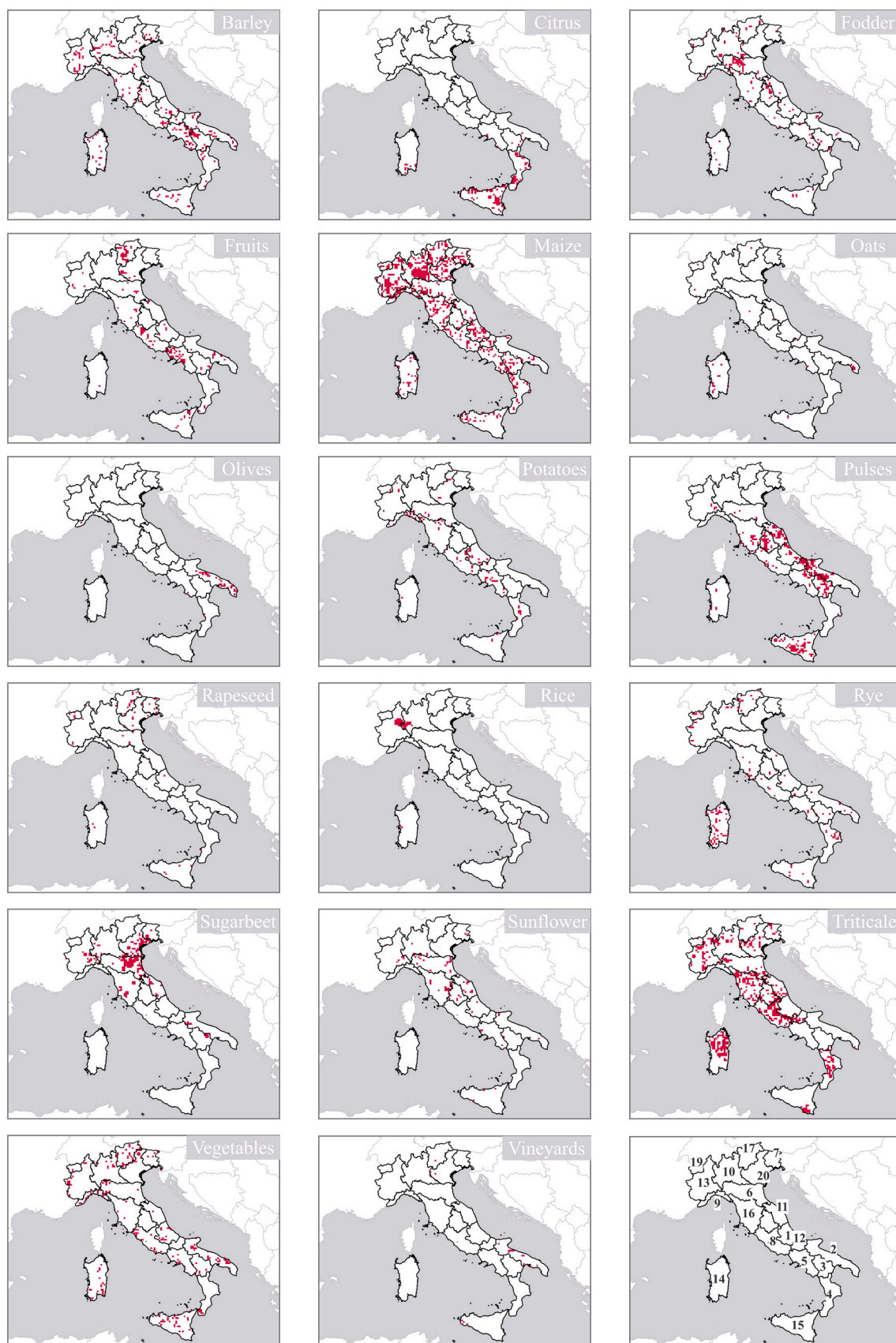


Fig. 5. Spatial distribution of grid cells where, for each pixel, the most critical crop (MCC) is displayed in red. The bottom right panel displays the boundaries of the 20 administrative regions and their corresponding identification numbers: 1 – Abruzzo; 2 – Apulia; 3 – Basilicata; 4 – Calabria; 5 – Campania; 6 – Emilia-Romagna; 7 – Friuli Venezia Giulia; 8 – Lazio; 9 – Liguria; 10 – Lombardy; 11 – Marche; 12 – Molise; 13 – Piedmont; 14 – Sardinia; 15 – Sicily; 16 – Tuscany; 17 – Trentino Alto Adige; 18 – Umbria; 19 – Aosta Valley; 20 – Veneto.

	VEN	EMI	UMB	PIE	MAR	LOM	LAZ	FRI	TOS	SIC	SAR	MOL	CAM	CAL	BAS	APU	ABR	VAL	TRE	LIG
maize	1.7%	1.1%	0.3%	3.3%	0.4%	3.8%	0.8%	0.8%	2.2%	0.8%	0.8%	0.3%	0.8%	0.8%	0.7%	0.4%	1.3%	0.3%	1.1%	0.9%
triticale	1.0%	0.9%	1.0%	1.6%	0.7%	1.0%	2.4%	0.4%	2.5%	0.4%	2.4%	0.5%		1.3%	0.1%	0.1%	0.3%	0.1%	0.2%	
pulses		0.1%	1.1%	0.2%	1.0%		0.5%		0.7%	1.9%	0.3%	0.5%	0.4%		1.0%	1.7%	0.6%			
vegetables	0.4%	0.3%		0.5%		0.5%	0.6%	0.2%	0.3%	0.8%	0.7%		0.2%	0.3%	0.2%	0.8%	0.5%	0.1%	0.9%	0.4%
barley	0.2%	0.2%	0.2%	0.9%		0.9%	0.3%	0.2%	0.4%	0.5%	0.5%	0.1%	1.0%	0.2%	0.6%	0.8%	0.3%			
sugarbeet	1.7%	2.6%		0.4%	0.5%	0.5%		0.2%	0.5%						0.1%	0.3%	0.1%			0.1%
fruits	0.3%	0.3%		0.2%	0.1%		0.8%		0.2%	0.4%			0.9%	0.2%	0.2%	0.3%	0.1%		1.0%	
fodder		1.5%	0.3%		0.2%	0.4%	0.1%		0.3%	0.1%	0.3%		0.3%		0.1%	0.2%	0.2%	0.1%	0.4%	0.2%
rye			0.1%	0.4%	0.1%	0.2%	0.2%		0.3%	0.2%	1.5%		0.1%	0.3%	0.1%	0.1%	0.1%	0.2%	0.3%	
citrus										1.9%	0.2%		0.1%	0.9%	0.1%	0.1%				
potatoes	0.2%	0.1%		0.2%			0.3%		0.6%	0.2%		0.1%	0.5%	0.3%			0.4%	0.1%		0.3%
sunflower		0.6%	0.2%	0.2%	0.3%	0.1%		0.1%	0.5%	0.1%			0.1%			0.1%	0.1%			
rapeseed	0.1%	0.2%	0.1%	0.1%		0.1%		0.3%		0.2%	0.1%						0.1%	0.1%	0.3%	
rice				0.7%		0.8%					0.1%									
oats			0.1%	0.1%							0.5%					0.2%				
olives																1.0%				
vineyard	0.1%									0.1%						0.4%				

Fig. 6. Heatmap showing the percentage of total cultivated pixels at the national scale for which each crop is identified as the Most Critical Crop (MCC) within each Italian region. Each value represents the share of national cultivated pixels where a given crop contributes the highest PRIME value in that specific region. Darker colours indicate higher MCC occurrence. Region abbreviations are defined in Fig. 1.

The prominence of northern Italy reflects both climatic exposure and agricultural structure. The Po River Valley is not only one of the most drought prone areas in the country, but also its main irrigated production hub (Monteleone and Borzì, 2024); therefore, recurrent drought in this region translates directly into national scale management relevance. Independent SPEI-based analyses similarly identify the Po River Valley and parts of the Tuscan hills among the areas most sensitive to drought, with clear vegetation responses observed in intensively managed agricultural systems (Baronetti et al., 2024). Climate projections further indicate that irrigated arable systems in northeastern Italy are among the most exposed to increasing aridity under future scenarios (Straffellini and Tarolli, 2023).

In central and southern Italy, hotspot emergence follows a different logic. High priority pixels are generally less spatially extensive but are associated with perennial and horticultural systems characterized by high value density, strong territorial specialization, and dependence on timely irrigation (Chiappini et al., 2025). This confirms that drought management priority is not solely driven by frequency, but also by the economic structure of agricultural systems.

PRIME assigns high priority to areas that are also known to sustain large economic damages during major drought events. García-León et al. (2021), using an entirely different impact-based framework, showed that drought costs in Italy are spatially uneven, relatively more concentrated in the north, but with considerable monetary losses also in southern regions such as Apulia and Sicily. In this sense, the agreement is not that PRIME reproduces observed losses exactly, but that it independently highlights many of the same territorial systems where drought has already translated into substantial economic damage. This is especially evident for the northern macro-area, where Veneto, Lombardy and Emilia-Romagna emerge as highly ranked in PRIME and also belong to the part of the country where García-León et al. (2021)

identify the strongest economic burden. Read in this way, PRIME can be interpreted as an ex-ante hotspot screening tool, while studies such as García-León et al. (2021) provide ex-post economic validation that the ranked areas are indeed those where drought is most likely to matter in productive and monetary terms.

At the crop level, maize cultivated pixels emerge as the dominant MCC nationally (22.3%), which is consistent with its role as the most widespread irrigated crop in Italy and a major carrier of drought-related production risk (Galli et al., 2025; Mysiak et al., 2013). Together with triticale (16.7%) and pulses (10%), it accounts for approximately 49% of all MCC occurrences, indicating that a limited number of crops drive a large share of drought management priority areas. From a water management perspective, this concentration is particularly relevant, as it suggests that targeted interventions on a relatively small number of crop systems could substantially reduce national drought risk. More generally, recent scenario analyses for Italian arable farming conclude that drought remains a structural vulnerability, with northern regions among the most exposed and maize among the most affected crops (Buttinelli et al., 2026). By contrast, fruits, citrus, vineyards, olives, and sugar beet emerge as MCC only in smaller localized areas because their smaller national extent is offset by high local value density and strong territorial specialization.

4.2. Added value and robustness of PRIME

The main contribution of PRIME relative to climate-only analyses is that it converts drought occurrence into management priority. Although both indices are derived from the same underlying SPEI, they produce markedly different priority maps: two thirds of the cultivated pixels change priority by two or more classes. This shows that the temporal window over which drought is evaluated (the crop-specific growing

season rather than a fixed accumulation period) and the inclusion of exposure and economic value are not secondary refinements, but the factors that determine where drought becomes a management priority. Climate-only indicators remain indispensable for identifying where drought develops and how it evolves (Baronetti et al., 2024; Bonaccorso et al., 2003; Bordi and Sutera, 2002; Granata and Di Nunno, 2026; Marini et al., 2019; Venturi et al., 2025), but they do not directly indicate whether recurrent deficits affect a marginal area or a strategically important irrigated production system. PRIME addresses this gap by explicitly evaluating drought at the temporal scale of each crop growing season and then combining hazard with irrigated area distribution and economic value. This distinction is particularly relevant for water management, where decisions must prioritize not only where drought occurs, but where it generates the greatest agricultural and economic impact. In practice, this shifts the question from “where does drought recur?” to “where is drought most likely to matter for agricultural management and resource allocation?”. For this reason, the methodology proposed here should be seen as a screening and prioritization tool that complements, rather than replaces, climate-only agricultural drought analyses. Indeed, PRIME is not designed to reproduce the specific footprint of an individual, unfolding drought event, whose timing, intensity and duration are inherently uncertain. Rather, it is suited to inform drought preparedness, the prioritization of long term investments in irrigation infrastructure and monitoring networks and targeted adaptation planning.

The equal weighting assigned to the drought hazard (DH) and agricultural value (AG) components provides a transparent and neutral baseline, ensuring that recurrent climatic pressure and productive relevance contribute symmetrically to the final ranking. This is appropriate for a first national-scale application because it avoids embedding an a priori policy preference in the index itself. Nevertheless, the robustness of the ranking to the equal weighting design choice was assessed under alternative weight combinations for the DH and AG components. The overall spatial pattern of priority proved stable: the vast majority of cultivated pixels remained within one priority class of the baseline (96–99% depending on the scheme), and fewer than 4% shifted by two or more classes, with the highest priority hotspots preserved across all schemes. This indicates that the identification of critical areas is not an artefact of the equal weighting choice, but a robust feature of the combined structure of the index. At the same time, the weighting scheme offers a transparent lever to adapt PRIME to different management objectives: a hazard-oriented weighting emphasizes chronically drought prone areas, suited to monitoring and preparedness, whereas a value-oriented weighting shifts attention towards strategic irrigated systems when the goal is to protect strategic irrigated systems, supply chains, or high value crops under limited investment capacity. In this sense, the sensitivity analysis confirms both the robustness of the baseline ranking and the adaptability of the framework, which can be tuned to different policy contexts. Since the pixel-level PRIME is obtained by summing the crop-specific contributions, individual crops can also be weighted differently according to the management objective. A food security perspective, for instance, could assign a higher weight to staple crops relative to higher value cash crops.

4.3. Operational implications and limitations

The operational value of PRIME lies in its potential to support transparent drought governance when water scarcity simultaneously affects multiple agricultural districts. Within proactive drought planning, PRIME can inform the targeting of Agricultural Strategic Water Shortage Preparedness Plans, Water Supply System Management Plans, and Drought Contingency Plans (Mendicino et al., 2008). When coupled with optimization-based approaches, PRIME hotspots can guide the allocation of scarce water resources toward areas where reductions in risk and economic losses would be greatest (Liu et al., 2021). At the district scale, the ranking may support crop-specific allocation

strategies: under severe water scarcity, studies from southern Italy show that economically optimal allocation may concentrate water on high value horticultural crops, while more extensive crops receive reduced irrigation (Rubino et al., 2012). PRIME can also inform the siting of structural and nature-based solutions. For instance, recent work from northern Italy shows that strategically located water retention ponds can improve irrigation availability, preserve ecological flows, and generate environmental co-benefits (Staccione et al., 2021); PRIME can help identify where such interventions are likely to deliver the greatest agricultural benefit.

Several limitations should nevertheless be acknowledged. First, PRIME is a relative prioritization framework and not a predictive loss model. It identifies where drought management attention should be concentrated, but it does not estimate yield losses, farm income losses, market feedbacks, or welfare effects for a specific drought event. Relatedly, the drought hazard component is based on the SPEI, which is a climatic drought indicator: a negative climatic water balance does not necessarily translate into crop level agricultural drought, since the latter also depends on soil moisture, irrigation supply, and fine scale phenology. Computing the SPEI over the crop-specific growing season and adopting an impact consistent threshold mitigates this issue but does not fully resolve it; PRIME should therefore be read as a growing season climatic hazard screening layer rather than a crop-water-stress or yield model. Second, the exposure and value components are effectively static representations, whereas cropping patterns, prices, and adaptation choices change through time. In particular, the irrigated crop-specific areas are derived from the recent AIDA dataset (Galli et al., 2025) and are treated as representative of the current cropping structure, while the drought hazard is computed over the full 1951–2022 climatology. To our knowledge, a spatially explicit, crop-specific, time varying dataset of irrigated areas covering the entire period at a comparable resolution does not currently exist for Italy; PRIME should therefore be interpreted as a relative priority ranking conditioned on the present irrigated agricultural structure, and historical land use change is not captured. The framework can be readily updated as time varying crop datasets become available. Third, PRIME does not explicitly account for irrigation water source, infrastructure performance, groundwater access, or reservoir buffering, although these features are known to shape actual vulnerability in Mediterranean systems (Masia et al., 2018). Finally, other potentially relevant processes such as crop quality deterioration, pests, fungal attacks, international price fluctuations, and long-term technological or behavioural adaptation are outside the current framework. These limitations imply that PRIME should be interpreted as a first order hotspot screening tool, ideally to be followed by region specific impact or water allocation analyses.

At the same time, these limits do not reduce the operational usefulness of the framework. At the national scale, PRIME can support the prioritization of monitoring, drought preparedness, and irrigation investments; at the regional scale, the MCC layer indicates which crop should be the primary target of crop-specific advisories, emergency water allocation, or adaptation planning. In northern Italy this points above all to maize and cereal-based systems, whose strategic relevance extends beyond farm output to feed chains and agro-industrial supply chains. In southern and insular Italy, it points more often to perennial and horticultural systems, where even relatively small, irrigated areas may have high economic value and strong territorial specialization. Because PRIME is transparent and based on nationally available data, it could be periodically updated and coupled with seasonal forecasts, reservoir status, or irrigation infrastructure information, thereby becoming a practical bridge between drought monitoring and agricultural water-management decisions.

5. Conclusions

This study developed and applied PRIME, a crop calendar-aware prioritization framework designed to identify where drought matters

most for irrigated agriculture. By combining recurrent drought exposure during crop-specific growing seasons with irrigated crop distribution and economic value, PRIME moves beyond the identification of climatic drought hotspots and translates drought occurrence into drought management priority. This shift is particularly relevant in Mediterranean agricultural systems, where increasing water scarcity requires administrations, irrigation agencies, and policymakers to prioritize mitigation strategies across regions, crops, and production systems.

The application to Italian irrigated agriculture shows that drought management priority is spatially uneven and does not simply correspond to the areas where drought occurs most frequently. Rather, priority emerges where recurrent crop season events intersect with widespread irrigated crops and localized high value systems. Indeed, priority is concentrated in major irrigated agricultural districts, especially in northern Italy, while localized hotspots emerge in central and southern Italy due to the presence of high value cropping systems. This indicates that the most critical drought hotspots are often spatially contained but economically significant, highlighting areas where water scarcity can disproportionately affect high value and strategically relevant production systems. The fact that several of these priority areas are consistent with areas known to sustain large economic damages during major drought events further supports the use of PRIME as a screening tool for drought management planning. At the crop level, maize growing areas emerge as the dominant national contributor to drought management priority, followed by triticale and pulses.

By integrating crop growing seasons and economic relevance, PRIME modifies hotspot identification compared with climate-only indicators. Areas with frequent drought may receive lower priority when agricultural exposure is limited, while areas with moderate drought frequency may become critical when water deficits affect valuable irrigated crops during their growing season. In this way, PRIME reframes the management question from “where does drought recur?” to “where is drought most likely to matter for agricultural management?”

Therefore, at a time when future projections point towards a decline in water availability, drought prone agricultural regions will increasingly face difficult choices in water allocation. PRIME’s simple, operational and reproducible structure can help address this need by supporting drought monitoring, preparedness planning, irrigation investments, and targeted adaptation under limited water management resources. At the national scale, it can help prioritize where attention and investments should be concentrated, while at the regional and district scales it can support administrations in identifying the crop systems and territories where targeted interventions are likely to deliver the greatest benefits. Because the framework is flexible, it can be periodically updated or adapted through alternative weighting schemes or other management relevant indicators. In this way, PRIME can act as a practical bridge between drought monitoring and agricultural water management decisions, offering a transferable framework to other drought-prone irrigated regions where limited water resources require transparent and spatially targeted prioritization.

As climate change progressively intensifies water scarcity across Mediterranean regions, drought management will increasingly require not only monitoring where drought occurs, but identifying where drought matters most for sustaining agricultural production and strategic water governance.

CRedit authorship contribution statement

Lorenza Cappellato: Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Benedetta Moccia:** Writing – original draft, Methodology, Data curation, Conceptualization. **Elena Ridolfi:** Writing – original draft, Supervision, Methodology, Conceptualization. **Fabio Russo:** Validation, Supervision, Methodology, Conceptualization. **Francesco Napolitano:** Validation, Supervision, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, Grammarly was used to assist with language editing and readability. After using this tool, the authors carefully reviewed and edited the manuscript and take full responsibility for the final content of the article.

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.

Acknowledgements

The authors gratefully acknowledge Harsh Nanesha for supplying the resampled AIDA dataset to match the resolution and spatial grid used in our analyses. This work was supported by the PRIN 2022 project CASTLE, funded by the Italian Ministry of University and Research, project code 2022XSERL4, CUP B53D23007580001.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.agwat.2026.110688](https://doi.org/10.1016/j.agwat.2026.110688).

Data Availability

Data will be made available on request.

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