REVIEW ARTICLE

A Systematic Review of Methods Used to Monitor and Predict Agricultural, Hydrological, and Meteorological Droughts

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Abstract

Droughts are among the most economically and ecologically destructive natural hazards, affecting more than half of the world's land surface annually and increasing in frequency and severity under anthropogenic climate change. Unlike episodic disasters such as earthquakes or hurricanes, droughts develop gradually and their full impacts may not be evident until months or years after peak conditions. This systematic review synthesises current knowledge of drought monitoring and prediction methods, encompassing approximately 27 drought indices—spanning meteorological, agricultural, hydrological, and remote sensing categories—and six major classes of prediction model: regression, time series, probabilistic, hybrid, machine learning, and deep learning. A structured literature search was performed across the Scopus, Web of Science, and Google Scholar databases. Following PRISMA-aligned screening, 95 primary studies were included. Results indicate that no single index performs optimally across all drought types, climates, or timescales. Multi-variable indices that integrate precipitation, evapotranspiration, and remote sensing data outperform univariate indices in complex settings. Among prediction models, hybrid architectures—most notably ARIMA-LSTM and wavelet-ANN combinations—consistently outperform individual models on both short- and long-term forecasting tasks, while deep learning approaches show strong potential but require large training datasets. Key research gaps include the limited integration of climate teleconnection indices into operational forecasting systems, the absence of standardised benchmarking across drought prediction studies, and the need for improved spatio-temporal modelling frameworks. This review provides a foundation for researchers and practitioners developing next-generation drought early warning systems.

Keywords: drought monitoring, drought prediction, drought indices, machine learning, remote sensing, ENSO, climate variability.

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1 Introduction

Droughts are recurrent natural phenomena that occur across all climatic zones, from arid deserts to humid temperate regions [1]. The Emergency Events Database (EM-DAT) has recorded hundreds of drought events globally over the twentieth century [2], with estimates suggesting 642 such events between 1900 and 2013, and observational and modelling evidence consistently indicate that drought frequency, duration, and intensity are increasing as a consequence of anthropogenic greenhouse gas emissions that amplify evapotranspiration and alter large-scale atmospheric circulation [3–5].

Unlike other natural hazards, droughts are characterised by a slow and spatially diffuse onset. Their cumulative effects—water shortages, crop failure, ecosystem degradation, forced migration, and famine—may continue for years after peak meteorological deficit [6, 7]. This temporal ambiguity complicates both the detection of drought initiation and the attribution of impacts. A widely accepted cascade model holds that a meteorological drought (precipitation deficit) propagates into agricultural drought (soil moisture deficit), then into hydrological drought (reduced streamflow and groundwater), and ultimately into socio-economic drought affecting water supply, hydropower generation, and human welfare [8, 9].

Effective drought risk management requires two complementary capabilities: timely monitoring to detect drought onset and spatial extent, and skillful prediction to anticipate drought development over lead times of weeks to seasons. Traditional monitoring based on rain gauge networks is spatially limited and inconsistent, particularly in data-scarce low- and middle-income countries. Satellite remote sensing has substantially enhanced monitoring capability by providing spatially continuous, temporally consistent observations of precipitation, soil moisture, vegetation health, and land surface temperature [10, 11]. On the prediction side, a diverse array of models—from classical statistical approaches to modern deep learning architectures—has been developed, though no consensus has emerged on best practice [12].

Despite the existence of multiple narrative reviews [1, 6], a comprehensive systematic synthesis that jointly evaluates drought indices and prediction models, characterises their strengths and limitations in a comparative framework, and identifies methodological research gaps is lacking. This paper addresses that gap. Existing reviews have addressed drought monitoring and modelling in important but partial ways. Mishra and Singh [1] provided a foundational synthesis of drought modelling approaches but predates the deep learning era entirely and does not cover satellite-derived remote sensing indices. Hao et al. [6] focused primarily on seasonal drought prediction and probabilistic forecasting, with limited treatment of agricultural and hydrological drought indices. Neither review adopts a systematic literature search protocol or applies PRISMA-aligned screening, meaning their conclusions rest on narrative rather than reproducible evidence synthesis. More recent contributions have tended to focus on specific drought types, regions, or model classes rather than providing a cross-cutting comparative framework. The present review addresses these deficiencies in four ways: (i) it applies a structured, PRISMA-aligned search across three major databases, ensuring reproducibility and reducing selection bias; (ii) it evaluates approximately 27 drought indices spanning meteorological, agricultural, hydrological, and remote sensing categories within a single unified framework; (iii) it incorporates the most recent advances in deep learning and transformer-based architectures published up to 2026, including transfer learning applications; and (iv) it explicitly evaluates the role of large-scale climate teleconnection indices — ENSO, NAO, PDO, and AMO — as predictors, a dimension underrepresented in prior systematic reviews. Prediction models — including statistical regression, time series, probabilistic, machine learning, and hybrid architectures — are reviewed and compared in Section 5.

The specific objectives of this review are to:

1. Identify and critically compare meteorological, agricultural, and hydrological drought indices, evaluating their input requirements, temporal scales, and performance characteristics.
2. Systematically review drought prediction models—including statistical, probabilistic, machine learning, and hybrid architectures—and synthesise evidence on their comparative performance.
3. Evaluate the role of large-scale climate variability indices (ENSO, NAO, PDO, AMO) as predictors in operational drought forecasting.
4. Identify key knowledge gaps and provide recommendations for future research and

operational practice.

2 Systematic Review Methodology

2.1 Literature Search Protocol

A structured literature search was conducted in three academic databases—Scopus, Web of Science (Core Collection), and Google Scholar—using combinations of the following terms: ("drought") AND ("monitoring" OR "prediction" OR "forecasting") AND ("index" OR "indices" OR "model" OR "machine learning" OR "remote sensing"). The search was restricted to English-language. It is acknowledged that 'deep learning' was not included as a standalone search term; papers employing deep learning architectures were instead captured through specific model-name terms including 'LSTM', 'long short-term memory', 'CNN', 'convolutional neural network', 'RNN', and 'recurrent neural network', supplemented by citation tracking from retrieved papers.

2.2 Screening and Inclusion Criteria

Retrieved records were screened at title and abstract level to exclude studies that: (i) focused exclusively on flood or frost rather than drought; (ii) reported model development without validation; (iii) were conference abstracts without full-text availability; or (iv) addressed only socio-economic drought without any physical monitoring or prediction component. Full-text screening was then applied to assess methodological rigour, data quality, and relevance to at least one of the four review objectives. Following PRISMA-aligned screening, 95 primary studies were included in the synthesis.

2.3 Data Extraction and Synthesis

For each included study, the following information was extracted: drought type addressed, index or model employed, geographic region, temporal scale, input variables, performance metrics, and reported limitations. Studies were then grouped thematically by drought type and methodology to enable comparative synthesis. Where multiple studies evaluated the same index or model, results were qualitatively compared and consensus findings highlighted.

The search was conducted in March 2026, covering publications from 2000 to March 2026, with no language restriction applied beyond the practical constraint that only English-language records could be screened by the review team.

3 Drought Types and Characteristics

There is no single universally accepted definition of drought [13, 14]. The World Meteorological Organization describes drought as a prolonged dry period arising from a lack of rainfall, but acknowledges that its expression depends on the hydrological component and socio-economic context in question. For the purposes of this review, we adopt the conventional four-category taxonomy: meteorological, agricultural, hydrological, and socio-economic drought [14], noting that these categories form a temporal cascade rather than independent phenomena.

3.1 Meteorological Drought

Meteorological drought is defined as a sustained deficit of precipitation relative to the long-term climatological average. It is the proximate driver of all other drought types [15] and develops most rapidly; it can also end quickly if precipitation resumes [6]. Its onset is modulated not only by precipitation amount but also by temperature, wind speed, relative humidity, and cloud cover, which collectively govern potential evapotranspiration and thus the effective water balance. At the synoptic scale, meteorological droughts are typically associated with anomalous blocking anticyclones and are ultimately forced by large-scale sea surface temperature anomalies—most notably those associated with ENSO [16, 17].

3.2 Agricultural Drought

Agricultural drought is characterised by a soil moisture deficit that impairs plant growth and reduces crop yields. It typically follows a meteorological drought after a lag period determined by soil type, land cover, and antecedent moisture conditions [6, 18]. Because soil moisture responds to both precipitation deficits and elevated evaporative demand, agricultural drought can intensify even during periods of near-average rainfall if temperatures are anomalously high—a pattern increasingly observed under climate change [19]. Remote sensing vegetation indices such as the Normalised Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Vegetation Health Index (VHI) provide operationally valuable proxies for agricultural drought, allowing near-real-time monitoring over large areas [18, 20].

3.3 Hydrological Drought

Hydrological drought is defined as a significant reduction in surface water flows, groundwater levels, and reservoir storage relative to long-term averages [1]. It develops more slowly than meteorological and agricultural drought owing to the buffering capacity of catchment storage [6]. Hydrological droughts are of primary concern for urban water supply, hydroelectric power generation, and irrigated agriculture, and their management requires long lead-time predictions. The propagation from meteorological to hydrological drought is not deterministic: catchment characteristics, antecedent storage, and snowpack dynamics all mediate the relationship [21]. The intensification of the global hydrological cycle under warming is expected to increase the frequency of severe hydrological droughts in many semi-arid regions [3, 22].

3.4 Socio-economic Drought

Socio-economic drought occurs when water supply deficits affect economic goods and services, leading to agricultural and livestock losses, reduced hydroelectric output, human migration, land degradation, and inter-community conflict over water resources [8]. While quantitative monitoring and prediction of socio-economic drought is beyond the scope of this physical-science review, it is important to recognise that effective early warning systems for meteorological, agricultural, and hydrological drought directly reduce socio-economic drought impacts.

4 Drought Indices and Indicators

Drought indices condense complex multi-variable hydrometeorological states into single scalar values that can be compared across regions and time periods. Table 1 provides a comprehensive comparative overview of 27 indices and prediction models examined in this review. The following subsections discuss key indices by category and highlight comparative performance findings from the literature.

4.1 Meteorological Drought Indices

The Standardised Precipitation Index (SPI, as described in Anshuka et al. [12]) is the most widely applied meteorological drought index globally owing to its computational simplicity—requiring only a long precipitation record—and its flexibility across timescales (1 to 48 months). Its principal limitation is that it neglects the temperature-driven component of drought through potential evapotranspiration (PET). The Standardised Precipitation-Evapotranspiration Index (SPEI; Anshuka et al. [12]) addresses this by incorporating PET, making it particularly relevant under warming conditions; however, SPEI values are sensitive to the PET estimation method employed (Thornthwaite vs. Penman-Monteith). A comparative analysis by Kamruzzaman et al. [23] found that the Effective Drought Index (EDI) outperformed SPI in capturing drought onset timing over Bangladesh due to its use of a precipitation accumulation scheme that weights recent observations more heavily.

The Palmer Drought Severity Index (PDSI; Svoboda and Fuchs [24]) provides a longer historical context and has been extensively validated across North America and Europe. Its complex water balance model makes it more physically comprehensive than SPI, but also more difficult to compute consistently across diverse climates.

Across the meteorological indices reviewed, a clear trade-off exists between data requirements and physical comprehensiveness. SPI remains the most operationally accessible index, requiring only precipitation data and performing consistently across 1–48 month timescales, but its neglect of evapotranspiration makes it increasingly unreliable in warming climates where temperature-driven demand amplifies drought severity independently of precipitation deficits. SPEI addresses this limitation directly but introduces sensitivity to the PET estimation method — Thornthwaite-based SPEI systematically underestimates drought severity in arid regions compared to Penman-Monteith-based SPEI. PDSI incorporates soil water balance but imposes a fixed ~9-month timescale that prevents flexible application, and its calibration to US climatic conditions limits transferability to other regions without recalibration. EDI outperforms SPI in capturing drought onset timing through its weighted accumulation scheme, as demonstrated by Kamruzzaman et al. [23] in Bangladesh, but its daily data requirement restricts use in data-scarce environments. Indices such as RAI, AAI, NDI, and KBDI serve specialised purposes — monsoon climates, fire risk, or agronomic early warning in specific regions — and are not intended as general-purpose meteorological drought monitors. The consistent finding across this category is that no single meteorological index performs optimally across all climates, timescales, and data environments, and multi-index approaches are recommended wherever observational resources permit.

Table 1. Summary of indices and indicators used around the world for drought detection, organised by category.

Drought Index / Indicator	Purpose	Advantages	Disadvantages	Origin (Author, Country, Year)	Key References
Palmer Drought Severity Index	Measures long-term meteorological drought severity using a soil water balance model.	• Physically comprehensive • long historical record • globally validated • includes soil moisture accounting	• Fixed 9-month timescale causes detection lag • poor handling of frozen soils • calibrated to US climate, limiting global transferability	PDSI	Svoboda & Fuchs [24] (2016)
Standardized Precipitation Index	Quantifies precipitation deficits at multiple timescales (1–24 months) for meteorological drought monitoring.	• Requires only precipitation data • spatially consistent • flexible across 1–48 month timescales • WMO-recommended	• Ignores temperature and evapotranspiration • insufficient alone for agricultural or hydrological drought in warming climates	SPI	Anshuka et al. [12] (2019); Svoboda & Fuchs [24] (2016)
Standardized Precipitation Evapotranspiration Index	Multi-scalar index incorporating precipitation and PET to monitor drought across all climate zones.	• Accounts for temperature-driven evapotranspiration • applicable globally • suited to climate change studies	• Requires complete temperature and precipitation records • sensitive to PET estimation method (Thornthwaite vs. Penman-Monteith) • limited in data-scarce regions	SPEI	Anshuka et al. [12] (2019); Svoboda & Fuchs [24] (2016)
Effective Drought Index	Detects drought onset, duration, and intensity using a weighted effective precipitation accumulation scheme.	• Single precipitation input • standardised across climates • accurately identifies drought episode timing • weights recent observations more heavily	• Does not incorporate temperature effects • daily data requirement complicates operational use	EDI	Kamruzzaman et al. [23] (2019); Svoboda & Fuchs [24] (2016)
Rainfall Anomaly Index	Quantifies normalised precipitation anomalies at monthly, seasonal, or annual timescales.	• Simple single-input computation • versatile across multiple timescales	• Requires serially complete dataset • within-year fluctuations must be small relative to temporal variability	RAI	Svoboda & Fuchs [24] (2016)
Aridity Anomaly Index	Assesses moisture stress over one- or two-week periods by comparing actual to normal aridity.	• Applicable to both winter and summer seasons • computationally straightforward	• Not suitable for long-term or multi-seasonal drought events	AAI	Svoboda & Fuchs [24] (2016)
NOAA Drought Index	Estimates agricultural production risk and provides early warning of drought in developing countries.	• Requires only monthly precipitation data • straightforward to apply	• Needs ≥30 years of record • requires conversion of monthly to weekly precipitation values	NDI	Svoboda & Fuchs [24] (2016)
Keetch–Byram Drought Index	Assesses drought conditions specifically for fire control and wildfire planning purposes.	• Scales to local climatic conditions • simple to compute • fire-management specific	• Designed for fire management only • unsuitable for agricultural or water resource applications	KBDI	Xanthopoulos et al. [50] (2006); Svoboda & Fuchs [24] (2016)
Reclamation Drought Index	Monitors river basin water supply conditions, incorporating temperature effects unlike SWSI.	• Includes both wet and dry monitoring scales • represents temperature impacts	• Basin-specific calculations prevent cross-regional comparison • multiple inputs may delay data generation	RDI	Svoboda & Fuchs [24] (2016)
Soil Moisture Anomaly	Monitors agricultural drought impacts by estimating soil moisture deficits at multiple depths.	• Incorporates both temperature and precipitation • more spatially flexible than PDSI	• Computationally demanding • PET estimation varies significantly by region	SMA	Svoboda & Fuchs [24] (2016)
Evapotranspiration Deficit Index	Monitors short-term agricultural drought using actual and potential evapotranspiration data.	• Directly captures both ET and PET to identify wet and dry periods	• Dependent on SWAT model output • spatial variability increases under high ET and variable precipitation	ETDI	Narasimhan & Srinivasan [30] (2005); Wambura [49] (2021); Svoboda & Fuchs [24] (2016)
Normalized Difference Vegetation Index	Detects and monitors agricultural drought stress through satellite-derived vegetation greenness.	• High spatial resolution and broad coverage • novel use of satellite data	• Sensitive to data processing quality • saturates in dense canopies • relatively short satellite record	NDVI	Kogan [38] (1995); Brown et al. [25] (2006); Svoboda & Fuchs [24] (2016)
Enhanced Vegetation Index	Identifies drought-induced vegetation stress in high-biomass regions with reduced canopy background effects.	• Reduces canopy background noise and atmospheric effects vs. NDVI • high spatial resolution	• Cannot distinguish drought stress from other canopy stressors • limited satellite record length	EVI	Huete et al. [28] (2002); Svoboda & Fuchs [24] (2016)
Vegetation Condition Index	Assesses vegetation drought status by normalising NDVI to multi-year pixel-level extremes.	• Removes inter-annual climate variability from vegetation signal • high spatial coverage	• Susceptible to cloud contamination • limited satellite record length	VCI	Kogan [38] (1995); Liu & Kogan [29] (1996); Svoboda & Fuchs [24] (2016)
Temperature Condition Index	Evaluates heat and moisture stress on vegetation using AVHRR thermal bands.	• High spatial resolution and broad regional coverage • captures thermal stress component	• Susceptible to cloud contamination • limited satellite record length	TCI	Kogan [38] (1995); Svoboda & Fuchs [24] (2016)
Vegetation Health Index	Composite indicator of moisture and heat stress combining VCI and TCI for agricultural drought monitoring.	• Robust composite signal of both moisture and thermal stress • operationally well established	• Susceptible to cloud contamination • equal weighting of VCI and TCI may not suit all regions	VHI	Kogan [38] (1995); Almamalachy [18] (2017); Kassahun et al. [37] (2025)
Normalized Difference Water Index	Detects canopy water content as a proxy for agricultural drought stress.	• High resolution • more sensitive to canopy moisture and water bodies than NDVI	• Cannot isolate drought as the sole cause of canopy stress	NDWI	Chandrasekar et al. [32] (2010); Svoboda & Fuchs [24] (2016)
Soil Moisture Deficit Index	Monitors agricultural drought using weekly soil moisture estimates from the SWAT model.	• Direct agricultural relevance • physically based soil water balance	• Dependent on SWAT model outputs • limited to gauged basins with calibration data	SMDI	Narasimhan & Srinivasan [30] (2005); Svoboda & Fuchs [24] (2016)
Soil Moisture and Evapotranspiration Revealed Drought Index	Combines MODIS soil moisture and Penman-Monteith ET to monitor agricultural drought in semi-arid regions.	• Integrates the two primary physical drivers of agricultural drought • strong correlation with LST • effective under warming conditions	• Weaker correlation with NDVI/NDWI due to irrigation variability • validated primarily in the Middle East	SERDI	Hamarash et al. [34] (2024)
Surface Water Supply Index	Detects hydrological drought by integrating precipitation, snowpack, streamflow, and reservoir storage.	• Extends PDSI by incorporating snow accumulation, snowmelt, and reservoir data • physically comprehensive	• Basin-specific computations prevent cross-regional comparison • requires multiple input data streams	SWSI	Doesken & Garen [31] (1991); Svoboda & Fuchs [24] (2016)
Streamflow Drought Index	Monitors and identifies hydrological drought at gauging stations across multiple timescales.	• Simple to implement • tolerates missing data • results are realistic across various timescales	• Single streamflow input may distort results during no-flow periods	SDI	Svoboda & Fuchs [24] (2016)
Standardized Runoff Index	Characterises hydrological drought through standardisation of monthly runoff volumes, analogous to SPI.	• Directly quantifies surface water availability • multi-timescale flexibility • computationally simple	• Requires reliable runoff or simulated discharge records • sensitive to land-use change and human modification of flows	SRI	Svoboda & Fuchs [24] (2016)
Standardized Streamflow Index	Monitors hydrological drought by standardising observed streamflow records at multiple timescales.	• Directly based on observed streamflow • flexible across timescales • comparable across basins when applied consistently	• Sensitive to regulation and abstraction • requires long stationary streamflow records for reliable fitting	SSI	Svoboda & Fuchs [24] (2016)
Standardized Reservoir Supply Index	Characterises water availability from reservoir storage using a probability distribution, similar to SPI.	• Simple SPI-like computation using a gamma distribution • directly reflects water storage status	• Does not account for changes in water use or evaporative losses	SRSI	Svoboda & Fuchs [24] (2016)
Standardized Water-level Index	Investigates drought impacts on groundwater recharge using well-level data.	• Directly captures drought effects on groundwater — critical for agricultural and municipal supply	• Considers only groundwater • interpolation between sites may not represent broader regional conditions	SWI	Svoboda & Fuchs [24] (2016)
Vegetation Drought Response Index	Monitors drought-induced vegetation stress by integrating remote sensing, climate, and land-use data.	• Innovative combination of surface and remotely sensed data • broad spatial coverage	• Not useful during periods of little or no vegetation • limited by short satellite record	VegDRI	Svoboda & Fuchs [24] (2016)
Microwave Integrated Drought Index	Integrates TRMM precipitation, AMSR-E soil moisture, and land surface temperature for multi-sensor drought monitoring.	• Enables monitoring in regions lacking dense meteorological networks • multi-variable physical basis	• Dependent on availability of specific satellite sensors • limited temporal record	MIDI	Zhang & Jia [33] (2013)

4.2 Agricultural Drought Indices

Optical remote sensing indices provide the most operationally practical route to agricultural drought monitoring over large heterogeneous areas. NDVI, derived from AVHRR, MODIS, SPOT-Vegetation, or Landsat sensors [25], remains the most widely used vegetation proxy. Its primary limitations include saturation in dense canopies and sensitivity to atmospheric correction errors. The Enhanced Vegetation Index (EVI; Huete et al. [28]) was developed to reduce canopy background noise and atmospheric effects that affect NDVI, improving performance in high-biomass regions. VCI normalises NDVI to multi-year minimum and maximum values for a given pixel and season, effectively removing the confounding influence of inter-annual climate variability on the raw vegetation signal [29]. VHI further combines VCI with a thermal condition index (TCI), providing a composite indicator of both moisture and heat stress [18].

The Soil Moisture Deficit Index (SMDI; Narasimhan et al. [30]) operates on weekly soil moisture estimates from the Soil and Water Assessment Tool (SWAT), providing direct agricultural relevance. Its dependence on hydrological model outputs, however, limits applicability in poorly gauged basins.

A recent addition is the Soil Moisture and Evapotranspiration Revealed Drought Index (SERDI; Hamarash et al. [34]), which combines MODIS-derived soil moisture with Penman-Monteith evapotranspiration to monitor agricultural drought in semi-arid regions. Validated across Iran, Iraq, Syria, Jordan, and Israel (2000–2020), SERDI showed a strong correlation with Land Surface Temperature and a moderate correlation with VHI, confirming its physical plausibility. Its explicit evapotranspiration component makes it particularly relevant under warming conditions where temperature-driven demand can intensify drought beyond what precipitation-based indices capture.

Among agricultural drought indices, the fundamental divide is between ground-based and satellite-derived approaches. Ground-based indices such as SMA and ETDI are physically explicit — directly measuring or modelling soil moisture and evapotranspiration — but are constrained to locations with adequate meteorological station networks and are poorly suited to spatial monitoring over heterogeneous landscapes. Satellite-derived vegetation indices — NDVI, EVI, VCI, TCI, NDWI, and VHI — offer near-global spatial coverage and consistent temporal repeat cycles but share a common limitation: they measure vegetative response to drought rather than drought itself, introducing a phenological lag of days to weeks and an inability to distinguish drought stress from other stressors such as pest damage, nutrient deficiency, or land use change. VCI and TCI partially address this by normalising raw vegetation and thermal signals to their multi-year pixel-level extremes, removing the confounding influence of inter-annual climate variability, and their combination in VHI produces a more robust composite signal of both moisture and heat stress. EVI improves upon NDVI specifically in high-biomass regions where canopy saturation limits NDVI sensitivity. The most recent addition, SERDI, represents a physically motivated integration of soil moisture and evapotranspiration that bridges the gap between ground-based and satellite-derived approaches, though its validation remains regionally confined to semi-arid Middle Eastern conditions. A general recommendation emerging from this category is that vegetation-based indices alone are insufficient for early detection of agricultural drought onset; combining a soil moisture index with a vegetation condition index provides more timely and physically grounded monitoring than either approach alone.

4.3 Hydrological Drought Indices

The Surface Water Supply Index (SWSI; Doesken and Garen [31]) integrates precipitation, snowpack, streamflow, and reservoir data into a single composite index, making it particularly suited to snowmelt-dominated basins. Its basin-specificity, however, prevents direct cross-regional comparisons. The Standardised Hydrological Index (SHI) is the hydrological analogue of SPI, applied to standardised streamflow anomalies; it is particularly useful for characterising hydrological drought propagation from meteorological deficits. The Normalised Difference Water Index (NDWI; Chandrasekar et al. [32]) and Land Surface Water Index (LSWI) provide satellite-derived estimates of surface and canopy water content applicable to both agricultural and hydrological drought monitoring. The Microwave Integrated Drought Index (MIDI; Zhang and Jia [33]) represents a newer class of satellite-derived multi-sensor index that integrates TRMM precipitation, AMSR-E soil moisture, and AMSR-E land surface temperature, enabling monitoring in regions lacking dense meteorological station networks.

Hydrological drought indices differ from meteorological and agricultural indices in their inherent temporal lag — streamflow, reservoir storage, and groundwater respond to precipitation deficits over weeks to months, meaning hydrological drought typically persists well beyond the meteorological events that trigger it. Among the reviewed indices, SWSI is the most physically comprehensive, integrating precipitation, snowpack, streamflow, and reservoir storage, but its basin-specific parameterisation means it cannot be transferred across watersheds without recalibration. SDI offers a computationally simpler alternative analogous to SPI that can be applied consistently across multiple gauging stations and timescales, and its tolerance of missing data gives it operational advantages in poorly instrumented basins. SRSI and SWI extend the standardised index framework to reservoir storage and groundwater levels respectively, enabling monitoring of specific components of the hydrological system that SWSI and SDI do not separately resolve. The key limitation across all hydrological indices is their dependence on in-situ monitoring infrastructure — stream gauges, reservoir records, and groundwater wells — which severely restricts applicability in the data-scarce regions that are often most drought-vulnerable. Integration of satellite-derived products such as GRACE-derived terrestrial water storage anomalies with traditional hydrological indices represents a promising direction for extending hydrological drought monitoring to ungauged basins.

4.4 Practical Guidance for Index Selection

The diversity of drought indices reviewed in Sections 4.1–4.3 presents practitioners and researchers with a non-trivial selection problem. The following guidance synthesises the comparative findings above into a scenario-based framework for rational index selection.

When data availability is limited to precipitation records only, SPI is the recommended starting point. It is WMO-endorsed, computationally simple, flexible across timescales, and has been validated globally. Where temperature data are also available and the study region is subject to warming trends, SPEI should be preferred over SPI as it captures the evapotranspiration component of drought that SPI systematically ignores.

For agricultural drought monitoring over large heterogeneous areas, satellite-derived indices are preferred. VHI — combining VCI and TCI — provides the most robust composite signal of moisture and thermal stress and is operationally well established. Where canopy density is high, EVI should be used in place of NDVI. Where soil moisture and ET data are available from MODIS or equivalent sensors, SERDI offers a physically motivated alternative that is particularly well suited to semi-arid and warming environments.

For hydrological drought assessment, index selection should be guided by the available monitoring infrastructure. Where streamflow records exist, SDI provides a consistent, transferable monitoring framework. Where snowpack and reservoir data are also available, SWSI offers a more comprehensive but basin-specific characterisation. In basins where groundwater is the primary water resource, SWI should be included alongside surface water indices.

For regional or global monitoring in data-scarce environments, multi-index satellite systems are the most practical options, as they require no ground-based input and provide near-real-time coverage. Their coarser spatial resolution limits their utility for field-scale agricultural applications but makes them well suited to national or continental early warning systems.

Where multiple drought types must be monitored simultaneously — as is typical in operational early warning systems — a tiered approach is recommended: SPI or SPEI for meteorological monitoring, VHI or SERDI for agricultural monitoring, and SDI or SWSI for hydrological monitoring. No single index spans all three drought types adequately, and multi-index frameworks consistently outperform single-index approaches in capturing the full drought continuum from meteorological onset through agricultural impact to hydrological response.

5 Drought Prediction Models

Drought prediction models can be organised into four broad categories that reflect their underlying assumptions, data requirements, and physical basis: (1) classical statistical and empirical models, encompassing regression, time series, and probabilistic approaches; (2) physical and process-based models, including general circulation models, regional climate models, land surface models, and hydrological models; (3) machine learning and deep learning models; and (4) hybrid and integrated models that combine two or more of the above approaches. This classification aligns with the structure adopted in recent comprehensive reviews of hydroclimatic prediction [1, 6] and reflects the full methodological spectrum from purely data-driven to physically explicit approaches.

5.1 Classical statistical and empirical models

Linear and multiple linear regression (MLR) models represent the most interpretable class of drought prediction approach. Kumar and Panu (1997, as described in Mishra and Singh [1]) demonstrated early applications of regression to agricultural drought forecasting, using crop yield as a response variable and meteorological drivers as predictors. MLR has been applied to spatiotemporal SPI analysis in Greece [12] and to the prediction of the Standardised Differential Vegetation Index from SPI. The principal limitation of regression models is the assumption of linearity and stationarity between predictors and the drought response variable, which restricts their performance in non-stationary hydroclimatic systems and limits their applicability beyond seasonal lead times [6, 12].

Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension SARIMA are the most widely applied time series methods for drought prediction. ARIMA models exploit temporal autocorrelation in drought index series—particularly SPI—and have demonstrated reasonable performance for 1–3 month lead times [1, 12]. SARIMA additionally captures intra-annual periodicity. However, both models assume linearity and stationarity, and comparisons with Artificial Neural Networks (ANN) have consistently shown that ANN and Wavelet-ANN (WANN) outperform ARIMA for SPI prediction [52], particularly at longer lead times where non-linear dynamics become dominant. In response, hybrid ARIMA-ANN frameworks that apply ARIMA to the linear component and ANN to the residuals have been shown to yield superior accuracy to either model alone [12].

Probabilistic models—including conditional probability models and Markov Chain (MC) models—are particularly well-suited to characterising drought transition dynamics and quantifying forecast uncertainty [1]. The MC model frames drought prediction as a state-transition problem, estimating the probability of transitioning from a wet or normal state to a dry state (and vice versa) based on historical drought index sequences [6]. MC models have been applied to the Palmer Drought Index, SPI, and the Standardised Hydrological Index (SHI). Their primary limitation is the Markov assumption of memorylessness (i.e., that future states depend only on the current state), which may underestimate persistence effects in multi-year drought sequences.

This category encompasses regression models, time series models, and probabilistic approaches, all of which share the common assumptions of stationarity and linearity in the relationship between predictors and drought response. Linear and multiple linear regression (MLR) models represent the most interpretable class, applied to SPI forecasting and crop yield prediction [12]. Time series models — principally ARIMA and SARIMA — extend this framework by explicitly modelling autocorrelation structures in drought index sequences, offering computational transparency and efficiency for short-to-medium lead times. Probabilistic models, including Markov Chain approaches, characterise drought as a state-transition process and are particularly well suited to quantifying forecast uncertainty and drought persistence probabilities [1, 6]. Across all three approaches, the principal shared limitation is the assumption of stationarity — the implicit expectation that historical statistical relationships between predictors and drought response will remain constant under future climatic conditions — which increasingly restricts their reliability under anthropogenic climate change.

5.2 Physical and process-based models

Physical and process-based models simulate drought through explicit representation of atmospheric, land surface, and hydrological processes, making them fundamentally distinct from data-driven statistical approaches. Their primary advantage is that predictions are grounded in physical first principles rather than statistical correlations, giving them theoretical transferability to future climatic conditions that statistical models lack. Their primary disadvantage is computational cost and the requirement for extensive input data to drive and parameterise the model.

General Circulation Models (GCMs) and Regional Climate Models (RCMs) constitute the foundation of seasonal-to-decadal drought prediction. GCMs simulate large-scale atmospheric and oceanic circulation to generate precipitation and temperature projections at global scale, from which drought indices such as SPI and SPEI can be derived. The CMIP6 ensemble of GCMs has been widely applied to project future drought frequency and severity under SSP emissions scenarios across all major drought-vulnerable regions [6]. RCMs dynamically downscale GCM output to finer spatial resolutions — typically 10–50 km — enabling regional drought characterisation that GCMs at 100–200 km resolution cannot resolve. A recognised limitation of both GCMs and RCMs is systematic bias in simulated precipitation, necessitating bias correction before drought indices can be reliably derived from model output.

Land surface models (LSMs) — including the Variable Infiltration Capacity model (VIC), the Noah land surface model, and the Community Land Model (CLM) — simulate the full soil-vegetation-atmosphere water and energy balance, generating soil moisture, evapotranspiration, and runoff outputs that directly underpin agricultural and hydrological drought monitoring. When driven by bias-corrected GCM or reanalysis forcing, LSMs provide physically consistent estimates of agricultural drought at spatial scales relevant to regional early warning systems. The Global Land Data Assimilation System (GLDAS), which assimilates satellite and ground-based observations into the Noah and CLSM land surface models, represents the most widely used operational implementation of this approach for multi-type drought monitoring.

Hydrological models — including SWAT (Soil and Water Assessment Tool), HBV, and VIC in its hydrological routing configuration — extend the land surface water balance to simulate streamflow, reservoir inflow, and groundwater recharge, enabling hydrological drought prediction at the catchment scale. SWAT has been applied extensively to SDI and SWSI prediction in gauged catchments, while VIC has been used for continental-scale hydrological drought projection under climate change scenarios. The principal limitation shared across hydrological models is their dependence on in-situ calibration data — stream gauges and soil surveys — which restricts applicability to ungauged basins that represent a large fraction of drought-vulnerable regions globally.

Despite their physical rigour, process-based models are less represented in the recent drought prediction literature than machine learning approaches, partly due to their computational demands and partly due to the rapid performance gains achieved by deep learning architectures on benchmark datasets. However, physical models retain irreplaceable advantages for long lead time prediction, climate change scenario analysis, and regions where observational training data are insufficient to support data-driven approaches.

5.3 Machine learning and deep learning models

Artificial Neural Networks (ANN) have been applied to drought prediction since the mid-2000s, with early influential work by Mishra and Desai [42] demonstrating the use of feed-forward recursive neural networks to forecast the Standardized Precipitation Index (SPI) in Indian river basins. Their capacity to model non-linear relationships between climate predictors and drought response without requiring explicit specification of physical process equations gives them a practical advantage over mechanistic models in data-rich but process-uncertain settings [44]. Support Vector Regression (SVR) offers theoretical advantages over ANN in terms of structural risk minimisation and resistance to overfitting, particularly for small training datasets. Mokhtarzad et al. [43] conducted a primary comparison of ANN, ANFIS, and SVM for SPI prediction in Iran and found that SVM outperformed the other two approaches across most temporal scales. ANFIS, which combines the approximation capability of ANN with the interpretable rule base of fuzzy logic, has also demonstrated competitive performance in SPI class prediction, though results vary by region and time scale [43]. All three approaches share a common limitation: reduced performance when trained data are non-stationary, and inability to extrapolate reliably beyond the range of training conditions.

Long Short-Term Memory (LSTM) networks have emerged as a powerful architecture for drought index prediction owing to their capacity to learn long-range temporal dependencies through gated memory cells, addressing a fundamental weakness of standard ANNs [51]. LSTM-based multi-scale prediction of SPI and SPEI has demonstrated superior handling of non-linear temporal dynamics and strong long-term predictive skill compared to ARIMA and ANN benchmarks [51]. A limitation is that LSTM is computationally expensive to train and requires substantial amounts of sequential training data; it may underperform ARIMA for very short time series or very short lead times.

5.4 Hybrid and integrated models

Hybrid models that combine the linear modelling capability of ARIMA with the non-linear approximation power of LSTM or SVR have consistently achieved the highest prediction accuracy across multiple benchmarking studies.

The ARIMA-LSTM hybrid captures both linear autocorrelation and non-linear temporal dynamics and has demonstrated improved performance on both short-term meteorological and long-term hydrological drought forecasting tasks [51]. Similarly, wavelet-transformed inputs pre-processed to remove non-stationarity before input to ANN or SVR models (WA-ANN, WA-SVR) have shown marked improvement over non-transformed counterparts across multiple SPI time scales [26]. These results suggest that the optimal prediction framework for operational drought forecasting is a hybrid architecture combining linear decomposition (ARIMA or wavelet transform) with a non-linear learner (LSTM or ANN), applied to multi-variable inputs that include both local hydrometeorological observations and large-scale climate teleconnection indices.

6 Climate Variability Indices as Drought Predictors

Large-scale climate oscillations modulate precipitation and temperature patterns at seasonal to multi-decadal timescales, making them potentially powerful predictors in statistical drought forecasting systems [16, 45].

6.1 El Niño–Southern Oscillation (ENSO)

ENSO is the dominant interannual mode of climate variability affecting drought at global scale. The warm phase (El Niño) is associated with drought conditions across Australia, southern Africa, parts of South America, and South and Southeast Asia, while producing anomalously wet conditions in the equatorial Pacific and western South America [16, 48]. The Southern Oscillation Index (SOI) and the Multivariate ENSO Index (MEI) are the most widely incorporated ENSO predictors in drought forecasting models. Huang et al. [36] found that ENSO exerted a significantly stronger influence on hydrological drought variability than the Arctic Oscillation (AO) in the Columbia River Basin.

6.2 North Atlantic Oscillation (NAO)

The NAO modulates winter precipitation and temperature across Europe and North America through alternating phases of the pressure gradient between the Icelandic Low and Azores High [45]. Positive NAO phases are associated with dry conditions in the Mediterranean and wet conditions in northern Europe, with the reverse occurring during negative phases. NAO has been incorporated as a predictor in several European drought forecasting models, improving seasonal predictability in the Mediterranean basin.

6.3 Pacific Decadal Oscillation (PDO) and Atlantic Multi-decadal Oscillation (AMO)

The PDO is a decadal-scale SST oscillation in the North Pacific that modulates the frequency and intensity of ENSO events and has been associated with multi-decadal drought regimes in North America and Central Asia [22, 45]. The AMO is a 60–90-year oscillation in North Atlantic SST that influences Atlantic hurricane activity and North American and European precipitation on multi-decadal timescales. Integration of PDO and AMO indices into drought prediction models remains limited but represents a promising avenue for extending forecast skill beyond seasonal timescales.

7 Synthesis and Discussion

Building on the comparative analysis of individual index categories in Sections 4.1–4.3 and the selection framework in Section 4.4, this section synthesises cross-cutting findings across drought indices and prediction models. Compared with prior narrative reviews, this systematic synthesis makes several methodological and substantive advances. The use of a structured PRISMA-aligned protocol across Scopus, Web of Science, and Google Scholar — with explicit inclusion and exclusion criteria — provides a level of reproducibility absent from earlier reviews. The concurrent evaluation of both drought indices and the models used to characterise drought dynamics within a single comparative framework is a distinguishing feature of this work. Furthermore, the integration of recent transformer-based deep learning architectures and transfer learning applications [7, 35] reflects developments that postdate all major prior reviews, ensuring that the synthesis reflects the current frontier of the field.

7.1 Comparative Performance of Drought Indices

No single drought index is universally optimal. The choice of index must be guided by the drought type of interest, data availability, and intended application. For data-scarce regions where only rain gauge data are available, SPI is the most practical choice. In regions with reliable temperature records, SPEI is preferable for capturing temperature-driven drought intensification under climate change. For agricultural applications with access to satellite imagery, composite indices such as VHI and NDVI-based products provide operationally timely information. In data-rich environments with hydrological model infrastructure, soil moisture-based indices (SMDI) or multi-sensor indices (MIDI) offer additional physical realism.

Among newer indices, SERDI [34] directly targets the two root-cause physical processes of agricultural drought — soil moisture and evapotranspiration — and showed strong agreement with LST across semi-arid Middle Eastern regions, though broader validation beyond this climate zone is still needed.

7.2 Comparative Performance of Prediction Models

Across the reviewed literature, hybrid models—particularly ARIMA-LSTM and wavelet-transformed ANN—consistently outperformed single-model approaches. Pure time series models (ARIMA, SARIMA) offer transparency and are computationally efficient but are limited to linear, stationary dynamics. Machine learning models (ANN, SVR, ANFIS) improve non-linear performance but require careful regularisation to prevent overfitting. Deep learning LSTM models provide strong long-range temporal modelling but are data-hungry. The absence of standardised benchmarking datasets and evaluation protocols across drought prediction studies is a significant limitation that prevents quantitative meta-analysis. Future work should prioritise the development of shared benchmark datasets and common evaluation metrics (e.g., ranked probability skill score, spatial correlation at multiple lead times) to enable rigorous model comparison.

Physical and process-based models — GCMs, RCMs, LSMs, and hydrological models — are not directly comparable to data-driven approaches on short-term prediction benchmarks, as they are designed primarily for seasonal-to-decadal prediction and climate change scenario analysis rather than index-scale forecasting. Their strength lies in physical interpretability and transferability to future conditions, dimensions on which purely statistical or machine learning models cannot be evaluated using historical validation data alone.

7.3 Integration of Climate Teleconnections

Despite strong evidence that ENSO, NAO, and PDO modulate drought variability at seasonal to decadal timescales [16, 36], their systematic integration into operational drought forecasting systems remains limited. Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA) have been used to reduce the dimensionality of large-scale SST predictor fields before incorporation into regression and machine learning models [6]. Recent transformer-based architectures that incorporate attention mechanisms across both spatial and temporal dimensions offer a promising avenue for exploiting climate teleconnection patterns at subcontinental to global scales [46, 47].

7.4 Recent Advances in Deep Learning for Drought Forecasting

Several methodologically significant contributions have appeared in the literature. Li et al. [40] applied an XGBoost framework with SHAP (Shapley Additive Explanations) analysis to hydrological drought prediction across the Huaihe River Basin, China, achieving 79.9% classification accuracy and confirming SPI as the single most influential predictor across all seasons, with soil moisture and evapotranspiration emerging as critical secondary drivers in spring and autumn. This SHAP-based interpretability approach represents an important step toward explainable machine learning in drought science.

Bouaziz et al. [27] evaluated SVR, Random Forest, k-Nearest Neighbour, and Linear Regression over a century-long precipitation record from semi-arid Tunisia for multi-scale SPI prediction, demonstrating that SVR outperformed all other methods at every timescale tested and confirming the value of century-long observational records for model training. Li et al. [41] investigated the performance of LSTM, CNN, XGBoost, and Random Forest for US Drought Monitor classification prediction across California, finding that LSTM emerged as the top performer with a macro F1 score of 0.90, and that county-level performance varied systematically by drought regime consistency.

On the deep learning frontier, Danandeh Mehr et al. [35] introduced the S-Transformer—a sequential-based transformer architecture for meteorological drought prediction using SPEI—reporting superior performance over LSTM in capturing long-range temporal dependencies. Pathania and Gupta [46] developed an interpretable national-scale transformer model for SPEI-3 forecasting across India's diverse climatic zones at 30-, 60-, and 90-day lead times, identifying the Indian Ocean Dipole (IOD) as the dominant large-scale climate driver. A subsequent study by Pathania and Gupta [47] demonstrated the transferability of this pre-trained transformer architecture across diverse precipitation datasets, opening new possibilities for drought forecasting in data-scarce regions through transfer learning.

For remote sensing-based monitoring, Kassahun et al. [37] applied a multi-index framework combining VCI, TCI, VHI, SPEI, and the Vegetation Drought Index (VDI) in the Ethiopian highlands, finding that no single index captured the full complexity of agricultural drought across heterogeneous terrain. Rahman et al. [7] conducted a spatiotemporal assessment of agricultural drought impacts on crop yields across Punjab, Pakistan, using MODIS-derived VCI, TCI, and VHI, quantifying crop-specific resilience for seven major crops and linking drought severity directly to yield losses. Lakshmi et al. [39] applied Google Earth Engine (GEE) to integrate NDVI, NDWI, NDDI, VCI, TCI, VHI, PCI, SDCI, and soil moisture indices for agricultural drought monitoring in the Antalya Basin, Türkiye (2001–2023), demonstrating the operational value of cloud-computing platforms for regional-scale multi-index assessment. Together, these recent studies confirm the ongoing transition in drought science from single-index, single-station approaches toward multi-index, spatially explicit, and interpretable machine learning frameworks.

7.5 Key Research Gaps

(1) Standardised benchmarking. The absence of shared benchmark datasets and common evaluation protocols is one of the most significant methodological limitations in drought prediction research. Studies employ different drought indices, time periods, geographic regions, and performance metrics, making direct model comparison across studies effectively impossible. This problem is compounded by the growing diversity of deep learning architectures, each evaluated under different conditions [27, 41]. Future efforts should prioritise the development of openly accessible benchmark datasets covering diverse climatic regions, alongside standardised evaluation metrics such as the ranked probability skill score and spatial correlation at multiple lead times.

(2) Spatio-temporal modelling. The majority of drought prediction studies focus on a single gauge, station, or pixel, treating drought as a temporally varying but spatially fixed phenomenon. This is a critical limitation given that drought is inherently a spatially continuous process whose extent and severity vary across landscapes. Transformer and convolutional LSTM architectures capable of simultaneously modelling spatial and temporal drought dynamics are beginning to emerge [35, 46], but these approaches have been validated in only a small number of regions. Broader application across diverse climatic and physiographic settings is needed before such models can be adopted in operational early warning systems.

(3) Non-stationarity under climate change. Statistical drought models are typically trained and validated on historical data under the implicit assumption that the statistical relationships between predictors and drought response are stationary over time. However, anthropogenic climate change is systematically altering precipitation patterns, evapotranspiration regimes, and large-scale atmospheric circulation, meaning that models calibrated on historical records may be poorly suited to future conditions. Ensemble approaches that combine outputs from global climate models with statistical downscaling and bias correction offer one route to addressing non-stationarity, but consensus on best practice remains elusive. Developing drought monitoring and prediction frameworks that are explicitly designed for non-stationary hydroclimatic systems represents an urgent research priority.

(4) Data-scarce regions. The majority of high-performance machine learning and deep learning drought studies have been conducted in North America, Europe, or eastern China, where long observational records and dense monitoring networks are available. Large parts of Africa, the Middle East, and Central Asia — regions that are among the most drought-vulnerable globally — remain severely underrepresented in the literature. Transfer learning applied to pre-trained transformer models [47] offers a promising route to extending predictive skill to under-observed regions by leveraging knowledge acquired in data-rich environments. Complementary investment in ground-based observation networks and satellite-derived proxy datasets in these regions is also essential.

(5) Explainability and operational trust. A persistent barrier to the adoption of machine learning and deep learning models in operational drought early warning systems is their lack of interpretability. Forecasters and decision-makers require not only accurate predictions but also physically plausible explanations for model outputs that can be communicated to stakeholders. SHAP-based interpretability methods [41] and attention-based transformers [46] are beginning to

address the black-box limitations of these models, providing quantitative attribution of predictions to specific input variables. Embedding explainability as a core design requirement — rather than a post-hoc analysis — in future drought prediction model development will be essential for building the operational trust necessary for real-world deployment.

8 Limitations

This review has several limitations that should be considered when interpreting its findings. First, despite a structured PRISMA-aligned search across three major databases, some relevant studies may have been missed due to language restrictions or indexing gaps. Second, the omission of 'deep learning' as an explicit search term represents a search protocol limitation; papers employing deep learning architectures were captured through specific model-name terms — including 'LSTM', 'CNN', 'RNN', and 'recurrent neural network' — supplemented by citation tracking, but papers using only the umbrella label 'deep learning' without naming a specific architecture may not have been systematically retrieved. The deep learning synthesis in Sections 5.3, 5.4, and 7.4 should therefore be interpreted with this caveat in mind. Third, the qualitative nature of the synthesis — necessitated by the heterogeneity of performance metrics, drought types, and geographic regions across included studies — prevents formal quantitative meta-analysis. Fourth, the review reflects the literature available at the time of the search and may not capture the most recently published studies.

9 Conclusions

This systematic review evaluated approximately 27 drought indices spanning meteorological, agricultural, hydrological, and remote sensing categories, and six classes of prediction model. The principal findings are as follows:

1. No single drought index is universally optimal. SPI is recommended for data-scarce meteorological monitoring; SPEI for temperature-sensitive environments; composite remote sensing indices (VHI, EVI) for agricultural early warning as confirmed by Kassahun et al. [37] and Rahman et al. [7]; multi-variable hydrological indices (SMDI, SWSI) for water resource management; and the newly proposed SERDI [34] for physically-based agricultural drought monitoring in semi-arid regions where both soil moisture and evapotranspiration are available from satellite data.
2. Among prediction models, hybrid architectures—ARIMA-LSTM and wavelet-ANN in particular—consistently outperform individual models. Emerging transformer and XGBoost-SHAP approaches [35, 40, 46] represent the new frontier of interpretable, high-accuracy drought forecasting.
3. Climate teleconnection indices (ENSO, NAO, PDO) are under-exploited as predictors in operational systems. Attention-based transformer models [46, 47] offer a principled framework for integrating large-scale climate drivers into spatially explicit, multi-scale forecasting systems.
4. Critical research gaps include the absence of standardised benchmarking, limited application of deep learning to data-scarce regions, inadequate treatment of non-stationarity under climate change, and insufficient integration of explainability methods. Transfer learning [47] and SHAP-based attribution [41] are beginning to address these challenges.
5. Addressing these gaps will require coordinated international efforts in data sharing, benchmark dataset development, and the adaptation of modern deep learning methods to the specific challenges of drought prediction in under-observed and rapidly changing environments.

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