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Effects of Climate Change on Drought: A Systematic Review of Drought Indices and Climate Change

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ABSTRACT

Global weather patterns are greatly impacted by climate change, making droughts more frequent and severe, especially in regions with limited adaptation capacity. This review evaluates the strengths and limitations of widely used drought indices in the context of climate change. Our analysis identifies the Standardized Precipitation Evapotranspiration Index (SPEI) and the Normalized Difference Vegetation Index (NDVI) as the most robust tools for monitoring drought under current and projected climate scenarios, with CMIP6 models indicating increased drought risk for vulnerable regions such as South Asia. The integration of remote sensing and artificial intelligence enhances the accuracy and adaptability of drought monitoring. The findings highlight the need for region-specific frameworks and actionable recommendations for researchers, policymakers, and technologists to improve drought resilience and management strategies.

INTRODUCTION

Environmental and climate change have been profound over the past century. Severe natural calamities, such as droughts and floods, have been triggered by global heating, leading to changes in water distribution throughout the hydrological cycle (Leng et al. 2015). Accelerated population growth and climate change have emerged as the most significant obstacles to sustainable human resource development and the conservation of natural systems. Humans have modified drought characteristics during the Anthropocene, so they may no longer be regarded as “natural hazards” in their entirety (Van Loon et al. 2016, Haile et al. 2020). Drought is generally characterised as an abnormal lack of moisture compared to a standard reference point, but it is more specifically categorised depending on the particular phase of the water cycle in which these deviations in moisture emerge (Wilhite & Glantz 1985).

The concept of drought lacks a broadly agreed-upon definition. According to McMahon and Diaz Arenas (1982), drought is a prolonged period of arid weather that affects the water supply, producing a moisture scarcity for human use. The drought phenomenon has long been a focal point of interest among ecologists. Research publications titled “Drought” have been published since at least the 1920s (Gorham & Kelly 2018), and the ecological effects of drought have long been studied. Due to climate model forecasts of increasingly frequent, severe, and pervasive water shortages, curiosity has grown in this subject in recent decades (Stocker et al. 2013). Globally, the impact of drought on terrestrial ecosystems has increased over the last century, as confirmed by many investigations (Schwalm et al. 2017, Du et al. 2018). Generally, drought severity can be measured by drought indices using drought indicators.

Drought is a complex phenomenon, often described as a prolonged period of water scarcity that results from significant moisture deficits compared to historical norms. It directly impacts agriculture, water supply, ecosystems, and economies. Historically, droughts have triggered severe consequences, including famines and ecosystem degradation. Unlike other natural hazards, drought's onset and termination are often slow and challenging to predict, making it particularly devastating. Understanding drought in the context of climate change is increasingly critical, as climate models project more frequent, severe, and widespread water shortages in the coming decades (Rahman 2017, Wilhite 2000).

Various drought indicators and indices have been developed to quantify and monitor drought severity, each tailored to specific aspects of the hydrological cycle and regional characteristics. For instance, indices such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and the Palmer Drought Severity Index (PDSI) are widely utilized but have varying degrees of effectiveness in capturing drought dynamics under changing climatic conditions (Dixit et al. 2022). These indices help contextualize drought severity, offering critical insights for policymakers and researchers. However, traditional methods often struggle with the challenges posed by climate change, such as non-stationarity and the increasing influence of human activities on hydrological patterns.

The main aim of this review paper is to provide a comprehensive synthesis of current research and understanding regarding the correlation between climate change and drought. The review systematically incorporates recent studies to analyze drought indices and indicators, emphasizing their applicability in evolving climatic conditions. A detailed evaluation of the 25 most widely recognized drought indices is presented, focusing on their methodological strengths, limitations, and relevance to contemporary research challenges. These indices are assessed within the context of changing climate scenarios to analyze the research undertaken on the connection between drought and climate variability. Most past reviews have focused either on specific drought indices or particular geographic regions, whereas this paper provides a broader comparative evaluation of 25 indices in the context of climate change, addressing a critical gap in current literature.

The study also explores the potential for integrating advanced technologies, such as remote sensing and artificial intelligence, to develop hybrid drought indices that address the limitations of traditional approaches. By highlighting these advancements, the review underscores the need for innovative, region-specific frameworks to enhance drought resilience.

This review synthesizes recent advancements in drought monitoring to address critical gaps in understanding how traditional and emerging indices perform under evolving climate conditions. By evaluating the robustness of drought indices across historical, CMIP5, and CMIP6 scenarios, we identify those most resilient to temperature-driven hydrological shifts and non-stationary climatic patterns. The analysis systematically compares their efficacy in capturing drought impacts across meteorological, agricultural, hydrological, and ecological domains, emphasizing regional applicability and scalability. Furthermore, we explore the potential of integrating remote sensing and artificial intelligence to overcome limitations in data resolution, socio-economic integration, and real-time adaptability. Through this synthesis, the review provides a foundation for developing adaptive frameworks that enhance drought resilience, offering actionable insights for researchers and policymakers to bridge the gap between theoretical advancements and practical implementation in water resource management.

MATERIALS AND METHODS

To achieve the aim and objectives of this research, a systematic and comprehensive approach was employed to analyse the correlation between climate change and drought, with a specific focus on drought indices and their applicability under evolving climatic conditions. The methodology began with a thorough review of existing scientific literature and research papers on climate change, drought characteristics, and drought indices, including peer-reviewed journals, IPCC reports, and datasets from CMIP5 and CMIP6 models. Relevant studies from the past two decades were prioritized to ensure the inclusion of recent advancements and findings. Publicly available datasets, including those from climate models and remote sensing technologies, were gathered to provide a robust basis for analysing drought patterns and their connection to climate variability.

The study then categorized droughts into distinct types-meteorological, agricultural, hydrological, socio-economic, ecological, groundwater, and flash droughts-to ensure a comprehensive understanding of the phenomenon. Drought indicators and indices, such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI), and other composite indices, were identified and evaluated, focusing on their methodological strengths, limitations, and applicability in the context of climate change. The CMIP6 Scenario Model Intercomparison Project was utilized to analyse future drought projections under different emission and socio-economic pathways. A comparative analysis of CMIP5 and CMIP6 models was performed to understand the advancements in sensitivity and accuracy in predicting drought conditions.

The study also explored the potential of remote sensing and artificial intelligence for drought monitoring and management, examining existing hybrid drought indices and proposing frameworks for integrating advanced technologies to improve the accuracy and applicability of drought monitoring tools. Gaps in existing methodologies were identified, particularly in terms of data availability, spatial resolution, and the inclusion of socio-economic factors in drought assessment. Challenges related to non-stationarity in climate models and the increasing influence of anthropogenic activities on hydrological cycles were also analysed.

Based on the findings, region-specific and innovative frameworks were proposed to enhance drought resilience and improve monitoring and mitigation strategies. Recommendations for improving water resource governance and addressing the economic impacts of drought were included to assist policymakers in developing effective strategies. This systematic approach ensured that the research covered all aspects of the complex relationship between climate change and drought, providing a detailed evaluation of drought indices and proposing advanced methodologies for drought monitoring and mitigation. Methodology adopted for the Systematic Review is shown in Fig. 1.

A rigorous search and screening process ensured extensive coverage and reduced bias in this review. We searched Scopus, Web of Science, and Google Scholar for recent peer-reviewed drought indices and climate change literature. We also incorporated pertinent IPCC reports and carefully chosen grey literature on CMIP5, CMIP6 forecasts, and AI-based drought monitoring frameworks to capture growing trends and state-of-the-art methodologies.

About 500 publications were found using keywords such as “drought indices,” “climate change,” “CMIP5,” “CMIP6,” “remote sensing,” and “AI-based drought monitoring.” About 150 full-text articles were eligible after removing duplicates and assessing titles and abstracts for relevance. Approximately 50 core papers were selected for further examination based on methodological rigour, relevance to climate-based drought assessment, and contribution to indices comparative understanding. Fig. 2 shows a PRISMA-style flowchart of research inclusion and exclusion.

This narrative review synthesises information from multiple sources; however, we included only peer-reviewed and high-impact research in the final comparative matrix. Since the review was a comprehensive, comparative overview rather than a quantitative meta-analysis, GRADE or risk-of-bias scoring was not performed. The Results and

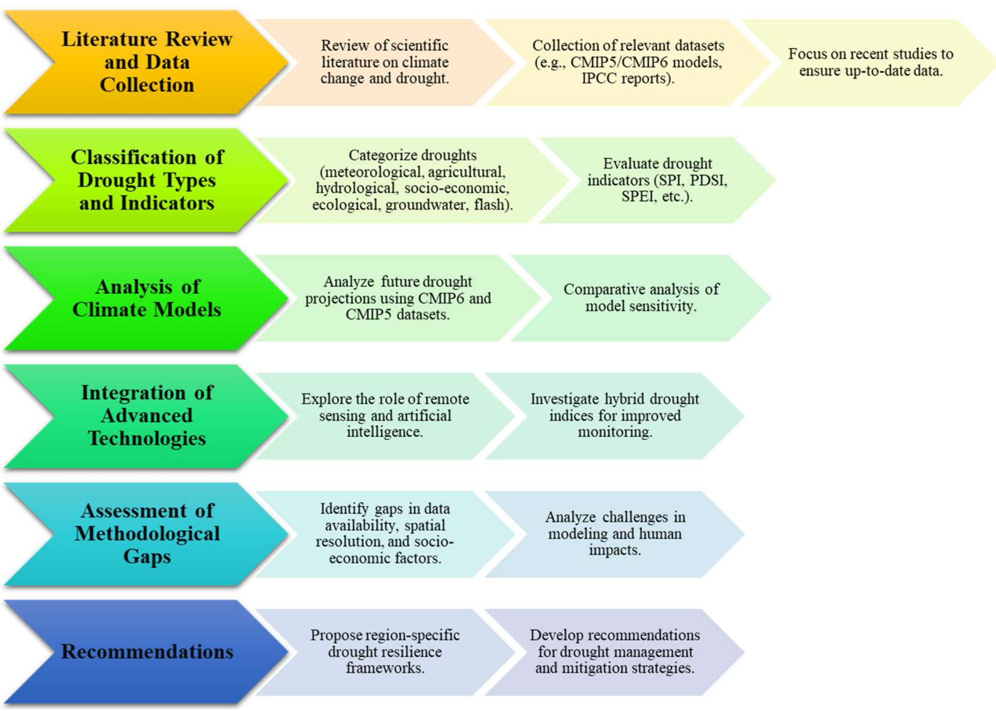

Fig. 1: Methodology Adopted for the Systematic Review.

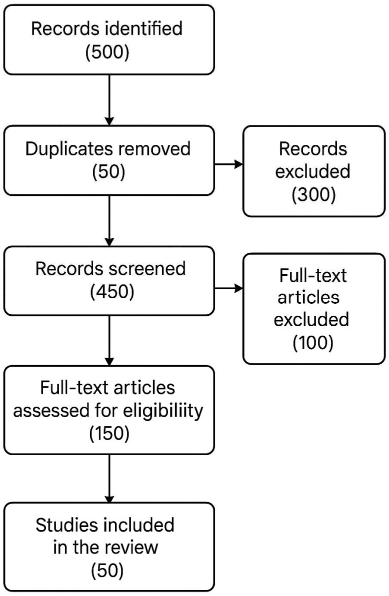

Fig. 2: PRISMA-style flow diagram of the literature screening and selection process.

Discussion sections provide theme evaluation and index ranking based on the chosen studies. The manuscript cites 123 references for contextual and conceptual support, but only 50 core studies were included in the systematic review matrix.

While this review does not directly apply artificial intelligence (AI) methods, it systematically examines how AI has been integrated into drought monitoring and index development in the existing literature. Our review process included identifying studies that utilize machine learning and other AI techniques to process remote sensing data, develop hybrid indices, and improve drought prediction accuracy. These studies were analyzed to understand the current state, advantages, and challenges of AI in drought research. Our methodology thus provides a comprehensive synthesis of AI's role in advancing drought monitoring, as reflected in recent scientific work.

Ranking System for Drought Indices

To objectively assess and compare the robustness of drought indices for monitoring under changing climatic conditions, we developed a transparent ranking system based on measurable criteria. The choice of criteria was informed by the need to evaluate indices according to their scientific rigor, practicality, and suitability for diverse climate scenarios, as recommended in the literature on drought indicators and indices (Svoboda & Fuchs 2016).

Criteria for Ranking

We selected the following six criteria, each relevant to the effective application of drought indices in operational and research contexts:

i. Climate Sensitivity: Measures the extent to which the index accounts for temperature, precipitation, and evapotranspiration, reflecting its responsiveness to climate change.

ii. Data Requirement: Evaluates the ease of obtaining the input data required for the index, including data availability and accessibility.

iii. Spatial Resolution: Assesses the suitability of the index for application at local, regional, or global scales.

iv. Temporal Resolution: Considers the frequency and flexibility of monitoring (e.g., daily, monthly, seasonal, annual).

v. Performance under Projected Climate Scenarios (CMIP5/CMIP6): Rates the index's reliability and adaptability under current and future climate model projections.

vi. Operational Usability: Reflects the ease of implementation, interpretability, and integration into existing drought early warning systems or policy frameworks.

Scoring Method

Each index was scored on a scale of 1 (low) to 5 (high) for each criterion, based on a review of published literature, expert consensus, and operational case studies. The total score for each index was calculated by summing the scores across all criteria, providing a quantitative basis for comparison. This approach ensures that the ranking is transparent, reproducible, and grounded in both scientific and practical considerations (Dikici 2020, Patil et al. 2023, Jain et al. 2015).

CLASSIFICATION OF DROUGHTS

The droughts are being recognised as a known natural calamity among water scientists, agricultural specialists, ecological researchers, geographers, and forecasters (Ashok et al. 2020). According to Wilhite and Glantz, there are four distinct types of droughts. Meteorological factors include insufficient precipitation, agricultural factors include insufficient soil moisture to sustain crop growth, hydrological factors include deficiency in streamflow and groundwater resources, and social factors include the inability to fulfil water requirements (Wilhite & Glantz 1985).

The conceptual definition of drought provides an overview of its fundamental ideas and a general explanation of the physical processes involved. This involves the lack

Table 1: Different types of drought classification and their description.

Type of Drought	Description
Meteorological Drought	Insufficient precipitation compared to normal levels over specific time scales (e.g., decadal, annual, monthly). Regional and climate-specific.
Agricultural Drought	Inadequate soil moisture to meet the needs of crops and pastures during critical growth stages, leading to reduced agricultural productivity.
Hydrological Drought	Deficiency in surface and groundwater resources, affecting streamflow, reservoir levels and the overall hydrological cycle.
Socio-Economic Drought	Water scarcity impacts society and industry, disrupting trade and reducing access to essential water-dependent commodities and services.
Ecological Drought	Prolonged water shortages that disrupt ecosystem functions, services and biodiversity, often exceeding ecosystems' adaptive capacities.
Groundwater Drought	Long-term decline in underground water supplies caused by reduced recharge rates or over-extraction.
Flash Drought	Rapid onset and intensification of drought conditions often affect multiple regions in a short timeframe.

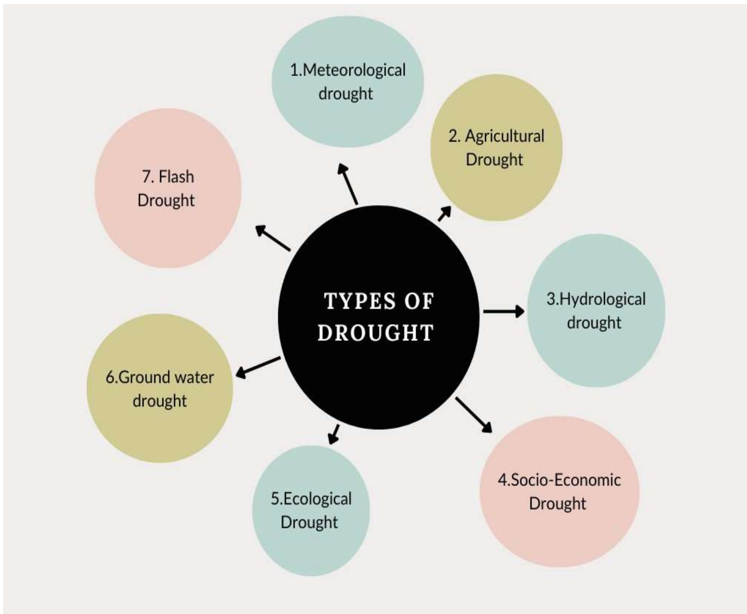

Fig. 3: Pictorial representation of the existing drought classes.

of rainfall in a meteorological drought, soil moisture in an agricultural drought, water in lakes and streams in a hydrological drought, and water availability for water management (Mishra & Singh 2010, Wilhite 2000, Mukherjee et al. 2018, Ezzahra et al. 2023). A summary visual representation of these drought classes is presented in Fig. 3 (Wilhite & Glantz 1985).

Drought problems and threats were thoroughly investigated and studied. The goal was to study its effects on agriculture, water, and ecosystems. This knowledge was used to create adaptable and sustainable strategies and solutions (Iqbal et al. 2020, Seleiman et al. 2021, Wahab et al. 2022). Further classification details are given in Table 1 (Wilhite & Glantz 1985, Mishra & Singh 2010, Mukherjee et al. 2018).

DROUGHT INDICATORS

Drought indicators and indices play a critical role in understanding, monitoring, and managing drought conditions. They provide quantitative and qualitative measures to assess the severity, duration, and spatial extent of droughts. Indicators generally rely on meteorological, hydrological, agricultural, and socio-economic data to reflect the specific components of drought, whereas indices combine multiple datasets into a single value for decision-making purposes (Salehnia et al. 2020, Kulkarni et al. 2020).

These tools are essential for researchers, policymakers, and water resource managers to identify drought conditions, predict potential impacts, and implement mitigation strategies. Effective drought indices enable a comprehensive analysis by capturing changes in climatic factors such as precipitation, temperature, evapotranspiration, and water availability.

The evaluation of drought indices is especially relevant in the context of climate change, as shifts in temperature and precipitation patterns intensify the frequency and severity of droughts. Modern advancements, such as the integration of remote sensing data and artificial intelligence techniques, have further enhanced the accuracy of drought indicators, enabling real-time monitoring and improved predictions (Dakhil et al. 2024).

Bachmair et al. (2016) referred to drought indicators and indices collectively as tools to characterize and quantify droughts, highlighting their widespread application in global drought research.

DROUGHT INDICES

An index is typically calculated using statistical methods such as normalization or by combining multiple processes to produce a single value. Using available data, an index measures drought duration and severity, offering a comprehensive overview for decision-making. It provides a single numerical value that combines hydrological and meteorological variables, including temperature, evapotranspiration, precipitation, runoff, and other indicators of water availability. Decision support tools used to assess drought intensity, duration, and severity rely on specific indices and indicators (Botterill & Hayes 2012). In the drought-monitoring community, hydrological cycles, drought indicators, and indices are often used interchangeably (Hayes et al. 2021). Common drought indicators, such as precipitation, temperature, groundwater levels, streamflow, and soil moisture, are widely used across different regions. In contrast, drought indices are determined and analysed based on hydro-climatic factors that influence drought. These indices represent singular quantities (Hayes et al. 2021).

The key characteristics of a drought are its intensity, duration, and geographic extent. Among these, the primary factor for drought analysis is the severity of the drought (Tigkas et al. 2015). Given the multiple factors contributing to drought, several composite drought indices—RAI, PDSI, SPI, RDI, SPEI, CMI, SPDI, SRI, and others—have been developed to monitor drought conditions by integrating individual remote sensing drought indices. Here is a list of the drought indices:

Rainfall Anomaly Index (RAI): The proposal was first put forward by Van Rooy (1965). The operation of this method relies on the comparison of computed precipitation with random values that span from −3 to +3. There are ten categories assigned to the variations in precipitation. Furthermore, it is executed on both a yearly and monthly basis (Smakhtin & Hughes 2007). The aforementioned research has assessed the effectiveness of RAI in specific, uniform regions classified by moist to moderate climates. It has identified the precipitation patterns and variations, as well as the intensity and frequency of rainfall (Costa & Rodrigues 2017, Siddharam et al. 2020, Goswami 2018). While a study by Loukas et al. (2003) looked at RAI's performance in temperate climate stations in Greece, where summers often have negative precipitation values, no data on RAI's performance in dry and extremely dry climates are available. In these climates, extended warm dry periods have severely skewed precipitation and produced many zero precipitation data points (Raziei et al. 2015).

Palmer Drought Severity Index (PDSI): Palmer (1965) bases its definition of drought on soil moisture, precipitation, and temperature. Four main factors-precipitation, temperature, soil moisture, and evapotranspiration—need to be calculated through sophisticated formulations in order to calculate the PDSI, which is employed on a monthly basis. PDSI is a soil moisture algorithm (Ntale & Gan 2003, Van der Schrier et al. 2011) that is calculated for comparatively uniform areas. This drought warning system is among the most advanced and precise available. Though it is a useful tool for identifying long-term drought every month, the PDSI is not appropriate for characterizing short-term drought every week (Hong & Wilhite 2004). The categorization of precipitation patterns based on index values provides a comprehensive scale to assess the severity of deviations from average rainfall (Table 2).

Standardised Precipitation Index (SPI)*:* McKee et al. (1993) developed the SPI index in 1993. This index is calculated by dividing by the standard deviation after subtracting the mean precipitation from the actual precipitation. Calculations are based on precipitation data for 3, 6, 12, 24, and 48 months. The use of SPI varies according to the chance of precipitation at different time scales. Meteorological droughts can be assessed through the use of the SPI (Diani 2019, Bhunia et al. 2020, Li et al. 2020). Furthermore, it has the ability to forecast droughts

Table 2: PDSI Classification and its Range.

PDSI Range	Classification
4 or above	Extremely wet
0.5 to 0.99	Very wet
-0.49 to 0.49	Normal
-0.5 to -0.99	Moderate drought
-4 or less	Extreme drought

Table 3: SPI classification and range.

SPI Range	Classification
2 or above	Extremely wet
1.5 to 1.99	Very wet
-0.99 to 0.99	Normal
-1.49 to -1	Moderate drought
-1.99 to -1.5	Severe drought
-2 or below	Extreme drought

before they occur and assists in determining drought intensity (Funk & Shukla 2020). SPI classification and range are listed in Table 3. This index is less complex in terms of processing requirements compared to the Palmer index (Yihdego et al. 2019, Liu et al. 2021).

Presently, individuals responsible for organising and making decisions on drought are aware that the SPI serves multiple purposes and understand its specific significance. In addition, they acknowledge that the input data values in SPI have the potential to be altered, and they consider this to be a limitation of the index (Ji & Peters 2003). These are the values into which precipitation variations are classified by SPI, where each range signifies the extent of departure from average precipitation, offering a structured assessment of drought severity within specific regions based on SPI values.

Reconnaissance Drought Index (RDI): The MEDROPLAN coordinating meeting introduced an innovative drought detection and assessment index (Tsakiris 2004) and further elaborated upon it throughout subsequent works (Tsakiris et al. 2007). The PET methodologies were implemented in the RDI index value computation (Halwatura et al. 2015). It provides a distinct framework for classifying and comprehending various degrees of drought intensity. This criterion evaluates the severity of drought by utilising numerical values. RDI classification and range are listed in Table 4.

Soil Moisture Drought Index (SMDI): Hollinyer et al. (1993) established the SMDI in 1993. It is calculated for one year by summing the daily soil moisture readings. This measure only considers soil moisture as a single meteorological variable (Karimi et al. 2001). Recent studies have examined the SMDI's effectiveness in monitoring drought (Cao et al. 2022, Sen Roy et al. 2023). Utilising historical data as a benchmark, it is conventionally computed as the discrepancy between present-day soil moisture levels and the long-term mean. Typically, it is denoted by a standardised value between −4 (extremely dry) and +4 (extremely moist). SMDI values of 0 and negative values, respectively, denote different levels of dryness.

Table 4: RDI classification and range.

RDI Range	Classification
-0.5 to -1.0	Mild drought
-1.0 to -1.5	Moderate drought
-1.5 to -2.0	Severe drought
-2 or below	Extreme drought

Table 5: SPEI classification and range.

SPEI Range	Classification
2 or above	Highly wet
1.5 to 2	Very wet
1 to 1.5	Moderately wet
-1 to 1	Normal
-2 to -1	Severely dry
-2 or below	Extremely dry

Standard Precipitation Evaporation Index (SPEI): The SPEI, similar to PDSI, considers the influence of reference evapotranspiration on drought severity. However, its ability to analyse several time scales allows for the identification of various types of drought and their effects on different systems (Vicente Serrano, S.M. et al. 2012a, Vicente Serrano, S.M. et al. 2012b, Vicente Serrano, S.M. et al. 2013a, Vicente Serrano, S.M. et al. 2013b). SPEI values vary from +2 to −2. SPEI classification and range are listed in Table 5

Therefore, the SPEI possesses the same level of sensitivity as the PDSI when it comes to measuring the demand for evapotranspiration, which is influenced by changes and patterns in climatic factors other than precipitation. Additionally, it is straightforward to compute and can be applied at various scales, similar to the SPI (Beguería et al. 2013).

Crop Moisture Index (CMI): The purpose of the CMI is to offer information that addresses broad-scale general inquiries rather than localized ones. The sensitivity study conducted on the Crop Moisture Index revealed that the index shows increased levels of moisture in response to rising temperatures under certain instances (Juhasz & Kornfield 1978). It is dependent on the available meteorological data, in particular, the data comprises the total precipitation and mean temperature for each week. It evaluates climate change's impact on water resources and equitable growth (Miryaghoubzadeh et al. 2019, Ampitiyawatta & Wimalasiri 2023). The evapotranspiration anomaly index and Wetness Index are added to generate the final CMI (Heim et al. 2002, Hogg et al. 2013). During the growth season, the value is near zero, stays near zero if crop moisture supply and weather conditions are normal, and returns to nearly zero at the conclusion (Palmer 1968).

Standardised Runoff Index (SRI): The SRI, according to McKee et al. (1993), requires calculating the unit standard normal deviation of the percentile of hydrologic runoff data over a period of time. Various timeframes (such as 1-month or 9-month) and varying levels of spatial grouping for the index can be computed based on the resolution of the source data and the intended use. SPIs, such as those computed by NOAA, are determined at a climatic division level and by state agencies at a county level (Shukla & Wood 2008). It is used to identify drought patterns in a region (Nalbantis & Tsakiris 2008, Wang et al. 2013), and different methods have been used to calculate the SRI (Sheffield et al. 2012).

Munger's Index: The Munger Index, created by Robert Munger in the 1920s, is a measure of drought. This method is straightforward and commonly employed; by considering precipitation, the severity of drought is evaluated. Short-term droughts can be assessed most effectively using this index (Yihdego et al. 2019). It aids in assessing the sufficiency of rainfall for crop development, where readings below a specific threshold indicate drought conditions and higher values imply ample moisture availability. Nevertheless, it is crucial to acknowledge that the Munger Index predominantly emphasises precipitation, and variables that may impact drought, such as soil moisture and temperature, are not considered. A timeframe without a 24-hour rainfall of 1.27 mm is noted. Munger made the interesting observation that the drying-out effect of drought on plant life in forests is independent of the duration that it lasts. The approach uses a right triangle whose height and base are proportional to drought length. The mathematical expression for the severity of drought is given by the formula $0.5\ L^2$, where L is the length of the drought in days (Hogg et al. 2013).

Kincer's Index: Kincer produced a set of essential maps and charts depicting the seasonal patterns of rainfall and climatological data on the average yearly frequency of rainy days. Kincer's definition of drought is a period of 30 or more consecutive days with precipitation of less than 6.35 mm (0.25 in.) within 24 hours (Hogg et al. 2013). Furthermore, it highlights the allocation of rainfall across several seasons, taking into account the average yearly precipitation (Qiao et al. 2014). The Kincer's Index evaluates the vulnerability of a watershed to drought and identifies regions most prone to drought (Mishra & Nagarajan 2010, Wu et al. 2016). Studies indicate that the Kincer's Index shows higher accuracy compared to the PDSI and SPI (Gouveia et al. 2019).

Marcovitch's Index: To calculate a drought index, Marcovitch created an equation that combines precipitation and temperature: Drought index = $0.5 \times (N/R)^2$, where N is the cumulative count of consecutive days, lasting for at least two days, with temperatures over 32.2°C (90°F), and R denotes the overall amount of rainfall during the summer for that particular month (Hogg et al. 2013).

Blumenstock's Index: In his climatic study, Blumenstock utilised probability theory to calculate the frequencies of droughts. The drought time in days was used to calculate the index. For a drought to end, 2.54 mm (0.10 in.) of precipitation was needed within 48 hours. Using the Munger and Blumenstock indices, short-term droughts were measured (Hogg et al. 2013). When compared to other indices, it becomes apparent that various indices provide unique expressions of drought (Yihdego et al. 2019). The findings highlighted the need for using evapotranspiration and precipitation data to assess drought severity, improve drought understanding, and help develop effective drought monitoring and control technologies (Silva et al. 2021, Johnson et al. 2021, Santos et al. 2022).

Antecedent Precipitation Index (API): Antecedent precipitation refers to the precipitation that occurs before a certain storm event and impacts the relationship between runoff and that storm event. The yield from the same rainfall event on a watershed that has already been wetted by earlier rainfall is less than the yield from a rainfall event on a dry watershed (Heggen 2001). The system includes precipitation, which is a reverse drought index used for flood prediction (Hogg et al. 2013), and the API decay constant k affects API value accuracy (Heggen 2001). Soil moisture is crucial in the connection between land and atmosphere. Estimating soil moisture levels can be done by several methods, such as in situ measurements, hydrological modeling, and satellite remote sensing. The utilisation of indicators to perform an index of soil moisture conditions is another effective strategy. This study examines one index known as the API. To match the physical process, two parameters were added to the standard API. The recession coefficient is initially allowed to change with air temperature to account for evapotranspiration. The maximum API value considers the soil's maximum water-holding capacity. The adjusted API was subsequently calibrated and validated through a comparison with soil moisture measured in situ (Zhao et al. 2019). Some recent studies utilise this index to assess drought intensity, track rainfall patterns, and forecast hydrological responses (Goswami 2018, Nguyen-Huy et al. 2022).

Moisture Adequacy Index (MAI): The MAI (McGuire & Palmer 1957) index, generated from prospective evapotranspiration, compares a region's moisture need to its actual moisture supply, which includes rainfall and soil moisture. It is computed by dividing the actual moisture supply by the moisture needed and expressing it as a percentage. Indicators such as precipitation and soil moisture are used, and 100% indicates that what is available has been enough to fulfil the need (Yihdego et al. 2019). Research has shown that the use of the MAI is an extremely effective technique to determine drought severity, optimise crop cultivation, and make accurate field assessments for agriculture (Rawat & Joshi 2010, Sarkar & Biswas 2017, Das et al. 2019).

Keetch and Byram Drought Index (KBDI): Its purpose is to evaluate the state of drought with a special focus on fire control management. It measures soil moisture depletion in hundredths of an inch, with 0 indicating no shortage and 800 indicating severe drought. The calculation relies on a soil moisture storage capacity of 203 mm (8 in.). The DI is calculated using a daily water budgeting approach that balances drought factor, precipitation, and soil moisture. For monitoring and predicting wildfires, this index is extensively used (Hogg et al. 2013). In situ soil moisture measurements might enhance wildfire threat estimates, which frequently use the KBDI (Krueger et al. 2017). Studies examine this technology's usefulness in assessing droughts and wildfires (Keetch & Byram 1968, Gouveia et al. 2019).

Surface Water Supply Index (SWSI): The SWSI is a hydrologic drought statistic developed in 1981, particularly for Colorado, based on empirical data. It incorporates snowfall, reservoir storage, streamflow, and high-elevation precipitation to improve the PDSI. A useful indicator of surface water resources is the SWSI (Wilhite & Glantz 1985, Shafer & Dezman 1982). Colorado's Drought Assessment and Response Plan incorporates SWSI and PDSI-like measurements. The SWSI is largely computed for river basins and has been adopted by other western states (Hogg et al. 2013). It includes precipitation, snowpack, reservoir storage, and runoff (Yihdego et al. 2019). The study of an area, its real-world applications, and its effectiveness in evaluating drought seriousness and predicting streamflow have been documented (Wilhite and Glantz 1985, Wu et al. 2016).

Vegetation Condition Index (VCI): The data utilised for drought identification and tracking is derived from satellite Advanced Very High Resolution Radiometer (AVHRR) radiance, namely in the visible and near-infrared spectrum. This data is modified for land climate, ecology, and weather. Kogan's 1995 research showed this approach's potential. The VCI capitalises on the strong correlation between vegetation and climate, drawing inspiration from ideas established by German biologist W. Köppen nearly a century ago in his climate classification system based on vegetation. VCI enables drought identification and serves as a potential worldwide benchmark for assessing the timing, severity, duration, and impact of drought on vegetation. Nevertheless, due to its reliance on vegetation, the VCI is predominantly valuable during the summer period of plant growth. Its us Dixit Dixit efulness is restricted during the winter months when plant growth is mostly inactive (Hogg et al. 2013). Recent studies have examined drought severity and evaluated drought trends (Wu et al. 2016, Khatri & Sharma 2019). Before 2000, the Anomaly Vegetation Condition Index (AVCI) predominantly had negative values, indicating a lack of soil moisture. Analysis of exceedance probability on an annual time scale revealed a 20% likelihood of severe drought (VCI $\leq$ 35%) and a 35% likelihood of regular drought (35% $\leq$ VCI $\leq$ 50%) occurring in Nepal (Baniya et al. 2019).

Drought Monitor Index (DM): The authors of the DM index rely on studies of various crucial indices and supplementary indicators from multiple organisations to construct the ultimate map. The main factors consist of the PDI (Palmer Drought Index), CMI, percentiles of soil moisture models, percentiles of daily streamflow, percent of normal precipitation, topsoil moisture (percent of short and very short levels) provided by the USDA, and a satellite-based Vegetation Health Index. The U.S. Drought Monitor employs a categorical framework to categorise drought severity: D0 (Abnormally dry) denotes conditions before drought, D1 (Moderate drought) indicates initial effects on crops and water supply, D2 (Severe drought) signifies significant harm to agriculture and water scarcity, D3 (Extreme drought) suggests critical losses and widespread water scarcity, and D4 (Exceptional drought) represents catastrophic impacts on agriculture and economy, coupled with severe water shortages. These categorisations facilitate communication of drought seriousness and consequences, guiding responses and allocation of resources in affected areas (Hogg et al. 2013). From 2000 to 2016, this research used the Integrated Drought Monitoring Index (IDMI) to measure agricultural drought in Tamil Nadu, the southern Indian peninsula, during the northeast monsoon season. PCI (Precipitation Condition Index), SMCI (Soil Moisture Condition Index), TCI (Temperature Condition Index), and VCI constitute the four indices of the IDMI. The indices are calculated based on time-series satellite observations of climate risks, namely infrared precipitation data from CHIRPS, the European Space Agency Climate Change Initiative (ESA-CCI), and Moderate Resolution Image Spectroradiometer (MODIS) (Kuma et al. 2021). The significance and effectiveness of measuring drought severity and vulnerability were assessed (Zargar et al. 2022, Liu et al. 2022).

Joint Deficit Index (JDI): Kao and Govindaraju (2010) developed the JDI, a measure using copula functions that integrates joint distributions of several SPIs. It accounts for precipitation and streamflow distribution while considering seasonal variations. This indicator detects incipient and protracted droughts quickly and allows for monthly evaluation of drought conditions. It predicts how much rainfall is needed in the coming months to restore normal conditions (Mirabbasi et al. 2013). The copulas used in JDI are multivariate distribution functions that provide a link between one-dimensional marginal distributions and joint probability distributions (Nelsen 2006). Geostatistics and spatial statistics explain multi-timescale covariance using a two-parameter function. Analysis of long-term precipitation data proves covariance model. Bootstrap tests demonstrate that the Gaussian copula model assesses drought severity better than the empirical copula. It measures droughts outside the empirical copula. Second, drought is well-quantified. Finally, it clarifies the estimate uncertainty (Van de Vyver & Van den Bergh 2018). This index's versatility, applicability, and capability to monitor droughts were confirmed (Wu et al. 2016, Liu et al. 2022).

Multivariate Standardised Drought Index (MSDI): The MSDI utilises a probabilistic approach for integrating the Standardised Soil Moisture Index (SSI) and the SPI to accurately represent drought conditions. MSDI assesses drought using meteorological and agricultural data. The suggested MSDI is used in California's climate divisions and in North Carolina to assess drought conditions. Studies employing the MSDI are compared to the SSI and SPI. The findings indicate that MSDI accurately recognises the beginning and end of drought situations by taking into account both SPI and SSI. SPI largely determines drought onset, whereas SSI more closely determines drought persistence. In short, the MSDI model demonstrates that it is possible to quickly merge multiple indices using stochastic approaches (Hao & AghaKouchak 2013). The joint cumulative probability is transformed using a standard normal distribution's inverse cumulative distribution function to obtain the MSDI. Standardisation is not achieved using this method. Since the joint cumulative probability is not evenly distributed on [0,1], negative index values are more likely. The Standardised Drought Analysis Toolkit (SDAT) (Farahmand & AghaKouchak 2015) computes non-parametric standardised univariate and non-parametric bivariate MSDI drought indices (Erhardt & Czado 2018). Methods of drought characterisation and risk assessment were evaluated (Zhang et al. 2022, Trigo et al. 2021, Albajes et al. 2022).

Reconnaissance Trivariate Drought Index (RTDI): The RTDI is a composite of soil moisture, evapotranspiration, and precipitation. Meteorological and agricultural droughts are effectively represented by the RTDI and MSDI, linking climatic status. For bivariate and trivariate analysis, the most appropriate copulas are the Student and Frank's t copulas, respectively. To analyse drought onset and withdrawal characteristics, the two drought indices are formulated and evaluated. Cross-wavelet analysis (CWA) can reveal how large-scale climatic anomalies affect drought indices. This research considers Indian summer monsoon rainfall (ISMR), Multivariate ENSO Index (MEI), Southern Oscillation Index (SOI), and Indian Ocean Dipole (Dixit & Jayakumar 2021).

Effective Drought Index (EDI): Byun and Wilhite (1999) created the EDI in 1999 to address index limitations. By assessing daily water collection over time, the EDI provides a full evaluation. Its specialised design for daily drought severity estimation and more accurate water resource evaluations makes the EDI advantageous (Kim 2009). EDI values range from −2.5 to 2.5. Index readings between −1.0 and 1.0 imply near-normal conditions, while −2.0 or below indicates severe drought (Salehnia et al. 2017, Raja Azman et al. 2022).

Relative Drought Indices: The relative Standardised Precipitation Index (rSPI) and Relative Palmer Drought Severity Index (rPDSI) improve drought evaluation in shifting climates. They provide an innovative method to compare drought conditions across time and geography. In order to apply drought indices to future climates, they must first be calibrated using aggregated observational data from all stations during a reference period. This process is known as achieving the former. This approach can be utilised to evaluate the spatial displacement of drought caused by climate change. However, the latter method uses station measurements to accurately track temporal drought changes in relation to the present climate. The second approach may provide indicators that are not comparable across climate zones (Mukherjee et al. 2018, Dubrovsky et al. 2009).

Standardised Streamflow Index (SSFI): Power spectrum and detrended fluctuation analysis are the employed techniques. The presence of the yearly oscillation indicates all the streamflows. This oscillation also acts as a transition point between two regions. For frequencies below the yearly cycle (or timescales longer than 1 year), the dynamics are roughly random. However, for frequencies above the yearly frequency (or timescales shorter than 1 year), the dynamics are consistently correlated (Telesca et al. 2012). The SSFI is useful in drought evaluation and monitoring, particularly in regions with enormous river systems and complex hydrology. The tool's ability to quantify drought's effect on streamflow makes it valuable for water resource management and environmental planning (Wu 2016).

Data Fusion-Based Drought Index (DFDI): The data fusion drought index is the process of combining several sources or types of data to form a comprehensive index that evaluates drought conditions. The index thoroughly encompasses all categories of drought by utilising a range of indices and

Table 6: Comparative Matrix of Drought Indices.

Index	Input Data	Type	Scale	Applicability under CC
RAI	Precipitation	Precipitation based	Local, regional, monthly	Limited (only precipitation)
PDSI	Precipitation, Temp., Soil moisture	Evapotranspiration	Regional, monthly	Moderate (needs calibration)
SPI	Precipitation	Precipitation based	Local, global, monthly	Limited (excludes temperature)
RDI	Precipitation, PET	Evapotranspiration	Regional, monthly	High (accounts for PET)
SMDI	Soil moisture	Agricultural	Local, regional, daily	High (soil moisture focus)
SPEI	Precipitation, Temp., PET	Evapotranspiration	Local, global, monthly	High (integrates temperature)
CMI	Precipitation, Temp., Soil moisture	Agricultural	Regional, weekly	Moderate (short-term focus)
SRI	Streamflow	Hydrological	Regional, monthly	Moderate (streamflow-dependent)
Munger's Index	Precipitation	Precipitation based	Local, daily	Limited (short-term focus)
Kincer's Index	Precipitation, Temp.	Composite	Regional, monthly	Moderate (empirical)
Marcovitch's Index	Precipitation, Temp.	Composite	Local, daily	Limited (experimental)
Blumenstock's Index	Precipitation	Precipitation based	Local, daily	Limited (historical focus)
Antecedent Precipitation Index	Precipitation, Soil moisture	Hydrological	Local, regional, daily	Moderate (soil moisture integration)
MAI	Precipitation, Soil moisture	Agricultural	Regional, monthly	Moderate (agro-climatic focus)
Keetch-Byram Index	Temp., Soil moisture	Ecological	Local, regional, daily	High (fire risk under warming)
SWSI	Streamflow, Snow pack, Reservoir storage	Hydrological	Regional, monthly	Moderate (water resource focus)
VCI	Satellite imagery (NDVI)	Vegetation-based	Regional global, monthly	High (real-time monitoring)
Drought Monitor Index	Multi-source (PDSI, CMI, VCI, etc.)	Composite	Regional global, monthly	High (integrates multiple proxies)
JDI	Precipitation, Streamflow (copula-based)	Composite	Regional, monthly	High (multi-variable)
MSDI	Precipitation, Soil moisture	Composite	Regional, monthly	High (non-stationary climates)
RTDI	Precipitation, Soil moisture, ET	Composite	Regional, monthly	High (multi-variable)
EDI	Daily Precipitation, ET	Evapotranspiration	Local, regional, daily	Moderate (short-term focus)
Relative Drought Indices	Precipitation, Temp. (calibrated)	Composite	Regional, monthly	High (non-stationary climates)
SSFI	Streamflow	Hydrological	Regional, monthly	Moderate (streamflow-dependent)
DFDI	Multi-source (remote sensing, climate)	Remote-sensing	Regional global, monthly	High (AI/RS integration)

proxies linked to each specific form of drought. The primary objective of data fusion, defined as the integration and consolidation of data from various sources and sensors, is to generate a solution that is either more precise or enables specialists to access a greater quantity of information than would be possible by using individual data sources alone.

To aid comparative evaluation, a matrix-style summary is presented in Table 6 below, highlighting key characteristics of major drought indices, including their input data, applicable drought type, strengths, limitations, scale of application, and suitability under changing climate scenarios.

This paper offers a method to objectively correlate water availability and plant characteristics to assess terrestrial ecosystem water stress. A set of drought indices (DIs) was considered. The combination approach determines each time step's water stress circumstances using multivariate statistical methods, such as independent component analysis, and eco-meteorological parameters, including land use, land cover, and climate. Three case study regions with varying land use, climate regimes, and surface and atmospheric variables are provided to assess the new approach's potential to generalize DIs (Azmi et al. 2010).

Table 7: Summary of commonly used drought indices.

Index Name	Description	Strengths	Limitations
SPI	Measures drought based on precipitation deviation from normal.	Simple, widely used, adaptable to different timescales.	Does not account for temperature and evapotranspiration.
SPEI	Combines precipitation and evapotranspiration to assess drought severity.	Considers temperature impacts, robust under climate change.	Requires detailed climate data.
PDSI	Incorporates soil moisture balance to measure long-term drought.	Effective for agricultural drought monitoring.	Complex calculations, not suited for short-term drought.
CMI	Focuses on short-term agricultural droughts using soil moisture.	Relevant for agricultural applications.	Not useful for long-term drought analysis.
RDI	Considers precipitation and potential evapotranspiration.	Versatile and adaptable.	Requires accurate climatic data.
SRI	Quantifies drought using runoff data.	Hydrologically relevant.	Requires extensive hydrological data.
VCI	Monitors drought impact on vegetation using remote sensing data.	Useful for agricultural and ecological droughts.	Relies on satellite data availability.
RAI	Compares rainfall anomalies to historical averages.	Simple and easy to calculate.	Limited by the exclusion of temperature and soil factors.
EDI	Considers precipitation deficits over time.	Dynamic and responsive to recent changes.	Requires detailed precipitation records.
EDI	Quantifies drought by analyzing evapotranspiration anomalies.	Relevant under warming climate scenarios.	Requires advanced climate models.

The following Table 7 provides an overview of 25 widely used drought indices, categorised based on their focus areas, such as meteorology, hydrology, and agriculture. Each index is evaluated for its strengths, limitations, and suitability under evolving climate conditions.

This section provides a comprehensive understanding of the tools used to measure and monitor droughts. Indices and indicators continue to evolve, with recent advancements integrating modern technologies and climate models, ensuring their relevance for addressing the challenges of climate change. Recent studies demonstrate the integration of diverse drought indicators or proxies from multiple data sources to offer a thorough evaluation of drought severity. The assessment of drought monitoring, early warning, and drought assessment can be conducted effectively (Azmi et al. 2016, Mishra et al. 2018, Wu et al. 2017).

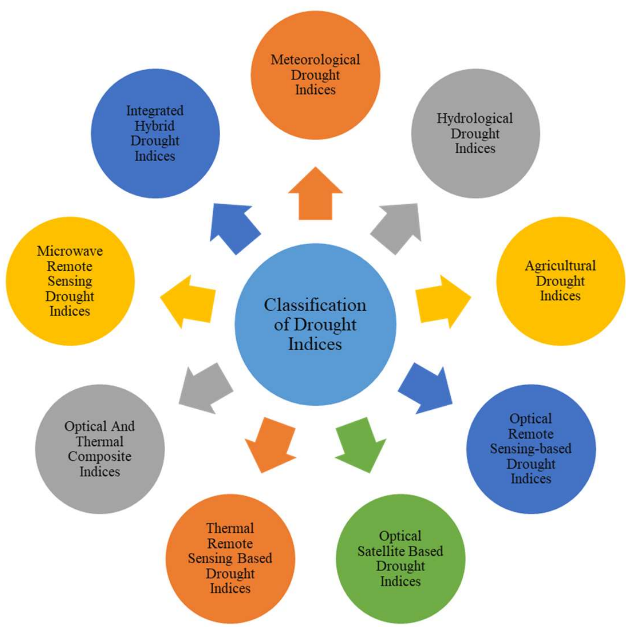

Fig. 4: Pictorial representation of the different classifications of drought indices.

Other drought indices are employed to thoroughly evaluate and describe drought conditions. These indices provide additional viewpoints on different aspects of drought, going beyond conventional measurements to offer a more detailed understanding. Drought indices, which quantify departures from typical local conditions based on historical distributions, are used to track drought (Dai 2011). Drought indices can be classified as shown in Fig. 4.

RESULTS AND DISCUSSION

This section provides a detailed explanation of the results from the literature analysis, key findings and their implications. It also discusses the challenges encountered during the research and outlines the future scope for advancing drought monitoring and management in the context of climate change.

Results

The results of this study demonstrate the complex and multifaceted relationship between climate change and drought, evaluated through a detailed analysis of drought indices, climate models and emerging trends. The findings are summarized as follows:

Analysis of Drought Indices

- Among the 25 evaluated indices, the Standardized Precipitation-Evapotranspiration Index (SPEI) and Normalized Difference Vegetation Index (NDVI) were identified as the most robust tools for monitoring drought under changing climatic conditions.
- SPEI's inclusion of evapotranspiration made it particularly sensitive to temperature increases caused by global warming, whereas NDVI proved useful for real-time monitoring of agricultural and ecological drought impacts.

Climate Model Comparisons

- Comparative analysis of CMIP5 and CMIP6 models highlighted advancements in the latter, with improved sensitivity to regional climate variations and better predictions of extreme drought events.
- The CMIP6 models projected a significant increase in the frequency and intensity of droughts in South Asia, especially under high-emission scenarios (SSP5-8.5).
- Results also showed non-linear trends in precipitation variability, indicating a potential for more severe meteorological and hydrological droughts in semi-arid regions.

Regional Projections for South Asia

The comparative analysis of CMIP5 and CMIP6 models reveals significant regional differences in projected drought patterns. For South Asia, CMIP6 models indicate a marked increase in the frequency and severity of droughts, especially under high-emission scenarios (SSP5-8.5) (Dixit et al. 2022). Projections suggest that agricultural and meteorological droughts will become more frequent, with soil moisture deficits and temperature-driven evapotranspiration playing a key role (Mukherjee et al. 2018). For example, in certain regions of South Asia, the frequency of severe agricultural droughts is projected to increase by 20–30% by the end of the century. These changes are closely linked to projected increases in temperature and shifts in precipitation patterns, which are more robustly captured by CMIP6 models compared to CMIP5.

The SPEI and NDVI indices emerge as particularly robust for monitoring these projected changes, due to their sensitivity to temperature and vegetation stress, respectively (Vicente-Serrano et al. 2012, Dixit et al. 2022). The integration of remote sensing and AI-driven models further enhances the ability to detect and predict drought severity in real time, supporting more adaptive management strategies for the region (Dakhil et al. 2024).

Integration of Advanced Technologies

a. Remote sensing and artificial intelligence showed significant potential in improving drought monitoring capabilities. For example, hybrid indices combining NDVI and surface water data offered higher spatial accuracy for drought predictions.
b. AI-based models reduced prediction errors and allowed for more adaptive monitoring frameworks tailored to regional conditions.

Role of Artificial Intelligence in Drought Monitoring

Several reviewed studies highlight the growing use of artificial intelligence (AI) techniques, such as machine learning, for processing remote sensing data and developing hybrid drought indices. AI-based models have been shown to reduce prediction errors and enable more adaptive monitoring frameworks. However, these approaches are still largely experimental or limited to well-resourced regions, and their broader application depends on data availability and computational infrastructure.

Best Performing Indices by Drought Type and Climate Scenario

To provide clear guidance for practitioners and researchers, we synthesized our findings to identify the most suitable drought indices for each drought type under current and projected climate scenarios (CMIP5 and CMIP6). This summary is based on the comparative analysis and ranking system described in Table 8.

Table 8: Recommended drought indices by drought type and climate scenario.

Drought Type	Current Climate	CMIP5 Scenario	CMIP6 Scenario
Meteorological	SPI, SPEI	SPEI	SPEI, MSDI
Agricultural	NDVI, VCI, SMDI	NDVI, SPEI	NDVI, SMDI, Hybrid/AI
Hydrological	PDSI, SWSI	PDSI	MSDI, Hybrid
Ecological	NDVI, VCI	NDVI, VCI	NDVI, Hybrid/AI

- **Meteorological Drought:** Under historical and current climates, both SPI and SPEI are widely used, but SPEI is preferable under CMIP5 and especially CMIP6 projections due to its sensitivity to temperature-driven evapotranspiration, which is increasingly relevant in warming scenarios. MSDI also shows promise for capturing multi-variable influences in future conditions.
- **Agricultural Drought:** NDVI and VCI are effective for real-time monitoring of vegetation stress, making them ideal for current and projected climates. SMDI is valuable where soil moisture data is available, and hybrid or AI-driven indices are recommended under CMIP6 for their ability to integrate diverse datasets and improve prediction accuracy.
- **Hydrological Drought:** PDSI and SWSI remain standard for long-term water resource assessment under current and CMIP5 conditions. However, under CMIP6, MSDI and hybrid indices are better suited to capture the complexity of hydrological droughts influenced by multiple climate variables.
- **Ecological Drought:** NDVI and VCI are robust for monitoring ecological impacts, and their effectiveness is enhanced under future scenarios when combined with AI and hybrid approaches for greater spatial and temporal resolution.

These recommendations provide a practical framework for selecting drought indices tailored to specific drought types and evolving climate scenarios. The following Discussion section expands on these findings and their implications for research and policy.

Ranking and Comparative Performance of Drought Indices

To objectively identify the most robust drought indices for monitoring under changing climatic conditions, we applied the ranking system described in the Methodology section. Each index was evaluated according to six criteria: climate sensitivity, data requirement, spatial resolution, temporal resolution, performance under projected climate scenarios (CMIP5/CMIP6), and operational usability. Scores for each criterion were assigned on a scale of 1 (low) to 5 (high), based on a literature review and expert consensus. Table 9 presents the scores for each index according to the six ranking criteria. The total scores indicate the overall robustness of each index for drought monitoring under changing climatic conditions. The results show that SPEI and NDVI are the most robust indices, with the highest total scores. This ranking supports their use for drought monitoring under both current and projected climate scenarios.

The results indicate that SPEI and NDVI achieved the highest total scores, reflecting their robustness for drought monitoring under current and projected climate scenarios. This ranking supports the selection of SPEI and NDVI as the most suitable indices for operational and research applications, particularly in the context of climate change.

Discussion

The findings underscore the growing complexity of drought management in the era of climate change. Several key insights and implications arise from the results:

Relevance of Drought Indices in Climate Change Context

The effectiveness of drought indices is highly dependent

Table 9: summarizes the scores and total ranking for each index.

Index	Climate Sensitivity	Data Requirement	Spatial Resolution	Temporal Resolution	CMIP6 Suitability	Operational Usability	Total Score
SPI	2	5	4	5	2	5	23
SPEI	5	4	4	5	5	5	28
NDVI	4	4	5	5	4	4	26
PDSI	3	3	3	3	3	4	19
MSDI	5	2	3	3	5	3	21

on their ability to incorporate climate variables such as temperature, evapotranspiration, and soil moisture. Indices like SPEI are better suited for capturing the multi-dimensional impacts of climate change compared to traditional indices like SPI, which focus solely on precipitation. However, challenges remain in adapting these indices to account for local socio-economic and ecological conditions.

Comparative Usability of Drought Indices Under Climate Change Scenarios

The increasing complexity of droughts under climate change necessitates a nuanced understanding of the strengths and limitations of various drought indices. The usability of each index depends not only on its methodological foundation but also on its sensitivity to evolving climate variables, data requirements, and suitability for different drought types and regional contexts. Here, we synthesize the comparative performance of widely used indices under historical and projected climate scenarios (CMIP5 and CMIP6), providing practical guidance for their application. Table 10 represents the comparative analysis of major drought indices.

Usability Under Projected Climate Scenarios

- CMIP5 vs. CMIP6: The transition from CMIP5 to CMIP6 models has improved the simulation of regional climate extremes, particularly in South Asia and other drought-prone areas. Indices that incorporate temperature and evapotranspiration (e.g., SPEI, MSDI) demonstrate greater sensitivity and reliability under high-emission scenarios (SSP5-8.5), where temperature-driven droughts are projected to increase in both frequency and severity.
- SPI remains a useful baseline tool but underestimates drought risk in warming climates due to its exclusion of temperature effects. Its simplicity and broad adoption make it suitable for initial screening but less so for future-focused risk assessments.
- SPEI is better suited for climate change contexts, as it

Table 10: Comparative analysis of major drought indices.

Index	Input Data	Drought Type	Strengths	Weaknesses	Performance under CMIP5/CMIP6	Best Use Cases
SPI	Precipitation	Meteorological	Simple, widely used, multi-scale	Ignores temperature, less sensitive to warming	Adequate for historical climates, less robust under projected warming (CMIP6)	Short-term meteorological drought, baseline monitoring
SPEI	Precipitation, Temperature/ ET	Meteorological, Agricultural	Captures temperature effects, multi-scale, climate-adaptive	Sensitive to ET estimation, data intensive	Highly robust under CMIP5/CMIP6, especially for warming scenarios	Climate change impact studies, semi-arid regions
PDSI	Precipitation, Temperature, Soil Moisture	Agricultural, Hydrological	Integrates soil moisture, long-term trends	Complex, less suitable for short-term drought, region-specific calibration needed	Useful for long-term drought under both scenarios, but calibration is critical	Water resource management, policy planning
NDVI/ VCI	Satellite Vegetation	Agricultural, Ecological	Real-time, spatially explicit, sensitive to vegetation stress	Seasonal limitations, indirect for meteorological drought	Effective for rapid drought detection under both scenarios, especially with AI integration	Agricultural monitoring, early warning systems
SMDI	Soil Moisture	Agricultural	Direct soil moisture assessment	Requires dense soil data, spatial heterogeneity	Valuable where soil data is available, especially for flash droughts under CMIP6	Crop yield forecasting, precision agriculture
JDI/MSDI	Multiple (Precipitation, Soil Moisture, Streamflow)	Meteorological, Agricultural, Hydrological	Integrates multiple variables, captures compound events	Computationally intensive, requires multi-source data	Strong performance under non-stationary, extreme events in CMIP6	Complex drought risk assessment, research applications
Hybrid/ AI-Based Indices	Remote Sensing, Climate, Socio-economic	All	Adative,customizable, high spatial/temporal resolution	Data and expertise intensive, validation needed	Promising for future scenarios, especially in data-rich regions	Integrated drought risk management, policy frameworks

integrates both precipitation and temperature, capturing the intensifying evapotranspiration and moisture deficits projected in CMIP6. SPEI is recommended for regions experiencing significant warming or variable precipitation patterns.

- NDVI/VCI and other remote sensing indices excel at real-time monitoring of agricultural and ecological droughts, especially when combined with AI for rapid data analysis. Their effectiveness is particularly notable in regions with high spatial variability and for early warning applications.
- Composite indices (e.g., JDI, MSDI, hybrid AI-based) are increasingly valuable for capturing compound and cascading drought events, which are expected to become more frequent under future climate scenarios. These indices are recommended for advanced research and operational frameworks in regions with sufficient data infrastructure.

Practical Guidance for Index Selection

- Meteorological droughts in semi-arid and warming regions: Prefer SPEI or MSDI, as these indices account for temperature-driven evapotranspiration and are responsive to projected climate variability.
- Agricultural and ecological droughts: NDVI, VCI, and SMDI are highly effective, especially when integrated with AI for real-time monitoring and prediction.
- Hydrological droughts and water resource management: PDSI and SWSI remain relevant for long-term planning, but require careful regional calibration and may benefit from integration with remote sensing data.
- Early warning and rapid response: Remote sensing indices (NDVI/VCI) and hybrid indices combining climate, vegetation, and soil data provide the most timely and spatially explicit information.
- Data-limited regions: SPI and RAI can serve as initial tools, but efforts should be made to build data infrastructure for adopting more advanced, climate-adaptive indices.

The usability of drought indices is context-dependent and should be aligned with both the type of drought and the prevailing or projected climatic scenario. SPEI and NDVI emerge as the most robust and versatile indices for monitoring drought under changing climate conditions, particularly when enhanced with AI and remote sensing technologies. However, no single index is universally optimal, a combination of indices, tailored to regional data availability and climate risks, is recommended for comprehensive drought assessment and management.

Regional Implications of Climate Model Projections

The CMIP6 projections for South Asia highlight the urgent need for region-specific drought mitigation strategies (Dixit et al. 2022). The increased frequency of flash droughts and long-term hydrological droughts underscores the importance of enhancing water resource management and adopting adaptive agricultural practices (Mukherjee et al. 2018). The findings also emphasize the value of advanced monitoring tools, such as remote sensing and AI, in providing actionable insights for policymakers and practitioners (Dakhil et al. 2024). However, it is important to note that model uncertainties and regional biases remain a challenge, and efforts should be made to validate projections with local observational data where possible (WMO & GWP 2016).

Advancements in Drought Monitoring Technologies

Integrating remote sensing and AI into drought management frameworks could revolutionize the field. Technologies such as satellite-based vegetation monitoring and AI-driven predictive models enable near real-time assessment of drought conditions, allowing for faster response times and more targeted mitigation efforts. The integration of artificial intelligence (AI) into drought monitoring represents a significant advancement, as evidenced by the reviewed literature. AI enables the rapid analysis of large datasets, improves the accuracy of drought predictions, and facilitates the development of adaptive, region-specific indices. However, challenges such as data scarcity, model interpretability, and the need for specialized expertise limit the widespread adoption of AI-driven approaches. Future research should focus on overcoming these barriers to fully realize the potential of AI in enhancing drought resilience.

Challenges in Drought Assessment and Mitigation

Despite advancements, significant challenges remain. Data availability and quality continue to hinder the application of sophisticated drought indices and climate models in many developing regions. Additionally, the increasing influence of anthropogenic activities on hydrological cycles complicates the prediction of drought impacts.

Policy Implications and Recommendations

The results emphasize the need for policymakers to prioritize investments in climate-resilient infrastructure and technologies. For instance, improving the accessibility of high-resolution climate data and implementing AI-driven drought monitoring systems could significantly enhance preparedness and response capabilities. The integration of climate, remote sensing, and socio-economic data into a hybrid drought monitoring system is illustrated in Fig. 5. This diagram illustrates the integration of climate data, remote sensing, and socio-economic information within a hybrid drought monitoring system. Climate models

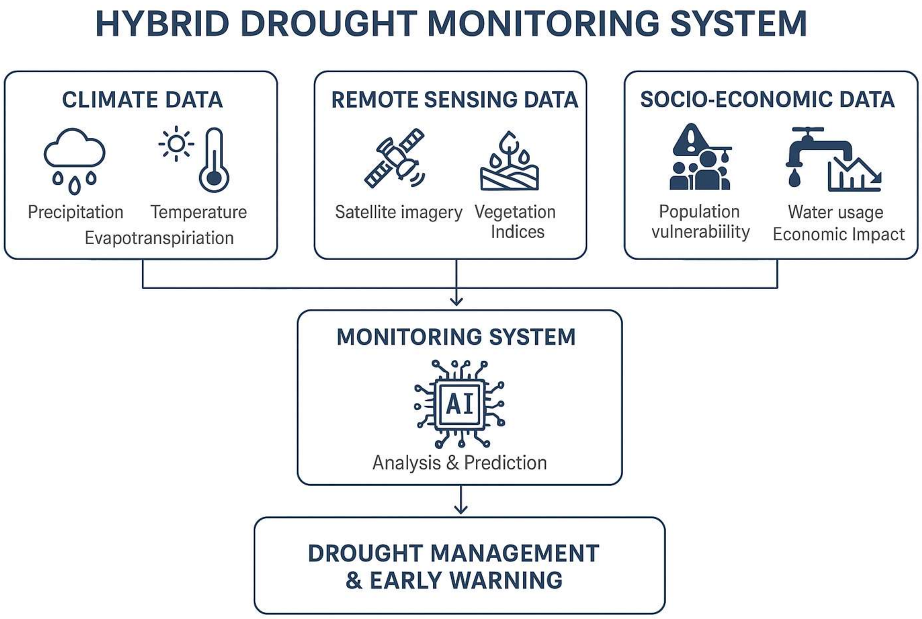

Fig. 5: Conceptual diagram of a hybrid drought monitoring system.

provide projections of temperature and precipitation, while remote sensing delivers real-time data on vegetation health, soil moisture, and surface water. Socio-economic data are incorporated to assess community vulnerability and adaptive capacity. Artificial intelligence (AI) processes these diverse data streams, enabling rapid, accurate drought prediction and early warning. The system supports adaptive management and policy decisions by providing comprehensive, actionable insights for drought resilience and water resource management.

Case Studies and Real-World Applications

In India, the Normalized Difference Vegetation Index (NDVI) has been widely used for early warning of agricultural drought. For instance, in the Marathwada region of Maharashtra, researchers have utilised NDVI data from MODIS and Landsat satellites to monitor vegetation health and detect drought onset up to several weeks before traditional ground-based indicators (Kulkarni et al. 2020). This approach has enabled local authorities to issue timely advisories and implement water-saving measures, reducing crop losses and supporting adaptive agricultural planning. Similar applications have been reported in other drought-prone regions of India, demonstrating the value of remote sensing indices for early drought detection and response.

Future Scope

While this study provides valuable insights, several areas for further research remain:

- Developing hybrid indices that integrate socio-economic factors for a more holistic assessment of drought impacts.
- Improving climate models to address non-stationarity and better capture the effects of anthropogenic activities.
- Exploring the role of groundwater and ecological droughts in shaping long-term resilience to climate change.

CHALLENGES AND GAPS IN EXISTING RESEARCH

Despite significant advancements in drought research, several challenges and gaps remain in both the methodology and technological applications, which hinder the accurate assessment and effective management of droughts under changing climate conditions. Challenges in Understanding and Managing Drought are shown in Fig. 5. The key challenges identified in this study are as follows:

Methodological Challenges

One of the primary challenges in drought assessment is the lack of uniformity in the application of drought indices. Many indices, such as the Standardized Precipitation Index (SPI) and the Standardized Precipitation–Evapotranspiration Index (SPEI), are predominantly based on precipitation data and do not adequately account for other crucial climate variables such as temperature, evapotranspiration, and soil moisture. While some indices have been adapted to include temperature and evapotranspiration, their application under non-stationary climate conditions remains a significant limitation.

Another challenge is the complexity of integrating multiple drought indices for comprehensive drought monitoring. While hybrid indices that combine remote sensing and ground-based data show promise, their development and validation are still in nascent stages, which makes their widespread application challenging.

Technological Challenges

Although advancements in satellite-based remote sensing and artificial intelligence have the potential to improve drought monitoring, challenges remain in terms of data accessibility, quality, and the integration of these technologies into operational frameworks. High-resolution satellite data can be expensive and difficult to access, especially for developing countries, which limits its use for real-time drought monitoring.

Furthermore, AI models require vast amounts of reliable and diverse data to accurately predict drought conditions. Inadequate datasets, coupled with the challenges of transferring these models to real-world applications, pose significant barriers to the deployment of AI-driven drought management solutions.

Limitations in the Application of Current Indices under Non-Stationary Climate Models

The increasing unpredictability of climate patterns due to human activities and natural variations complicates the application of traditional drought indices. Current models often fail to account for the non-stationarity of climate systems, which means that indices developed under stationary climate conditions may not perform well in future scenarios characterised by abrupt climatic shifts. The adaptation of these indices to more dynamic, non-stationary models is a crucial gap in the current research.

Additionally, the ability of existing indices to predict extreme droughts with sufficient accuracy under new climate conditions is still a matter of concern. Many indices are not sensitive enough to capture the nuances of severe drought events, especially in regions with complex climates or rapid climatic changes.

Integrating Socio-Economic Factors into Drought Assessments

Another significant gap in existing drought research is the difficulty of incorporating socio-economic factors into drought assessments. While climate data and drought indices can provide insights into environmental conditions, they often overlook the socio-economic vulnerabilities of the affected populations. Factors such as local economic dependencies, social resilience, and governance structures are critical in assessing the full impact of droughts but are challenging to quantify and integrate into existing models.

The lack of socio-economic data, coupled with difficulties in assessing the combined effects of climate and socio-economic variables, makes it challenging to develop comprehensive drought assessments that inform policy and adaptive strategies effectively. Research efforts that focus on integrating socio-economic aspects with environmental data are still limited, but are essential for improving the resilience of communities to droughts.

How Future Tools Could Resolve These Challenges

Recent advances in artificial intelligence (AI) and remote sensing offer promising solutions to many of these challenges. AI-driven models can integrate diverse datasets, including socio-economic and ecological variables, to better capture the complexity of drought impacts and vulnerabilities. By leveraging machine learning and big data analytics, these tools enable more accurate, real-time monitoring and prediction

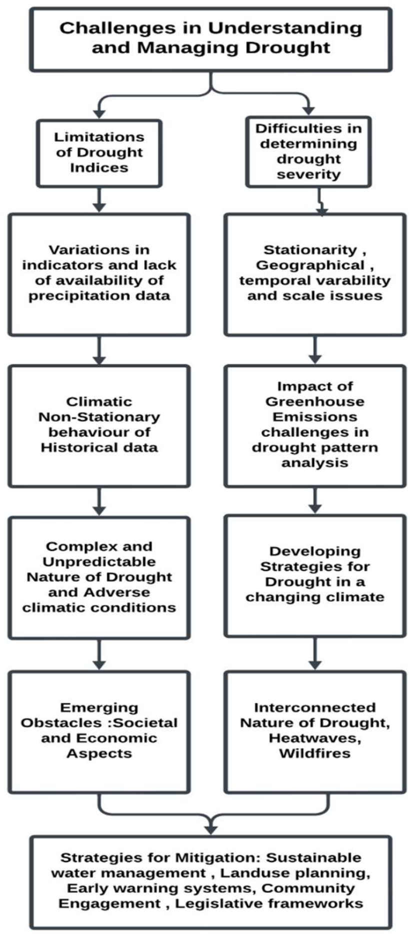

Fig. 6: Challenges in Understanding and Managing Drought.

of drought conditions, supporting adaptive management and targeted interventions. Furthermore, the integration of AI with remote sensing facilitates the development of hybrid indices that address data gaps and improve the spatial and temporal resolution of drought assessments, ultimately enhancing the resilience of vulnerable communities and ecosystems. A flow chart of challenges in understanding and managing drought is shown in Fig. 6.

RECOMMENDATIONS AND FUTURE FRAMEWORKS

To address the challenges identified in this study and improve drought management and mitigation strategies, several key recommendations are proposed. First, region-specific solutions should be prioritised, considering the unique climatic, geographical, and socio-economic conditions of each area. Implementing localized drought monitoring systems that integrate advanced technologies, such as satellite-based remote sensing, AI, and machine learning, can provide real-time data, enabling more accurate and timely responses. Additionally, drought indices should be enhanced by incorporating cutting-edge tools, such as AI-driven predictive models and hybrid indices that integrate multiple data sources, to improve their sensitivity and applicability under non-stationary climate conditions.

To support an actionable application, we recommend that SPEI and NDVI be prioritised for drought monitoring in semi-arid and warming regions due to their sensitivity to temperature-driven evapotranspiration and real-time vegetation stress. Policymakers should integrate SPEI and NDVI into early warning systems by leveraging remote sensing and AI-driven predictive models, such as Support Vector Machines (SVM), Random Forest (RF), and Deep Learning, which have proven effective in recent studies.

Policy directions should focus on improving water management systems, with an emphasis on sustainable practices, water conservation, and efficient resource allocation. Policymakers must also address the socio-economic impacts of drought by supporting vulnerable communities through adaptive agricultural strategies, investment in climate-resilient infrastructure, and the development of social safety nets. By fostering greater integration between scientific research, technological innovation, and policy development, the resilience of communities to droughts can be significantly improved, ensuring a more sustainable future in the face of climate change.

CONCLUSIONS

The findings of this study underscore the intricate relationship between climate change and drought, highlighting the significant role of advanced drought indices, climate models, and emerging technologies in enhancing drought monitoring and management. The comprehensive evaluation of 25 drought indices and climate model comparisons offers valuable insights into the growing complexity of droughts under climate change scenarios. The integration of remote sensing and AI-based tools provides a promising avenue for more accurate, real-time assessments of drought conditions, which is crucial for adaptive strategies in the face of increasingly erratic weather patterns. Moreover, the study emphasizes the need for innovative, region-specific frameworks that consider local socio-economic, ecological, and climatic conditions to enhance drought resilience. These frameworks can serve as a foundation for more effective drought management and mitigation efforts, providing tangible solutions for addressing the challenges posed by climate-driven droughts.

To translate these insights into practice, we recommend that researchers prioritise the development of hybrid indices integrating socio-economic factors and advanced technologies, policymakers invest in robust data infrastructure and region-specific monitoring systems, and technologists advance the integration of AI and remote sensing for real-time, adaptive drought monitoring. Ultimately, this research calls for continued collaboration between researchers, policymakers, and stakeholders to develop actionable strategies and ensure sustainable water resource management, particularly in regions most vulnerable to droughts.

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