Drought Monitoring and Forecasting in Saudi Arabia: Methods, Challenges, and Future Directions Under Climate Change

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Abstract
Saudi Arabia is considered as one of the driest countries with an arid climate, extremely low rainfall and high temperatures. Rapid population growth, and expansion of both agriculture and industrial sectors have intensified water scarcity and increased the frequency and severity of droughts across the country. This article reviewed and summarized peer-reviewed research that have explored drought monitoring and drought forecasting in Saudi Arabia over the past three decades. The studies included in this review were categorized into two main groups: research on drought monitoring and research on drought forecasting. These studies were reviewed in terms of drought indices used, data sources, modeling approaches and major findings. Results revealed that drought conditions have intensified in many parts of the country since the late 1990s with multi-year droughts recorded in 2007–2008 and 2013–2014. Results of meteorological indicators revealed noticeable drying trends at medium- and long-term temporal scales. However remote sensing–based studies reported an increasing vegetation stress particularly across the central and southern regions. In addition, climate projection studies suggest that potential evapotranspiration is expected to increase at a considerably higher rate than precipitation indicating that future drought conditions may intensify under both moderate- and high-emission scenarios. Although drought forecasting studies in Saudi Arabia remain relatively limited, the existing studies showed considerable potential for short- and medium-term prediction. However, the application of these existing studies is still constrained by limited geographical coverage. This review reported several issues such as limited field observations network, insufficient integration of multi-source datasets and the need for advanced national-scale drought forecasting framework. Addressing these issues by improving the monitoring and forecasting approaches is high priority to enhance early warning systems, support sustainable water resource management and to improve climate adaptation strategies in accordance with Saudi Arabia's Vision 2030.

Keywords: Satellite-based drought monitoring; Drought forecasting; Hybrid hydrological–machine learning models; Saudi Arabia.

1. Introduction

Drought is a prolonged period of deficit in water availability that affects ecosystems, agriculture, water supply, energy production and socio-economic development. Unlike sudden-onset disasters such as hurricanes, floods, and tornadoes, droughts emerge gradually over wide areas and can persist for extended periods, causing considerable harm to communities, ecosystems, and natural resources. Four principal types of droughts are commonly distinguished: meteorological drought (precipitation anomalies), agricultural droughts (soil-moisture deficit affecting crops), hydrological droughts (which reduce streamflow, groundwater and reservoir levels), and socio-economic drought (when water shortages impact society) [1, 2]. Drought events have been commonly represented as a part of natural climatic variability. However, climate change projections indicated that global warming is expected to increase the frequency, the duration and the severity of drought events [3]. Arid and semi-arid regions particularly in the Middle East are expected to experience the most severe drought-related impacts which potentially affect food security, human health, and economic stability.

Saudi Arabia is situated between 15° – 30° N latitude and 37° – 52° E longitude (Fig. 1). The country is bordered by the Red Sea along its western side with approximately 2250 km and by the Arabian Gulf along its eastern side for about 500 km. Both water bodies act as important sources of atmospheric moisture that influence regional climatic conditions. The country consists of several distinct geomorphological regions including coastal plains, the Western Heights, the Western plateau, the central Najd plateau, the Eastern plateau, the Northern plateau and the Empty Quarter desert. The climate of the country is characterized by extremely low rainfall (<100 mm yr^{-1} in large areas), high temperatures and high potential evapotranspiration (PET). Analysis of the 42-year records (1978–2019) of annual mean rainfall demonstrated significant decadal-scale variability in annual rainfall across Saudi Arabia (Fig. 2) [4]. Time-series regression analysis indicated a statistically significant downward trend in rainfall with rate of −5.89 mm per decade [5]. Most water resources of the country originate from non-renewable fossil groundwater aquifers and

limited periodic surface runoff. Rapid population growth, urbanization and agricultural expansion have increased water demand and resulted in greater stress on the limited water resources. Recent meteorological studies reported that both drought severity and frequency have increased across the country since the late 1990s [5, 6]. The period from 2006 to 2015 was characterized by recurrent multi-year drought conditions and the drought intensity reached its highest levels in the northern and western regions [5].
High mountain areas such as Asir and Al-Baha also experience extended dry spells that affect vegetation and reservoir storage [7, 8]. Climate projections based on CMIP6 models (considering high-emission scenarios [SSP5-8.5 or SSP3-7.0]) indicate that PET will increase five times faster than precipitation, resulting in substantial increases in drought severity across the Arabian Peninsula [9, 10]. Recent decades are characterized by exceptional warming of the global climate system because of the human-induced increases in greenhouse-gas emissions [11 -15]. Global warming can modify large-scale circulation patterns and moisture transport pathways affecting the Arabian Peninsula. These modifications may increase drought impacts in some regions and increase extreme rainfall and flood events in others [16-17]. Furthermore, higher temperatures are expected to increase the evapotranspiration rate and accelerate the drying of surface water reservoirs and aquifers as well. Therefore, the identification of these impacts is important for advancing drought forecasting and appropriate climate adaptation measures.

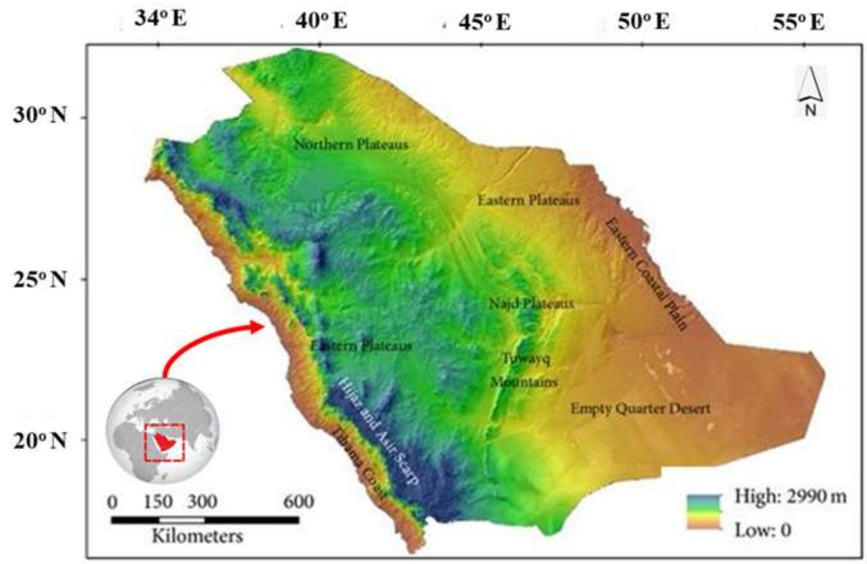

Figure 1. Regional map of Saudi Arabia illustrating spatial variations in surface elevation (m).

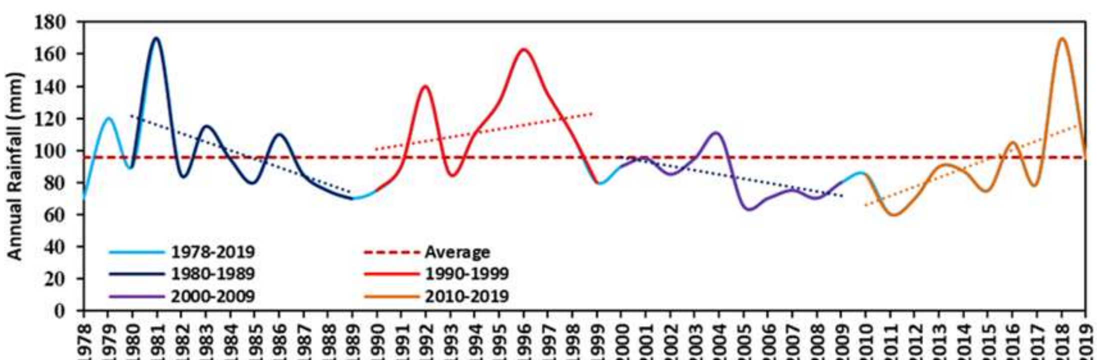

Figure 2. Temporal variation of the average annual rainfall (mm) across Saudi Arabia.[4]

Accurate drought forecasting provides valuable support for early decision-making by enabling proactive measures such as water management, agricultural planning, reservoir management and groundwater extraction adjustments. Drought forecasting in Saudi Arabia faces significant challenges as a result of the limited observation networks, insufficient historical hydrological data, complex climate drivers and uncertainties associated with climate change and land–atmosphere interactions. Researchers have developed a range of droughts indices and drought forecasting models to address these challenges. Recent Studies based on the Standardized Precipitation Evapotranspiration Index (SPEI) identified significant drying trends across the Arabian Peninsula from 1951–2020 particularly over the western and northern regions [4, 18, 19]. CMIP6 climate models projected that PET will increase faster than precipitation resulting in more severe droughts in future [3]. Downscaled GWTVDI projections indicated that high-emission pathways may expand drought-prone areas toward central and eastern Saudi Arabia by 2100 [20]. The analysis of drought variability over the period 1985–2022 using the Standardized Precipitation Index (SPI) showed significant negative trends with severe drought events recorded mainly in northern and western regions during 2007–2008 and 2013–2014 [3]. A multivariate assessment based on SPEI and copula models reported significant negative trends and periodicities of 1–3 years associated with ENSO. The study confirmed the increase in the drought severity and emphasized the importance of integrating remote sensing techniques with statistical approaches for drought monitoring [21]. A remote-sensing assessment in Asir region (1987–2019) reported that the fraction of vegetation cover has declined since 2004 corresponding with a long-duration drought which was identified using SPEI [22]. Another study using remote sensing in Al-Lith and Khafji watersheds (2001–2020) indicted that SPEI identified more severe droughts than those captured by the SPI [23]. The study reported that the total drought months were 166 for (SPEI) and 139 (SPI) in Al-Lith watershed and 129 vs 72 months in Khafji watershed [23]. Overall, the results confirmed that climate change combined with unsustainable water use can intensify drought conditions across Saudi Arabia which emphasizes the need of reliable drought forecasting.

Despite recognition of increasing drought risk particularly under climate change, there is no comprehensive synthesis of drought forecasting methodologies applied to Saudi Arabia. Existing studies are scattered across hydrology, remote sensing and artificial intelligence disciplines that generally focus on single indices or methods. Comparisons among methods seem to be rare and the integration of physical and data-driven approaches remains limited. Furthermore, most studies rely on short precipitation records or coarse-resolution climate data that can make significant local variations in climate and lead to uncertainties. This article aims to (1) summarize and evaluate the performance of hydrological models, remote sensing models and machine learning models in droughts forecasting over Saudi Arabia; (2) synthesize results from regional case studies to identify spatio-temporal patterns and drivers; (3) highlight challenges and gaps in current research; and (4) recommend future research directions and policy actions to improve drought early-warning system and resilience.

2. Materials and Methods

2.1. Methodology

As shown in Figure 3, this study presents a systematic review of the literature concerning assessment, monitoring and forecasting of drought. Relevant studies were obtained from the Web of Science and Scopus databases to address the research objectives. A keyword-based search strategy was applied using terms related to drought monitoring, forecasting, drought indices, climate variability and Saudi Arabia. We considered only peer-reviewed articles and book chapters in this search strategy. The selected publications were subjected to a multi-stage screening process in order to select the studies which are related to the study objectives. This screening process included an initial evaluation of titles and abstracts to identify relevant drought monitoring and forecasting studies. The initial evaluation was then followed by full-text analysis to assess methodological relevance and scientific contribution of these publications. The search was finally refined to include works published between 2000 and 2025 which were about 43 documents as shown in Figure 4. As illustrated in Figure 4, there is a notable upward trend in drought-related research conducted in Saudi Arabia.

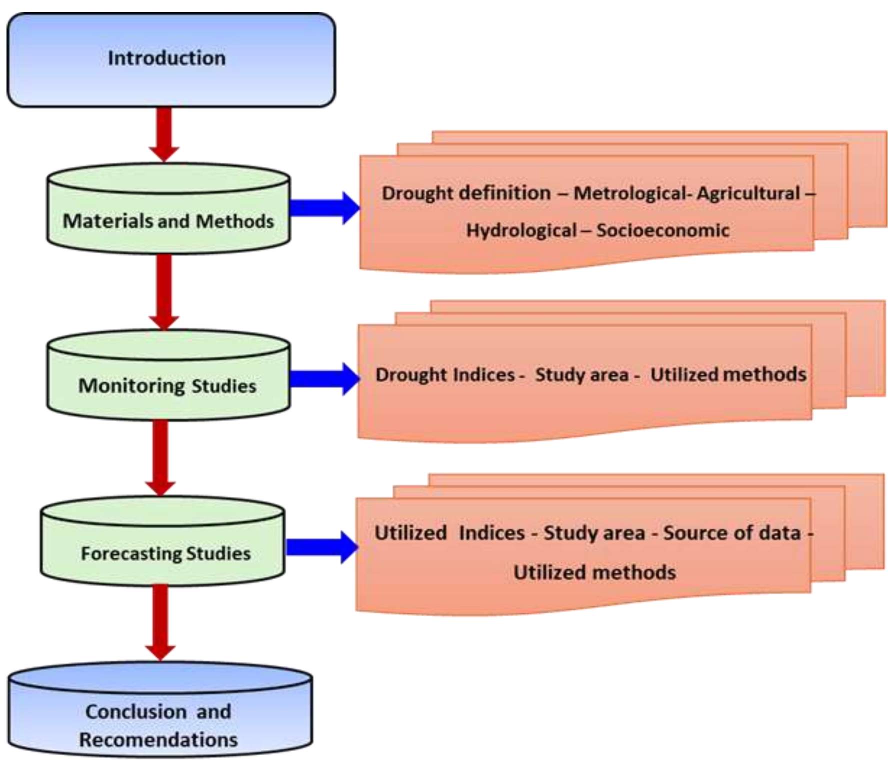

Figure 3. Methodological framework and procedural workflow adopted in the present study.

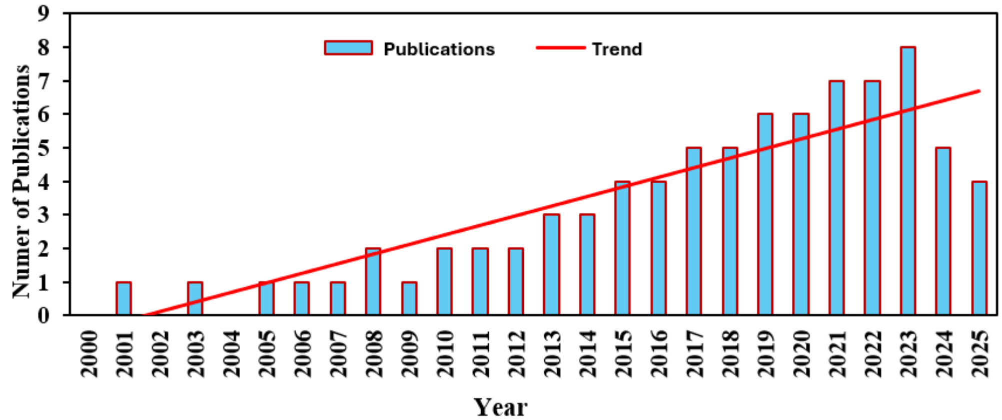

Figure 4. Total number of drought studies that were published between 2000 and 2025

2.2. Overview of drought types and drought indices

Droughts develop as a consequence of prolonged deficits in essential hydrological components, such as rainfall and available water resulting in negative impacts on all forms of life [24]. Drought phenomena are typically divided into meteorological, agricultural, hydrological and socioeconomic drought [25-27] (Figure 5). The sequential transition from meteorological to agricultural and hydrological droughts illustrates the unique processes and mechanisms which control the development of each drought category. Agriculture sector is typically the primary sector which is impacted when the drought event begins because this sector has a strong dependence on soil moisture reserves [28, 29]. Continued absence of rainfall deficits can lead to widespread reductions in water availability. Communities that depend on surface water resources are affected first while communities that rely on groundwater usually experience the impacts later.

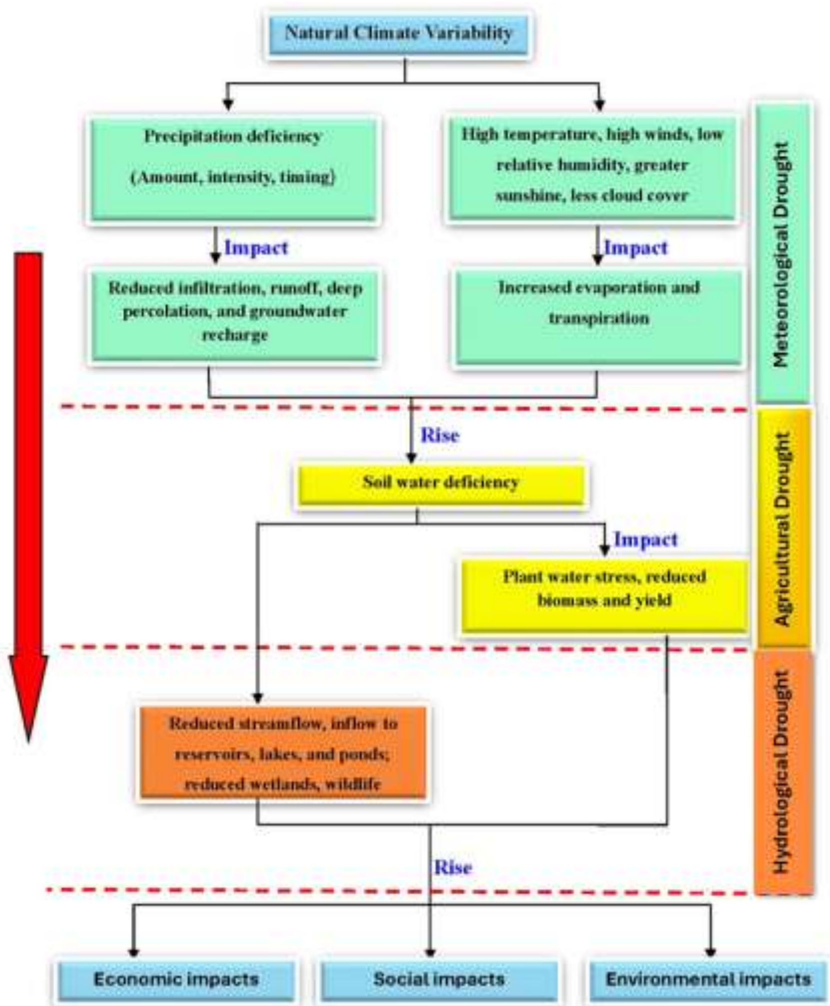

Figure 5. The progression over time and cascading impacts of meteorological, agricultural, and hydrological droughts (adapted from [35]).

Table 1. Overview of drought indices

`	Drought indices
Meteorology	- Standardized Precipitation Index (SPI) [36, 37] - Aridity Anomaly Index (AAI) - Deciles [38] - China Z Index (CZI [39] - Percent of Normal Precipitation [38, 40] - Weighted Anomaly Standardized Precipitation (WASP[38, 40] - Aridity Index (AI) [[41]] - Drought Reconnaissance Index (DRI) [42] - Effective Drought Index (EDI) [43] - Palmer Drought Severity Index (PDSI)[44] - Rainfall Anomaly Index (RAI) [45] - Evapotranspiration Index (SPEI) [46]
	- Vegetation Health Index (VHI) [43]
Agriculture	- Soil Moisture Anomaly Index (SMA) [47] - Evapotranspiration Deficit Index (ETDI) [48] - Soil Moisture Deficit Index (SMDI) [48] - Normalized difference vegetation index (NDVI)[49] - Vegetation Condition Index (VCI) [50] - Temperature Condition Index (TCI) [51]
Hydrology	- Palmer Hydrological Drought Severity Index (PHDI) [52] - Standardized Reservoir Supply Index (SRSI) [53] - Standardized Streamflow Index (SSFI) [54] - Streamflow Drought Index (SDI) [55] - Standard Streamflow Index (SSI) [55] - Surface Water Supply Index (SWSI) [56]

However, groundwater users are the last to experience drought effects and they are also the last to recover once the drought event ends. The duration of the recovery period is governed by multiple variables such as drought intensity, duration and the volume of rainfall that was received subsequently. As illustrated in Figure 5, drought events typically originate from specific meteorological conditions such as a prolonged anticyclone or high-pressure system. This leads to reduction in the rainfall and an increase in temperatures which indicates a meteorological drought. The subsequent deficit in rainfall accompanied with severe evapotranspiration resulted in a decrease the soil moisture, which can initiate an agricultural drought if it coincides with a growing season [30]. Reduction in precipitation within a catchment area also can lead to declining streamflow which eventually depends solely on groundwater recharge, and over time groundwater levels also decrease. Therefore, hydrological droughts and agricultural droughts often emerge as delayed responses to prolonged meteorological drought due to the gradual reduction in soil moisture and water availability. Surface water and groundwater are frequently utilized by different sectors with competing priorities such as agricultural irrigation, flood control, hydroelectric energy production and environmental protection [31, 32]. Socioeconomic drought occurs when water demand exceeds supply causing impacts on communities, economic activities, and water management systems. Several drought indices have been developed to assess all types and characteristics of drought and enabling decision-makers to develop appropriate mitigation and contingency strategies. [33, 34]. The derivation of these indices is based on multiple hydro-climatic parameters such as precipitation, temperature, surface runoff, soil moisture and both reservoir and aquifer storage levels. The selection of an appropriate drought index depends on several factors such as the study region, drought type and data availability. Recent developments in satellite-based meteorological observations, remote sensing applications and data-mining methods have significantly contributed to improving drought monitoring and forecasting. Table 1 presents different drought indices that have been developed for monitoring and forecasting various types of droughts.

2.3. Meteorological Drought Indices

2.3.1. Standardized Precipitation Index (SPI)

SPI was introduced by McKee in 1993 [36, 37, 57-58] and it was derived from an equiprobable transformation of accumulated monthly precipitation into a standardized normal variable. The calculation of the SPI is based on fitting a probability distribution to the aggregated monthly precipitation data (for example, over 3, 6, 12, or 24 months). The non-exceedance probability of the aggregated precipitation values is subsequently calculated and converted into standardized normal values. In this process the gamma distribution is commonly applied to represent precipitation characteristics and the maximum likelihood estimation is used to determine the distribution parameters. SPI has some advantages such as its simplicity, limited data requirement and the statistical reliability. SPI has also the capability to represent both short- and long-term drought events across multiple time scales. However its primary limitation is its dependence on only a single input variable. Previous studies have confirmed the effectiveness of SPI for assessing different drought categories.

2.3.2. Standardized Precipitation Evapotranspiration Index (SPEI)
SPEI provides an assessment of climatic water balance through the integration of precipitation inputs and atmospheric evaporative demand represented by potential evapotranspiration (PET)[38]. SPEI is an extension for the SPI by including temperature effects to capture the influence of global warming on the dynamics of drought. SPEI is computed from the differences between precipitation and PET across a specified time scale. This difference is then fitted to a probability density function and standardizing the resulting values to enable the comparison across different regions and time scale. SPEI can effectively identify both short- and long-term droughts events which makes it suitable for agricultural, hydrological and ecological studies. SPEI is particularly valuable in regions where rising temperatures intensify severity and duration of drought because it is calculated for temperature-driven evaporative demand,

2.3.3 Palmer Drought Severity Index (PDSI)
The PDSI was developed by Palmer [44, 59-60], and it employs a soil–water balance approach to quantify drought, incorporating precipitation and evapotranspiration alongside runoff and soil moisture dynamics. The PDSI is highly sensitive to the considered calibration period, and its applicability becomes limited outside the region for which it was calibrated. Therefore, it is not suitable to use PDSI for spatial comparisons. The Self-Calibrated Palmer Drought Severity Index (sc-PDSI) was introduced to address this issue by offering improved spatial comparison. However, SPEI still presents limitations related to multi-scale drought representation and its sensitivity to previous climatic conditions over several years[40]. When soil moisture content or level of surface water exhibit significant departures from the climatological norm following an extreme event, the Palmer Hydrological Drought Index (PHDI) can be applied as a more suitable measure as it integrates both precipitation and soil moisture storage rather than focusing only on meteorological factors. Since the PDSI and PHDI consider only rainfall as precipitation, excluding other forms, their timing estimates may occasionally be inaccurate. Although PDSI offers information on the beginning and end of drought events, it is criticized for its delayed response time, sensitivity to calibration and poor cross-climate transferability.

2.3.4 China Z Index (CZI)
The CZI was developed by the National Climate Centre of China, is utilized for the operational monitoring and assessment of drought conditions. This index relies only on monthly precipitation records and is preferable alternative to the SPI due to its simpler computation particularly when precipitation records are incomplete [39]. The CZI is based on the Pearson Type III distribution which is considered most suitable for modeling precipitation data. Consequently, it employs Wilson–Hilferty cube-root transformation to convert the chi-square variable into a standardized Z-scale. An improved version of CZI, (MCZI), is known as the Modified China Z Index in which the mean value is replaced with the median of precipitation data in its calculation [41].

2.4 Agricultural Drought Indices
2.4.1 Normalized Difference Vegetation Index (NDVI)
The NDVI is widely recognized as a key remote sensing indicator for evaluating vegetation conditions. It is derived from the reflectance measurements of the red and near-infrared (NIR) bands in satellite imagery. Healthy vegetation absorbs most of the visible red light for photosynthesis and reflects a large portion of near-infrared light resulting in higher NDVI values. However, sparse or stressed vegetation shows lower NDVI values due to reduced chlorophyll activity. NDVI values typically range between −1 to +1, with higher values near to +1 representing dense, healthy vegetation. The values close to or less than zero represent barren land, water bodies or non-vegetated surfaces. Because of its simplicity and efficiency, NDVI is commonly applied in environmental monitoring, drought evaluation, agriculture and land-use studies.

2.4.2 The Vegetation Condition Index (VCI)
TheVCI is a remote-sensing-based index which is applied to evaluate vegetation health and monitor drought events. It is derived from the NDVI by comparing current vegetation conditions with historical context (maximum vs. minimum) records for the corresponding period. The VCI is useful in distinguishing between short-term weather-related vegetation changes and long-term climatic or environmental factors. Values of the index lie between 0 and 100 where low values indicate stressed or drought-affected vegetation and high values reflect healthy growth. The VCI is extensively used in agricultural drought monitoring, ecosystem assessment and early warning system because of its proficiency in capturing spatio-temporal variations of vegetation response.

2.4.3 Temperature Vegetation Dryness Index (TVDI)
The TVDI was derived from the triangle relationship between land surface temperature (LST) and vegetation indices (usually NDVI)[41]. The TVDI estimates both the soil moisture and the drought stress by positioning a pixel relative to wet and dry edges. It can be calculated using NDVI or the Enhanced Vegetation Index (EVI). Previous studies showed no agreement on which index is superior as the performance varies by geography and vegetation density [41, 61]. TVDI is particularly useful where ground data is scarce.

2.4.4 Temperature Condition Index (TCI)
The TCI applies remote sensing measurements to evaluate temperature-related vegetation stress in the areas which are affected by drought [51]. The TCI is derived from satellite-based LST observations through comparing current thermal conditions with historical temperature extremes over a specified period. The higher values of TCI generally indicate to suitable thermal conditions that support vegetation growth. While the lower TCI values reflect increased temperature stress and potential drought effects on vegetation. The integration of TCI with NDVI and VCI can enhance

the drought assessment and provides a more comprehensive evaluation of the climatic and environmental factors that affect plant health.

2.4.5 Vegetation Health Index (VHI)

The VHI combines VCI and TCI to characterize vegetation stress and it is widely recognized as a reliable remote sensing index for drought assessment in Saudi Arabia[8, 43, 62].

2.5 Hydrological Drought Indices

2.5.1 Standard Streamflow Index (SSI)

The SSI is used to assess the variations in streamflow by standardizing monthly discharge records using gamma or log-normal distributions [55, 63–64]. The process allows SSI to describe streamflow anomalies as differences from the long-term average to compare drought severity at different regions and time periods. Negative SSI values indicate hydrological drought events while positive values reflect above-normal streamflow. Due to its ability to provide information about river basin behavior it is widely used in water resources management and for supporting reservoir operation and hydrological assessments.

2.5.2 Surface Water Supply Index (SWSI)

The SWSI is used to assess the availability of surface water resources within a specific basin or watershed. The index integrates several hydrological variables such as streamflow, reservoir storage, and precipitation to give comprehensive assessment of the surface water status [55]. The index follows a standardized range between −4.2 to +4.2 where negative values represent drought and positive values indicate wetter conditions. SWSI is considered as a useful tool for integrated water resources management, drought monitoring and mitigation planning.

3. Results

3.1 Overview of Drought Monitoring Studies in Saudi Arabia

Table 2 provides an overview of previous research that were conducted between 2000 and 2025 to investigate drought occurrences and their characteristic across various regions of Saudi Arabia. The reviewed studies provide valuable information on the drought characteristics and the different approaches used for drought assessment in Saudi Arabia as described below.

• The watershed or the drainage basin that was chosen on the study.
• The drought indices that were applied to evaluate drought conditions.
• The main findings of each study and how were these results interpreted by the authors?
• The type of data that was used to derive the drought indices.

Table 2. Summary of previous drought studies across different regions of Saudi Arabia.

Reference Name	Drought Type	Index Type	Studied Region
Munir et al. [65]	Meteorological	SPI	Gassim, Taif, Madinah
Mohammed et al. [22]	Agricultural	NDVI	Saudi Arabia (Northern Asir)
Almazroui [66]	Meteorological	SPI, PDSI	Saudi Arabia (national scale)
Syed et al. [67]	Meteorological	SPI, RDI, Decile Index, etc.	Saudi Arabia (national scale)
Ibrahim et al. [7]	Agricultural and Meteorological	SPI, RDI	Saudi Arabia (Al-Baha)
Alqadhi et al. [21]	Meteorological	SPEI	Saudi Arabia (national scale)
Ejaz & Bahrawi [23]	Meteorological	SPI, SPEI	Saudi Arabia Al-Lith & Khafji
Hereher et al. [68]	Agricultural	NDVI	Saudi Arabia Ha'il (Qa'a Al-Milh)
Assiri et al. [69]	Agricultural	NDVI	Buraydah, Hail, Wadi Al-Dawasir, Tabuk
Ejaz et al. [1]	Agricultural	VCI, TCI, VHI	Saudi Arabia Al-Lith
Alazba et al. [70]	Agricultural	TVDI	Al-Kharj (At-Tawdihiya)
Alharbi [71]	Meteorological	GIS-based Index	Saudi Arabia Neom
Mallick et al. [8]	Agricultural	VHI (SPEI, VCI, TCI)	South & Central Saudi Arabia
Tarawneh [72]	Meteorological	SPI	Saudi Arabia (national scale)
Alhathloul et l. [3]	Meteorological	SPI	Saudi Arabia (national scale)

Munir et al. [65] applied SPI approach to analyze the meteorological drought conditions across Saudi Arabia using rainfall records from 28 meteorological stations during the period 1985–2023. Results indicated that many parts of the country have become relatively wetter in recent years. Since 2010, an increase in precipitation was observed at 25 of the 28 stations with the highest rainfall increases recorded in areas such as Gassim, Taif, and Madinah. The study also reported that the drought severity has decreased in most regions during the last decade. Some regions provide positive average SPI values which indicate reduction in drought occurrence in these regions. However future climate projections suggested that drought risk could increase in the near term before a possible shift toward wetter conditions by the end of the century. This study highlighted the recent improvement in rainfall patterns and SPI-based drought conditions across Saudi Arabia and also emphasized the potential for increased drying during the mid-century period under future climate change scenarios.

Almazroui [66] investigated meteorological drought patterns from 1978 to 2017 using ground observations and multiple drought metrics. This study applied both the SPI and the PDSI to map drought spatially. Results showed that drought occurrences in Saudi Arabia are primarily driven by precipitation deficits in the dry season even if rains during wet season are above normal. Seasonal analysis showed that April at the end of the wet season was the month with the lowest drought risk. June and September which correspond to the beginning and end of the dry season were more susceptible to drought occurrences. The spatial analysis of SPI and PDSI reported some differences in drought patterns among regions with some areas showed drier conditions. Results emphasized the strong seasonality of drought and the importance of considering local climate patterns when assessing drought risk.

Syed et al. [67] identified major drought events in Saudi Arabia using six different meteorological drought indices. These indices included SPI and the DRI, as well as Decile and Percent of normal indices and two new effective rainfall-based indices (aSPI and eDRI). By comparing these indicators over 1985–2020, the study identified eight significant nationwide drought and the year 2007 was identified as an extreme event . The study revealed that the period 2007–2012 (except 2010) was the longest continuous drought event during which about 70% of the country area was under moderate to extreme drought conditions. An empirical orthogonal function analysis of SPI revealed coherent drought patterns, and a strong link was found between variability of drought in Saudi Arabia and large-scale climate oscillations. In particular, the Pacific Decadal Oscillation (PDO) showed a significant correlation with the occurrence of drought years, which suggests the possibility of drought prediction based on global teleconnection signals.

Alqadhi et al. [21] applied SPEI to evaluate both short and long-term meteorological drought across Saudi Arabia. They applied innovative trend analysis, wavelet transformation and bivariate copula to analyze patterns and return periods of drought events. The analysis identified significant negative trends in both SPEI-6 and SPEI-12 that reflected mid to long term drought conditions in the study are. Wavelet spectra identified major drought periodicities of about 1–3 years that were associated with the influence of large-scale climate oscillations such as ENSO. The copula models reported that the detected severe drought events were relatively rare with return intervals longer than 50 years. The authors recommended the integration of remote sensing and machine learning to enhance drought monitoring and improve mitigation strategies.

Ejaz et al. [23] used SPI and SPEI to assess the meteorological drought in two hydrologically different watersheds in Saudi Arabia. The first region was Al-Lith located along the Red Sea coast and the second region was Khafji on the Arabian Gulf coast. The study applied SPI and SPEI at multiple time scales (1, 3, 6, 12 months) to compare drought duration and intensity using records from 2001 to 2020. They reported that SPEI identified more significant prolonged and severe drought events than SPI in both watersheds. In Al-Lith the total duration of drought months that detected by SPEI was 166 months versus 139 months by SPI. The drought duration that reported by SPEI in Khafji was almost double this by SPI (129 vs 72 months). These differences confirmed that involving the temperature effects in SPEI can capture additional drought stress especially in the hotter inland.

Hereher et al. [48] investigated agricultural drought in the Hail region in northwestern Saudi Arabia during the period 2000-2019. The study used NASA MODIS satellite data to derive the NDVI and land surface temperature (LST) combined with TRMM satellite rainfall records. The results reported a significant decrease in NDVI which indicated the persistence of drought stress on the plants. The vegetation browning accompanied by a rising trend in LST and a significant drop in rainfall totals confirmed hotter and drier conditions.

Assiri et al. [69] assessed the spatio-temporal dynamics of vegetation and land surface temperature in eight main agricultural regions during the period 2010–2023 in Saudi Arabia. The study investigated NDVI using high-resolution Landsat satellite data to assess vegetation greenness. The study identified significant seasonal and annual variability in NDVI across the study area. They reported that vegetation cover expanded in several locations despite aridity. Between 2014 and 2023 the irrigated cropland around Buraydah grew by over 300 km² and the vegetated area in Hail increased by about 33 km². The study reported that some sites provided declines such as Wadi Al-Dawasir green area which shrank by about 275 km² and Tabuk which shrank by about 89 km². The analysis also showed that vegetation presence has a cooling effect on local land surface temperatures as the dense crop covers reduced surface temperature by about 3–6 °C compared to bare soil. The study showed that climate change is already influencing these patterns and that picking up vegetation responses is high priority for sustainable agriculture and mitigating of heat stress in arid areas.

Ejaz et al. [1] investigated the application of remote sensing techniques to monitor drought and compare the remote sensing-retrieved drought indices with SPEI. The study derived several satellite-based drought indices from Landsat data including VCI, TCI and the VHI to track vegetation stress from 2001 to 2020. The performance of these remote sensing indices was examined by comparing their correlation with SPEI. The VHI showed the highest correlation with SPEI among the tested indices especially at long time scales (such as $r \approx 0.74$ for VHI vs SPEI-12). The TCI and VCI had somewhat lower agreement with SPEI (r is about 0.5 and 0.6 at 12-month scale). These results indicated that VHI can be employed as a reliable index in evaluating impacts of drought on vegetation in data-scarce areas.

Alazba et al. [70] investigated agricultural drought at a local scale using a satellite-derived metric that combines land surface temperature and vegetation cover data the (TVDI). The study was applied Al-Kharj Governorate which is classified as a water scarce agricultural area in central Saudi Arabia. The study provided a detailed description of soil water deficit and effectively identified sub-areas that reexperienced more intense drought conditions. The results showed a positive trend in TVDI values over time which reflected the growing problem of water shortage and confirmed that the soil water drought in this area was getting worse. The study validated the satellite-based drought mapping with ground data and reported strong correlations and confirmed the reliability of the TVDI method for land surface drought monitoring. The authors provided a useful decision-support tool for local water managers by identifying where irrigation or other interventions are most needed to sustain agriculture in arid environments.

Alharbi [71] implanted a geospatial analysis to characterize drought-prone zones in the Neom region in northwestern of Saudi Arabia. They applied a multi-criteria GIS overlay method to identify the areas with various levels of drought, flood and groundwater potential. Several environmental parameters were considered for drought risk assessment such as long-term precipitation patterns, soil characteristics, topography and drainage density. A hybrid drought vulnerability index was generated and mapped by adding weights to these factors. Results showed that large portions of the region were vulnerable to drought. About 10615 km^2 of the region was classified as moderate drought risk and about 8266 km^2 as high drought risk. In contrast, only a small part of the area (about 44 km^2) was rated as very low drought risk. These findings indicated that the inland and the topographically elevated areas of Neom are most at risk of water scarcity. This research suggested baseline data for water managers as it illustrated where water resource development and drought mitigation may be most needed. The applied GIS-based methodology confirmed that remote sensing and measured data could be integrated for sustainable water management in arid regions under climate-related challenges.

Mallick et al. [8] investigated impact of drought on vegetation health across Saudi Arabia using remote sensing approaches. They used both drought indices and satellite-derived vegetation indicators to examine the influence of drought progression on the land cover and on the agriculture. The drought analysis included earth observations records from 2004 to 2021 and provided several meteorological and vegetation indices such as SPEI and VHI. Trend analysis detected a significant increase in drought severity over time with frequent extreme drought events during the period from 2014 to 2018. These recurrent drought conditions with the rising temperatures caused severe stresses on vegetation with significant negative trends in VHI in both the southern and central regions of Saudi Arabia. The wavelet analysis detected recurrent drought patterns which reflected periodic fluctuations associated with a general drying trend.

Alhathloul et l. [5] provided a comprehensive evaluation of drought pattern in Saudi Arabia from 1985 to 2022 using the SPI at multiple scales. The analysis revealed positive trends in SPI series in some parts over the past few decades. More frequent and prolonged meteorological droughts were observed in the northern regions while the western parts of the country were affected by the most severe drought events. Relatively few drought events were recorded before 2000 but their frequency increased markedly after that period and Large-scale drought events around 2007–2008 and 2013–2014 affected multiple provinces.

Although theses previous considerable research that were conducted on drought variability in Saudi Arabia, several methodological gaps still exist. It was noticed that these analyses depended mostly on the short-term records or a limited number of meteorological stations which might affect the accuracy of long-term drought trend analysis. Most of the reviewed works focused mainly on precipitation-based indices and did not include other variables such as temperature, soil moisture or remote sensing data. Such limitations might provide an incomplete representation of drought characteristics in arid environments where evapotranspiration and land–atmosphere interactions influence water availability. The remarkable differences between studies that reported long-term drying trends and those that indicated recent wetter conditions may be attributed to the variations in the study period, drought indices selection and data sources. Research that considered both long-term records and evapotranspiration-based indices found that drought conditions have become more severe as a result of the rising temperatures and the increased evaporative demand. In contrast, analyses that considered shorter precipitation records or SPI alone captured temporary increases in rainfall during specific decades.

3.2 A Review of Drought Forecasting publications in in Saudi Arabia

This section critically reviews drought forecasting studies conducted in Saudi Arabia with focus on their methodological development and spatial applicability. The reviewed articles included different approaches for drought forecasting. Some of these approaches included hybrid frameworks that combined hydrological data with remote sensing observations. Evaluation of each study considered its forecasting objectives, drought type, selected drought indices and the spatial-temporal dimensions of the analysis. Table 3 summarizes the main characteristics and methodological differences of the selected studies and presents a comparative overview of their principal parameters. These studies showed a gradual improvement in drought modeling capabilities with a shift from empirical approaches to data-driven forecasting systems that can improve early warning performance and water resources management under changing climatic conditions. However, the number of peer-reviewed drought forecasting studies available for Saudi Arabia is still relatively limited. Forecasting frameworks and predictive analyses are still in their early stages of development despite the climatic vulnerability and the rising occurrence of extreme aridity events. The reviewed articles showed that the focus of drought research in Saudi Arabia was basically on monitoring and assessment of drought events rather than long-term drought forecasting.

Table 3. List of the studies that forecast drought in Saudi Arabia.

Reference Name	Drought Type	Index Type	Studied Region
Al Moteri et al. [73]	Meteorological	SPEI	Coastal arid region (Red Sea coast, KSA)
Saharwardi et al. [9]	Meteorological	SPI, SPEI	Arabian Peninsula (incl. Saudi Arabia)
Mossad [74]	Meteorological	SPEI	Al-Qassim and Hail regions
Alsubih et al. [75]	Meteorological	SPI-6	Asir region
Abd El-Hamid et al [76]	Agriculture	NDVI- NDWI	Eastern Saudi Arabia
Alquraish et al. [2]	Meteorological	SPI	Bisha Vally, Saudi Arabia

Al Moteri et al. [73] developed a deep learning model to improve drought forecasts in coastal arid regions of Saudi Arabia (areas with <100 mm annual rainfall). The study used the SPEI to investigate coastal meteorological drought conditions since SPEI. The study trained a self-attention ConvLSTM model (SA-CLSTM) to predict SPEI-based drought indices using climate data from the CRU dataset covering the period 1901–2018. The developed model achieved very high accuracy with $R^2 > 0.99$ for one-month-ahead predictions of SPEI-1 and SPEI-3 and the Area Under Curve (AUC) was about 0.99 in classifying drought severity. These results outperform traditional machine-learning benchmarks and demonstrate the ability of deep learning model in reliably forecasting of short-term drought intensity under various drought conditions. The authors suggested that such advanced models could support early warning and mitigation efforts in coastal zones of Saudi Arabia .

Saharwardi et al. [9] evaluated drought changes across the Arabian Peninsula (with Saudi Arabia as the primary case study) using CMIP6 climate models. SPI and SPEI indices were implemented in order to capture hydro-climatic changes. The study first identified the best-performing climate models for the region and noted a key challenge. Several models struggle to simulate the sparse rainfall accurately, leading to high uncertainty in SPI-based projections. However, these models more consistently captured the effects of rising temperatures and increasing potential evapotranspiration, which were reflected in the SPEI projections. Using an optimized method (Hargreaves) for PET, they found that the rate of increase in evaporative demand far exceeds that of rainfall in all future scenarios. Accordingly, SPEI predicted significant increases in future drought frequencies and severities, especially under high-emission pathways (SSP3-7.0 and SSP5-8.5), whereas lower-emission scenarios (SSP1-2.6, SSP2-4.5) still see worsening drought albeit to a lesser degree. Their results indicate that even with some model and scenario uncertainties, a general drying trend is robust warming will likely amplify droughts in Saudi Arabia and the broader region. The authors emphasize improving regional rainfall simulation in climate models to refine these drought forecasts for better planning and adaptation strategies.

Mossad [74] applied linear autoregressive integrated moving average (ARIMA) models to forecast meteorological drought in central Saudi Arabia's hyper-arid zones. The SPEI was applied as the drought indicator, computed at various time scales, and developed site-specific ARIMA models for several locations in Al-Qassim and Hail provinces. The fitted ARIMA models demonstrated good skill in short-term drought prediction. The model structures (ARIMA parameters) were quite similar for a given SPEI time scale across different stations. An ARIMA model (1,1,0)(2,0,1) was selected as best model for the SPEI series in Al-Qassim region while in Hail region fitted an ARIMA(1,0,3)(0,0,0) for SPEI-3 and ARIMA(1,1,1)(2,0,1) for SPEI-24. Forecasting models of SPEI-24 had generally the best performance with $R^2 > 0.9$ and lowest RMSE. The relatively high forecasting accuracy at longer aggregation periods indicates ARIMA-based forecasts may provide useful information for water resources managers in Saudi Arabia by enabling them to anticipate drought severity several months ahead and prepare suitable mitigation measures.

Alsubih et al. [75] investigated meteorological drought trends over 1970–2017 in the Asir region located in southwestern Saudi Arabia. The study applied a machine-learning approach to forecast drought using SPI-6 as an indicator. The analysis showed that drought events in Asir have become more frequent and more severe during recent decades. Mann–Kendall trend tests (including modified and sequential versions) revealed statistically significant increasing trends at most meteorological stations with evidence of a shift toward drier conditions around the late 1990s. A hybrid Particle Swarm Optimization–Artificial Neural Network (PSO–ANN) model was developed for forecasting SPI-6 values. The model showed good performance and the predicted SPI-6 values were in close agreement with the observed values. Forecast results suggested recurrent moderate to extreme drought events in Asir during the near future period. Such forecasts are important for the agricultural sector in Asir because it depends mainly on seasonal rainfall.

Abd El-Hamid et al. [76] proposed a hybrid framework that combined remote sensing datasets with machine learning algorithms to improve the performance of drought forecasting in the arid eastern region of Saudi Arabia. Several predictive models including Random Forest and Support Vector Machine classifiers were trained and validated using satellite-derived indices such as NDVI, LST, and SPEI. The findings showed that the integration of multi-source remote sensing data improved model performance and provided a high forecasting accuracy for both short- and medium-term drought events. The authors recommended such data-driven and machine learning–based approaches as valuable tools for operational drought monitoring and early warning in water-stressed environments.

Alquraish et al. [2] developed a set of hybrid models to improve meteorological drought forecasting in Bisha Valley which is a semi-arid watershed in Saudi Arabia. The study combined the SPI with three modelling approaches namely Hidden Markov Models coupled with Genetic Algorithms (HMM–GA), ARIMA–GA, and a further integration with Artificial Neural Networks to capture both linear and nonlinear dependencies in the rainfall data. The study trained these models on rainfall records cover the period 1968–2008 and validate them against data from 2009–2019. The proposed hybrid HMM–GA–ANN model produced the lowest RMSE and the highest predictive skill among the evaluated models. This approach demonstrated the advantages of integrating statistical and machine learning techniques to generate accurate short-term drought forecasts.

Overall, the reviewed studies demonstrate that drought forecasting in Saudi Arabia has evolved from traditional statistical approaches toward more advanced machine learning techniques. While machine learning models generally provide higher predictive accuracy, their effectiveness depends on the availability of high-quality meteorological datasets. Table 4 summarizes the main characteristics of drought forecasting models applied in Saudi Arabia. The comparison shown in Table 4 illustrates the methodological transition from traditional statistical models toward hybrid and deep-learning frameworks that integrate climatic and remote-sensing datasets. Model performance in the reviewed studies was commonly evaluated using statistical indicators such RMSE, MAE and R^2. Deep-learning models and hybrid machine-learning approaches generally demonstrated higher predictive accuracy particularly for short-term forecasts. However, these models require large datasets and computational resources which currently limit their widespread operational use.

Table 4. Comparative summary of drought forecasting models applied in Saudi Arabia.

Study	Model Type	Drought Index	Forecast Horizon	Reported Performance
Al Moteri et al. [73]	Deep Learning (SA-ConvLSTM)	SPEI	1–3 months	$R^2 > 0.99$, AUC ≈ 0.99
Saharwardi et al. [9]	Climate model projections (CMIP6)	SPI, SPEI	Long-term projections	Increased drought frequency under high emissions
Mossad [74]	ARIMA	SPEI	Up to 24 months	$R^2 > 0.9$ with low RMSE
Alsubih et al. [75]	PSO-ANN hybrid model	SPI-6	Seasonal prediction	High predictive accuracy
Alquraish et al. [2]	HMM-GA ARIMA-GA	SPI-3, SPI-6	3–6months	$R^2 > 0.91$ with low RMSE

5. Climate change impacts and uncertainties

Climate change is intensifying drought over Saudi Arabia and the broader Arabian Peninsula. CMIP6 simulations indicate that potential evapotranspiration (PET) increases about five times faster than precipitation under high-emission scenarios, leading to severe drying. SPEI projections show that future droughts will intensify even under moderate scenarios [9]. Hydro-meteorological analyses of 1951–2020 records revealed coherent drought regions across the Arabian Peninsula with significant drying trends and accelerated drought frequency after 2000. These trends were associated with reduced synoptic activity and an increase in high-pressure systems. In addition, potential evapotranspiration was found to play a dominant role in summer droughts, whereas precipitation and temperature were the main drivers of winter droughts [19]. Saudi Arabia is characterized by an arid climate with average annual rainfall of around 114 mm and summer temperatures exceeding 50 °C, making the country highly sensitive to even small increases in atmospheric evaporative demand [56]. Projections of drought remain uncertain because global climate models struggle to reproduce convective precipitation and orographic processes in the peninsula; ensemble spreads, internal variability and choices of drought indices and PET calculation methods create large uncertainties [9]. Downscaled and bias-corrected regional climate models, informed by land-use and socio-economic scenarios, are needed to capture local extremes. New tools such as GWTVDI integrate temperature, vegetation and topographic signals via geographically weighted regression; when combined with high-resolution climate projections they reveal spatial shifts and intensification of drought hotspots across the Middle East by 2100 [57]. Statistical techniques also provided useful insights as bivariate copula models applied to SPEI time series showed significant negative trends and indicated that severe drought events (SPEI < -2) may have return periods of more than 50 years [21]. Hybrid deep-learning models which integrate bi-directional LSTM and standard LSTM layers were able to improve rainfall forecasting accuracy [58]. The use of remote sensing and wavelet analysis also contributed to identifying drought patterns linked to ENSO [21]. These advances suggest that future drought forecasting in Saudi Arabia should integrate high-resolution climate projections, machine learning approaches and remote sensing observations with consideration of model uncertainties and socio-economic drivers.

4. Discussion

The review highlights that Saudi Arabia has experienced several drought events with varying degrees of severity. The results of the considered studies demonstrated that the drought in Saudi Arabia is not simply a natural aspect of its

dry climate but is also additionally influenced by climate change and excessive water use. Therefore, drought should be recognized as a critical issue affecting the sustainable development of the country. Long-term observational and satellite-based studies indicated that Saudi Arabia is experiencing more recurrent and increasing drought conditions. Analyses based on SPI over multi-decadal periods revealed an increase in drought frequency and severity after the year 2000, with recognized events in the northern and western regions. Major events in the periods 2007–2008 and 2013–2014 affected multiple areas [3, 5]. These findings were confirmed by SPEI-based assessments that detected significant negative trends at 6- and 12-month scales which indicated mid- to long-term water deficits [3, 21].
Vegetation-focused studies confirmed these findings from an impact perspective. In Hail, long-term decline in NDVI accompanied by rising land surface temperature and decreasing rainfall indicated agricultural drought stress on natural vegetation [48]. At the national scale, combined analyses of SPEI and VHI showed that southern and central parts of the Saudi Arabia suffered from critical vegetation stress during recent years particularly during the period 2014–2018 [8].
Climate-projection-based studies showed that potential evapotranspiration is projected to increase significantly faster than precipitation across the Arabian Peninsula. These projections suggest a strong indication of severe drought under high-emission scenarios and under lower-emission pathways [3, 9, 10]. These projections are also consistent with the conceptual role of global warming in enhancing evaporative demand and drying soils and reservoirs, and they align with SPEI-based future drought assessments that highlighted more severe and frequent events in the coming decades [9].
In contrast, not all studies reported a continuous increase in drought conditions. Munir et al. [45] reported wetter conditions in many parts of the country during the most recent decade with 25 of the 28 stations showing increasing precipitation and most recent years being characterized by positive SPI values. This inconsistency from the general drought pattern indicates that drought assessment is highly sensitive to the selected study period, drought index and data source. SPEI-based assessments and vegetation indices showed that underlying water stress remains a developing concern especially when temperature-driven evapotranspiration is considered. However the analysis of SPI at some stations reported a recent reduction in meteorological drought severity.
The reviewed literature demonstrated that no single drought index can fully capture the multi-dimensional nature of drought in Saudi Arabia. It also revealed clear differences in the strengths and limitations associated with each drought metric. The SPI was found to be the most widely used meteorological drought index because of its simplicity, low data requirements and its ability to represent drought at multiple time scales [3, 5, 45, 47]. The main limitation of SPI is its reliance on precipitation only therefore it cannot capture the effects of temperature-driven evaporative demand particularly in warming arid regions. SPEI-based analyses at the national scale revealed significant drying trends and multi-year drought periodicities linked to ENSO [21]. These outcomes support the use of SPEI as a more climate-sensitive index in Saudi Arabia particularly under ongoing warming and projected increases in PET.
In agricultural drought monitoring the NDVI has been widely used to assess vegetation greenness and detect long-term reductions in natural vegetation regions such as Hail [48]. The multi-year NDVI mapping in major agricultural zones captured both expansion of irrigated crops and contraction of other green areas [49]. The use of VCI, TCI and their combined index VHI improved drought assessment by accounting for vegetation conditions relative to historical extremes and by explicitly incorporating thermal stress. Empirical evaluations in the Al-Lith watershed showed that VHI correlated more strongly with SPEI than VCI or TCI alone particularly t longer time scales (e.g., 12-month). These findings indicated that indices which combine moisture and heat signals are particularly effective in hyper-arid settings [1].
The review indicates an overall increasing shift from single-variable such as precipitation-only indices toward integrated frameworks that merge meteorological indices (SPEI, SPI) with vegetation and thermal indices (VHI, TVDI). This enhances the ability to link climate anomalies to on-the-ground impacts. However, limited studies in the available literature applied hydrological indices such as SSI and SWSI in Saudi Arabia. These studies suggested that hydrological and socio-economic dimensions of drought remain comparatively under-represented relative to meteorological and agricultural aspects.
Compared to the relatively extensive monitoring literature, drought forecasting studies in Saudi Arabia are still few but methodologically diverse. The reviewed studies illustrated clear methodological progress from completely statistical time-series models toward hybrid and deep-learning frameworks that integrate multiple data sources. In central Saudi Arabia ARIMA models achieved high forecasting accuracy of SPEI at different time scales and particularly at 24-month time scale [53]. Machine-learning approaches added the ability to model nonlinear relationships and to optimize forecasting performance. A PSO-ANN hybrid model was trained in Asir region on SPI-6 successfully resulted in observed drought patterns and projected recurrent moderate to extreme droughts in the near future [54]. This is particularly important for a region whose agriculture is strongly dependent on seasonal rainfall. Combining remote sensing indices (NDVI, LST) with SPEI in Random Forest and Support Vector Machine models significantly enhanced predictive performance of drought in eastern part of Saudi Arabia [55]. Hybrid models that integrate statistical and machine-learning models represented another promising direction. The integration of Hidden Markov Models, Genetic Algorithms and ANN provided the best performance among several candidate models [2]. This confirms that the integration of linear and nonlinear modeling elements with optimization algorithms can improve the accuracy of meteorological drought forecasting.
Drought forecasting models were applied for specific watersheds or provinces across Saudi Arabia using a limited set of indices (primarily SPI or SPEI). These models have not yet been embedded into operational early warning systems.

This review recognized that the total number of forecasting studies is small relative to monitoring studies and reported that the comprehensive national wide studies remain in their early stages. While the improved drought monitoring and forecasting modeling can play a critical role in enhancing water management strategies in Saudi Arabia. Early identification of drought conditions allows water managers to implement mitigation measures such as optimizing water allocation, adjusting crop patterns and improving groundwater recharge strategies. Integrating remote sensing observations with predictive models can furthermore provide spatially distributed information on drought severity. This information enables decision-makers in prioritizing regions which are most vulnerable to water shortages. These tools are particularly important for arid countries such as Saudi Arabia where sustainable water management and efficient allocation of limited water resources are essential for supporting economic development and achieving the objectives of Saudi Arabia's Vision 2030.

The review identified several gaps in drought forecasting research in Saudi Arabia as follows:

1. Sparse observational networks as many regions of Saudi Arabia have few meteorological stations and the monitoring of streamflow or groundwater is limited. This constrains the calibration and validation of models. Efforts to expand monitoring networks and integrate Internet of Things (IoT) sensors and data assimilation are needed.
2. The remote-sensing indices are rarely combined with ground measurements or socio-economic data. The integration of multiple data sources through data assimilation can improve accuracy and provide early warnings.
3. There is a lack of systematic comparison of different models (hydrological, remote sensing and hybrid model) under the same conditions. Benchmark datasets should be developed to evaluate model performance and identify best practices.
4. Most models assume natural systems and ignore irrigation, groundwater extraction and land-use change. These factors nevertheless strongly influence drought impacts in Saudi Arabia.

5. Conclusion and Recommendations

Drought conditions in Saudi Arabia are intensifying in both frequency and severity as a result of long-term climate change and the increasing demands from agricultural expansion, groundwater extraction and rapid socio-economic development. SPI and SPEI- based studies that investigated meteorological drought identified negative trends since the late 1990s. It also reported that many regions of Saudi Arabia experienced multi-year drought cycles with limited recovery periods. Remote-sensing indices such as VHI, NDVI and TVDI added essential spatial dimensions by capturing vegetation stress, land-surface temperature anomalies and soil-moisture deficits across diverse landscapes. Hydrological models have strengthened the ability of drought forecasting. The performance of these models nevertheless remains constrained by the limited in-situ records, gaps in groundwater data and the difficulty of representing human-driven water use within model formulations. Climate projections typically showed that the rising temperatures and the acceleration in the potential evapotranspiration (PET) will likely reduce any modest gains in rainfall. This outcome indicates that temperature-driven water deficits become the dominant force behind both agricultural and ecological drought in the future.

The review also showed that forecasting research in Saudi Arabia remains limited compared to those of drought monitoring. Existing forecasting research revealed clear methodological progress, transitioning from traditional statistical to machine-learning and hybrid models. These models that integrated hydrological and remote-sensing data showed strong forecasting skill for short- to medium-term meteorological drought. The applications of these forecasting models nevertheless remain geographically restricted and often constrained by sparse observational networks and limited long-term datasets. The review highlighted some research gaps such as insufficient integration of ground and satellite data, lack of national-scale forecasting frameworks and the minimal incorporation of human influences. Future research should prioritize the developing of multi-source, high-resolution forecasting systems, expanding monitoring infrastructure, benchmarking modeling approaches and coupling physical and socio-economic components to better capture drought dynamics. Such advancements are essential for supporting early-warning systems, climate adaptation strategies and sustainable water management within Saudi Arabia's Vision 2030 framework.

Acknowledgments: The authors are thankful to the Deanship of Graduate Studies and Scientific Research at the University of Bisha for supporting this work through the Fast-Track Research Support Program.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full Term
CMIP6	Coupled Model Intercomparison Project Phase 6
IPCC	Intergovernmental Panel on Climate Change
AAI	Aridity Anomaly Index
AD	Agricultural Drought

AI	Aridity Index
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
AUC	Area Under Curve
CMIP6	Coupled Model Intercomparison Project Phase 6
CRU	Climatic Research Unit
CZI	China Z Index
DRI	Drought Reconnaissance Index
EDI	Effective Drought Index
ENSO	El Niño–Southern Oscillation
ETDI	Evapotranspiration Deficit Index
EVI	Enhanced Vegetation Index
GA	Genetic Algorithm
GEE	Google Earth Engine
GIS	Geographic Information System
GWTVDI	Geographically Weighted Temperature Vegetation Dryness Index
HD	Hydrological Drought
HMM	Hidden Markov Model
HMM–GA–ANN	Hidden Markov Model–Genetic Algorithm–Artificial Neural Network
IoT	Internet of Things
IMERG	Integrated Multi-satellite Retrievals for GPM
LST	Land Surface Temperature
MAE	Mean Absolute Error
MCZI	Modified China Z Index
MD	Meteorological Drought
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
NAO	North Atlantic Oscillation
NASA	National Aeronautics and Space Administration
NDWI	Normalized Difference Water Index
PDO	Pacific Decadal Oscillation
PET	Potential Evapotranspiration
PDSI	Palmer Drought Severity Index
PHDI	Palmer Hydrological Drought Index
PSO	Particle Swarm Optimization
PSO-ANN	Particle Swarm Optimization–Artificial Neural Network
R^2	Coefficient of Determination
RAI	Rainfall Anomaly Index
RDI	Reconnaissance Drought Index
RMSE	Root Mean Square Error
RS	Remote Sensing
SA-ConvLSTM	Self-Attention Convolutional Long Short-Term Memory
SD	Socioeconomic Drought
SDI	Streamflow Drought Index
SMA	Soil Moisture Anomaly Index
SMDI	Soil Moisture Deficit Index
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SPI-3	3-Month Standardized Precipitation Index
SPI-6	6-Month Standardized Precipitation Index
SRSI	Standardized Reservoir Supply Index
SSI	Standardized Streamflow Index
SSP	Shared Socioeconomic Pathway
SSP1-2.6	Shared Socioeconomic Pathway 1–2.6
SSP2-4.5	Shared Socioeconomic Pathway 2–4.5
SSP3-7.0	Shared Socioeconomic Pathway 3–7.0

SSP5-8.5	Shared Socioeconomic Pathway 5–8.5
SVM	Support Vector Machine
SWSI	Surface Water Supply Index
TCI	Temperature Condition Index
TRMM	Tropical Rainfall Measuring Mission
TVDI	Temperature Vegetation Dryness Index
UAE	United Arab Emirates
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WASP	Weighted Anomaly Standardized Precipitation
WoS	Web of Science

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