IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 27 March 2025, accepted 25 April 2025, date of publication 6 May 2025, date of current version 23 May 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3567257

TOPICAL REVIEW

Toward Drought Modeling in South Asia: Machine Learning Approaches, Challenges, and Opportunities

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This work was supported by the Deanship of Graduate Studies and Scientific Research at Najran University through the Growth Funding Program under Grant NU/GP/SERC/13/84.

ABSTRACT Drought is an environmental and economic problem. Sustainable ecosystems, water resources, food security, and ecosystem sustainability. Machine all are severely affected by drought. Due to the increasing frequency and severity of droughts caused by climate change. Effective drought modeling is crucial for early warning systems and risk mitigation. Recent advances in machine learning (ML) and deep learning (DL) techniques have been developed as potential drought modeling tools, which offer accurate and reliable drought detection. This review paper summarizes the drought modeling(Drought Prediction, Drought Detection and Drought Forecasting) approaches. This paper focuses on three main aspect. 1) The selection of the region for this study, for this study South Asia(SA) is selected as region of interest (ROI) that offer accurate drought modeling, providing policymakers and decision-makers with insightful information. The geographical scope of this study is the region of South Asia. This region is selected because of its heavy reliance on agriculture. 2) This paper focuses on the current and future trends, challenges, and advances of and vulnerability to droughts. The review offers a thorough grasp of how drought conditions are evaluated by gathering and analyzing the most important drought indicators and metrics specific to South Asia. The paper explores the current state-of-the-art in ML and DL for drought modeling. 3) This review encapsulates the indicator and metrics (Complex Machine learning and deep learning models) for drought modeling which are most relevant to the SA region. This study sum up as most common challenges in drought modeling are, highlighting current challenges such as incomplete and inconsistent datasets, lack of explainable and interpretable models, and unavailability of data for model uncertainty analysis. This study proposes that these problems can be solved with modern machine learning techniques such as explainable machine learning and federated or Lack of explainability and interpretability in complex ML/DL models, unavailability of benchmarks. Based on these challenges, this review suggests the following techniques to address these challenges: Data integration (Data fusion), distributed machine learning. (Federated Learning) and explainable AI (XAI, SHAP, LIME, etc.).

INDEX TERMS Drought modeling, drought prediction, machine learning, deep learning, South Asia.

The associate editor coordinating the review of this manuscript and approving it for publication was Tariq Masood.

I. INTRODUCTION

A. BACKGROUND

The rapid rise in Earth's temperature has caused several changes in the environment, such as the melting of ice/glaciers and the global warming phenomenon. The rate of water circulation has also increased, which in turn has made doors open for natural disasters like drought. Droughts have become more frequent and occur at a very fast pace, where there is a lack of water availability [1]. The drought causes serious problems in agricultural production and thus, it leads to food insecurity and to the worst form of negative socio-economic effects [2]. Drought is considered one of the most lethal disasters, that cause severe implications for water resources, agriculture, and ecosystems. In recent years, the frequency of droughts has increased and resulted in water scarcity, crop failure, and food insecurity. Droughts occur regardless of regional differences around the world. It occurs in both developed and under-developed nations, for instance, drought in the USA, California from 2012 to 2014 [3], drought in East Africa from 2010 to 2011 [4]. South Asia (Pakistan, India, Bangladesh, Nepal, Afghanistan, Sri Lanka, and Bhutan) heavily relies upon rain-fed subsistence agriculture, which is vulnerable to droughts [5], [6] [7]. South Asia (SA) is among the world's most disaster-prone and heavily inhabited regions, accounting for more than one-fifth of the global population [8]. Food and water shortages have been aggravated by population growth and regular drought disasters [9]. Droughts have become more common in South Asia as evident in recent studies [10]. The drought situation is very alarming; it is expected that its frequency and duration may increase in the coming days.

B. MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR DROUGHT PREDICTION

The recent developments in technology have paved ways to cope with several issues in human life. Machine learning (ML) techniques have been applied in the literature to time and accurately handle the uncertain issues of the environment. To deal with droughts, machine learning may be considered one of the tools in helping resource management and early drought detection. Effective water resource management can be achieved through accurate and timely drought modeling [11] and through early warnings of potential disasters [12]. However, drought prediction [13] is one of the biggest challenges for meteorologists, climatologists, and environmentalists. Prediction of drought is very vital in decision-making as it can alert and caution stakeholders to take proactive measures to handle the disastrous situation effectively and prudently. Traditional drought monitoring [14] methods rely on climate models and ground-based observations, which have limitations in spatial and temporal resolution and can be affected by measurement errors and uncertainties. Remote sensing of the drought indexes [15] is another method that is used for monitoring [16], forecasting, and prediction of drought. The emergence of machine learning (ML) and deep learning (DL) in the prediction of drought is among the latest methods [17], [18] [19]. Machine learning and deep learning techniques have shown great potential in drought modeling, providing accurate and reliable predictions of drought conditions. These techniques can integrate multiple data sources, including remote sensing data [20], climate data [21], and social and economic data [22], to improve the accuracy and reliability of the models. Moreover, these techniques can provide real-time monitoring and forecasting of drought conditions, enabling more effective management of water resources. The indexes such as Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) obtained via remote sensing techniques are generally used to predict and forecast drought [22], [23] with the help of machine learning algorithms [24], [25].

The study [26] presents a systematic literature review of 100 studies. Based on study precipitation is the most common input for ML-based forecasting using SPI and SPEI. The most popular machine learning technique (77%) is regression. The study [27] shows SSI and SPI are used to analyze hydrological droughts, which are characterized by extended water shortages. The study [27] shows ML techniques (ANN, SVM, hybrid models) enhance forecasting, although traditional methods (ARIMA, SARIMA) continue to be used. [28] represents the systems for early warning of drought detection that ignore socioeconomic effects in favor of statistical indicators. The goal of impact based forecasting (IbF) is to predict "what the weather will do" in order to connect science and action. The effects of the global drought can be lessened and timely mitigation enhanced by advancing IbF. The review [29] shows the use of remote sensing for drought monitoring, with an emphasis on developing drought indices using information on precipitation, soil moisture, and land surface temperature. The study in [29] shows that the indices improve knowledge of drought dynamics, but there are still issues with data access and validation.

C. RESEARCH GAP

Even though ML-based drought prediction has been studied extensively, there isn't a thorough comparison of approaches across climatic zones in the reviews that are currently available. Most concentrate on particular models without assessing their wider applicability. Furthermore, little research has been done on the integration [30] of remote sensing data with machine learning models, most existing studies primarily focus on SPI and SPEI indices [31], [32], with limited exploration of a broader range of drought indicators that could enhance predictive performance. Previous research on machine learning-based drought prediction does not thoroughly examine data integration techniques. Despite their potential, distributed ML and DL models have not yet been widely used for large scale drought prediction. Lastly, the role of explainable AI (XAI) [33] in enhancing the transparency of complex machine learning models for drought prediction remains largely unexplored.

This study reviews the literature on drought modeling in South Asia using machine learning (ML) and deep learning (DL) methods in a methodical manner. Formulating research questions, locating pertinent studies, extracting and synthesizing data, and publishing findings are all steps in the review process. To guarantee thorough coverage, a structured search approach is employed, combining keywords such as remote sensing, machine learning (ML), and drought modeling. Two screening rounds were carried out following an initial search of 7150 papers, and 142 studies were ultimately chosen based on quality and relevance.

This study provides a comprehensive survey of the state-of-the-art research on drought modeling using machine learning and deep learning techniques for South Asia. An overview of the different types of machine learning and deep learning techniques used in drought modeling is reported and their performance evaluation is presented. The study as shown in Fig.1 also discusses the challenges and limitations of these techniques and identifies future research directions to enhance their effectiveness and reliability. This study shall be a valuable resource for researchers, practitioners, and policymakers who are interested in using machine learning and deep learning techniques for drought modeling and water resources management.

The main contributions of the study are as follows:

1) Most of the reviews in this domain provide a global perspective, this review paper is focuses on South Asia (SA) due to significant impact of drought in the region.as SA relies on rain for agriculture. The paper focus addressing the key issue of drought modeling using machine learning and deep learning.
2) This paper provides detailed insights into the application of ML and DL techniques, which are effective in the context of SA, also how local and global datasets are integrated with these models to provide a perspective into drought modeling.
3) This paper also shows the indexes and indicators of drought that are used for South Asia. The importance these indicator specific SA is apparent from overall monsoon variability, and socioeconomic disparity around the region.
4) Based on the gap in existing studies, this study proposes advanced machine learning solutions such as explainable AI, federated learning, and real-time drought monitoring systems developed for a specific region.

The rest of the paper is organized as section II reports searching criteria for the targeted literature in the field of drought. Section III describes the essential terminologies in the drought types and their possible implications. The dataset for the drought modeling is discussed in section IV. The use of machine learning and deep learning techniques for the drought is presented in section V, along with their evaluation parameters. The research trends and challenges are discussed in section VI and section VII respectively. Finally, conclusions and future directions are provided in section VIII.

II. RESEARCH METHOD

We set up this study in accordance with [34] suggestions. According to these standards, the review procedure consists of a number of steps, including developing the review protocol, selecting and identifying main studies, extracting and synthesizing data, and lastly publishing the findings. The first step is to formulate research questions for this study.

1) **RQ1:** What has been done for drought modeling using ML and DL in South Aisa
2) **RQ2:** What are current trends and challenges reported for Drought modeling using ML and DL in South Asia
3) **RQ3:** What should be the future research based on the literature for drought modeling using ML and DL

As per [34], existing literature used in this study is mostly indexed in one of the following digital libraries.

Web of Science: Web of Science (WOS) is a research database and also a citation index that includes scholarly articles, conference proceedings, and other scientific literature from interdisciplinary fields of study.

Scopus: Scopus is a comprehensive research database, primarily used for academic research and covers a wide range of different subjects, providing articles, conference papers, and other scientific research material.

EI Compendex: EI Compendex also known as Engineering Index Compendex is a premium engineering/scientific literature database. It focuses on engineering and applied science disciplines and provides access to articles, conference proceedings, and technical reports.

IEEE Xplore: IEEE Xplore is a digital library and research database which is maintained by the Institute of Electrical and Electronics Engineers (IEEE). It provides the access to a vast collection of technical papers, conference papers, standards, and publications in the fields of electrical engineering, electronics, and computer science. IEEE Xplore is a valuable resource for researchers in these fields to obtain quality literature.

A. SEARCHING PARAMETERS

In this section, the systematic development of search queries is presented using three sets of keywords: drought modeling (DM), machine learning (ML) approach, and remote sensing (RS). The strategy present in this study involves creating separate queries for each keyword set, then combining two sets using the Cartesian product and taking the Cartesian product of all three sets to thoroughly find intersections between various subjects under consideration in this study. DM, ML, and RS represent the sets of keywords for each domain of this paper. In the first phase, search queries are formed using individual keywords from the sets so the set of search queries is similar to the set of keywords.

$$DM = \{dm_1, dm_2, dm_3, \ldots, dm_n\}$$
$$ML = \{ml_1, ml_2, ml_3, \ldots, ml_n\}$$
$$RS = \{rs_1, rs_2, rs_3, \ldots, rs_n, \}$$

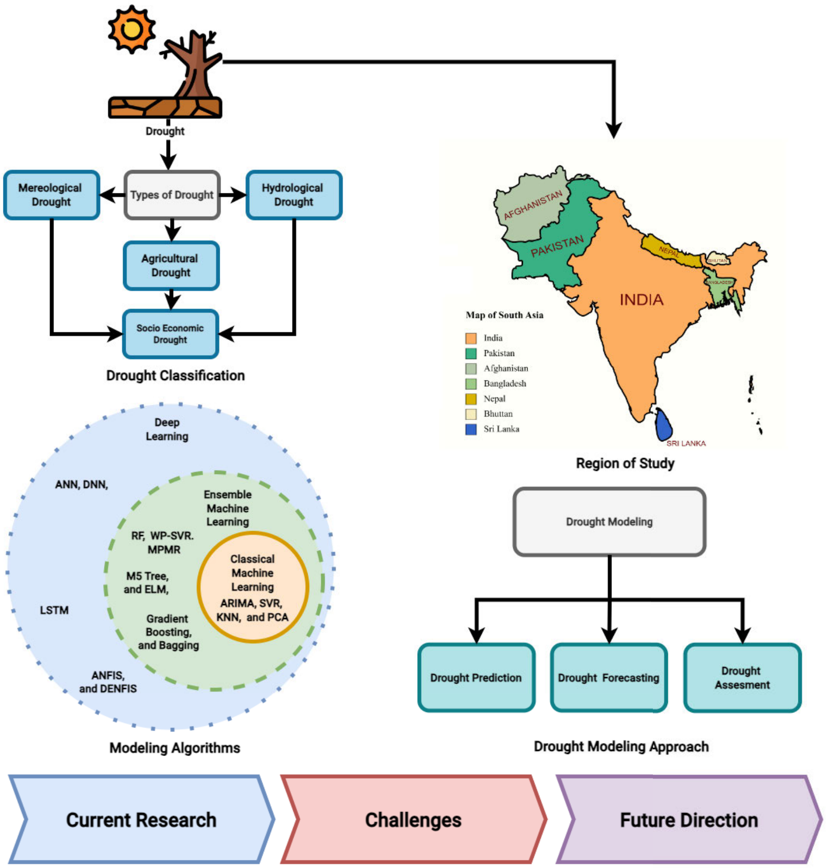

FIGURE 1. Graphical abstract of entire study.

In the second phase, query strings are made by combining keywords from two sets using the Cartesian product. QS_{DM-ML} represents the combiation of keywords from DM and ML similarly QS_{DM-RS} and QS_{ML-RS} are combination of DM and RS, and ML and RS respectively.

$$QS_{DM-ML} = \{(dm_i, ml_j) \mid dm_i \in DM, ml_j \in ML\}$$
$$QS_{DM-RS} = \{(dm_i, rs_j) \mid dm_i \in DM, rs_j \in RS\}$$
$$QS_{ML-RS} = \{(ml_i, rs_j) \mid ml_i \in ML, rs_j \in RS\}$$

In the third phase, a comprehensive search is performed by creating a query string using keywords from all three sets DM, ML, and RS. $QS_{DM-ML-RS}$ is the Cartesian product of all the keywords in all the sets. This set of query strings takes all the domains of this study altogether.

$$QS_{DM-ML-RS} = \{(dm_i, ml_j, rs_k) \mid dm_i \in DM, ml_j \in ML, rs_k \in RS\}$$

Examples of search queries generated in different phases are shown in Fig. 2. All these query strings created in different passes were supplemented with additional information regarding regions, i.e., South Asia or a country such as Pakistan, India, etc. A huge number of papers were found as a result of this comprehensive search strategy, which is also shown in the figure. The selection criteria for including and excluding the paper is discussed in the next section.

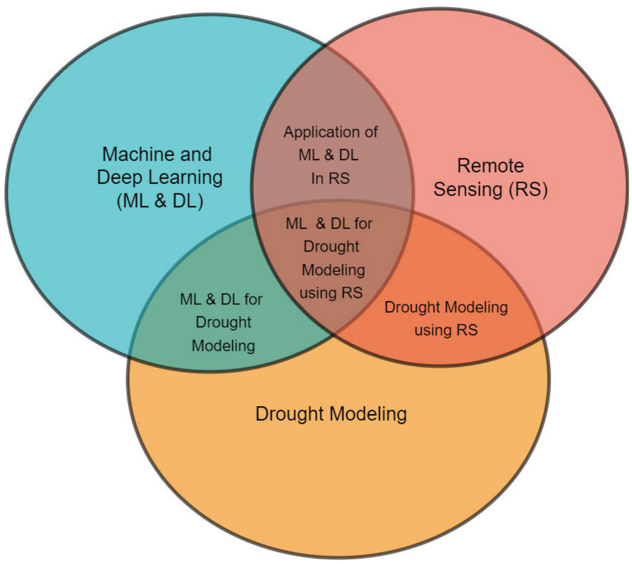

FIGURE 2. Venn diagram for search queries used in this study.

B. SELECTION CRITERIA

This study employed a systematic strategy to choose relevant academic publications that suited the goal of the study. This procedure included several levels of evaluation and screening to make sure that the selected papers significantly contribute to the analysis and findings of our research. Initially, searches resulted in 7150 papers, and following a careful screening procedure, ultimately 142 papers were used in this study.

1) INCLUSION CRITERIA

To choose the most relevant paper out of 7150 papers that were the result of the initial search following inclusion criteria were defined.

1) **Relevance:** Selected Paper should be directly related to the topic under consideration in this study, i.e. drought modeling, machine learning approaches for drought modeling, the role of remote sensing in drought modeling, and the area of study should be South Asia
2) **Quality:** Selected Paper should be of high quality or of utter importance for this study. The paper selected should be peer-reviewed or show some substantial contribution to the body of the work.
3) **Timeliness:** Selected papers should be timely in context with the content of the paper. A paper discussing technological advancement should be newer, while a paper regarding the general understanding of drought its impact can be older.

2) SCREENING

We started by conducting a thorough search using a query string generated as a result of the process discussed in section II-B. Initially, 7150 research publications were found. Every manuscript was subjected to 2 passes screening during which we evaluated their relevance, quality, and timeliness, and based on these, the final papers were selected. The whole process is mentioned in Fig. 3

1) **Pass 1** In the first pass, the relevance of the manuscript is checked by reading the title and abstract of the manuscript and measuring it on the parameters or relevance defined in section II-B1. At the end of the first pass, we are left with 1234 papers.
2) **Pass 2** After the relevance check, the quality and timeliness of research are checked on the parameter defined in section II-B1. The final count of the paper at the end of this step is 146.

III. DROUGHT - ITS TYPES AND IMPACTS

This section reports the drought phenomenon, its types, and their effects on the climate. According to the UN Convention to Combat Drought and Desertification [35]. Drought can be defined as follows:

1) Drought is a naturally occurring phenomenon that occurs when precipitation is significantly below average compared to records, leading to severe hydrological imbalances that have a negative impact on systems to produce land resources [36].
2) A drought is an extended period of inadequate rainfall in comparison to the empirical multi-year mean for a region, which might last for a season, a year, or even several years [37].

However, depending on the factor used to define the drought, many definitions exist. As a result, there are four categories (i.e., types) in which definitions of drought can be classified, namely, 1) meteorological, 2) hydrological, 3) agricultural, and 4) socioeconomic [37], [38]. The detail of each drought type is described in the subsequent section.

A. DROUGHT TYPES

This section discusses the types of drought: 1) meteorological, 2) hydrological, 3) agricultural, and 4) socioeconomic [37], [38].

1) METEOROLOGICAL DROUGHT

When there is a prolonged shortage of precipitation, a meteorological drought develops [39], [40], [41]. A reduction in soil moisture content brought on by prolonged meteorological droughts can cause agricultural droughts [39].

2) HYDROLOGICAL DROUGHT

It is Hydrological drought, when watershed, groundwater, or overall water storages fall below long-term means [42], resulting in low stream flows and aquifer levels [39]. This implies that a particular water source cannot provide the volume of water necessary for its intended usage resulting in a limited supply of water [42].

3) AGRICULTURAL DROUGHT

Contrarily, agricultural drought happens when the soil isn't getting enough rainfall [43]. Agricultural growth is impacted by the shortage of water in the soil and subsoil brought on by insufficient precipitation, which lowers crop yields [40], [43] [42]. The physical and biological qualities of the soil, actual and potential evapotranspiration, the biological traits of certain plants, and other factors all affect the amount of moisture in the soil [44].

4) SOCIO-ECONOMIC DROUGHT

Socio-economic drought happens when there is a lack of water resources. The drought process influences production resulting in a shortage of some economic commodities [43]. Due to a lack of water supply, there is a gap between supply and demand in this area [37]. As a result, the other 3 drought types occur and it leads to the socio-economic drought [39].

B. DROUGHTS IN SOUTH ASIA REGION

Drought, unlike all other natural disasters, develops gradually over time and isn't visible till a threshold of rainfall shortage is reached. The most prevalent droughts reported in South Asian nations are caused by variations in rainfall volume (i.e., less or no rain), onset, and distribution pattern during the major monsoon season [45], [46] [47], [48] [5], [6] [7]. Based on the features of the droughts as observed, each country defined its separate drought years. In [10], the occurrence of drought and its recurring patterns are comprehensively reported. The drought occurrences in each country of the

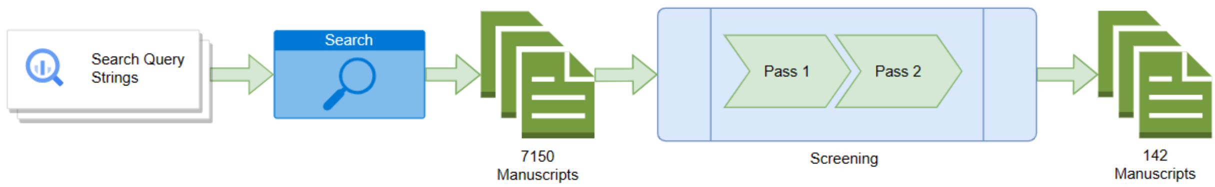

FIGURE 3. Literature searching, screening, and selection process used in this study.

South Asia region as shown in Fig. 4 is discussed in the following.

FIGURE 4. South Asia Region - Map.

1) AFGHANISTAN

The study in [10] indicated that the 1998-2006 drought in Afghanistan was the longest and most severe in the last five decades. Furthermore, droughts were exceptionally severe in Afghanistan between 1971 and 2001, according to Zhai et al. [9]. The Asian Development Bank (ADB) stated localized droughts occur every 3 to 5 years, whereas spatially extended droughts occur every decadal period. Nonetheless, Afghanistan is susceptible to a countrywide drought every 2-3 decades [9], [10], [49] [50].

2) BANGLADESH

According to Zimmermann and Stössel [51], the intensity and frequency of droughts in Bangladesh have increased in recent years. Interestingly, several studies found that many times drought in Bangladesh lasted between 2.5 and 5 years. Although there was no defined interval or pattern for their occurrence [52], [53] [54], [55]. Extreme droughts have also been recorded in 1961, 1975, 1981, 1982, 1984, 1989, 1994, and 2000. The studies [8], [55] discovered that the shortest length of drought was seen annually in Chittagong Hill tracts from November to May [10].

3) INDIA

Aside from the eastern areas, India is vulnerable to drought; the western arid areas of the country undergo periodic droughts [56]. According to [57], the Indian Meteorological Department (IMD) investigated the drought throughout India and discovered that it has become more frequent and severe since 1965. Droughts recorded in 1972, 1987, 2002, and 2009 were rated as severe, whereas droughts observed in 1965, 1966, 1974, 1979, 1982, 1985, 2000, and 2012 were categorized as moderate. Drought increased dramatically in northeast and central India [10], [58].

4) PAKISTAN

Droughts occur regularly in Pakistan. Due to increased changes in climate patterns, the central-eastern, southwestern, southern, and certain dispersed south coastal regions are most prone to severe droughts, particularly during winter and dry-wet intervals [59]. Severe droughts were reported in the Punjab province in 1899, 1920, and 1935; the North-West Frontier (NWFP, currently Khaiber Pakhtoon Khuwa - KPK) Province of Pakistan in 1902 and 1951; the Sindh region in 1871, 1881, 1899, 1931, 1947, and 1999; and a countrywide drought from 1999 to 2002 [60]. The 1998-2004 drought severely impacted over half of Pakistan's districts, more than 15 million of the country's poor residents [10].

5) NEPAL

It was discovered that both natural changes and manmade activities influenced Nepal's recent decadal drought [61]. Droughts have been observed in Nepal in 1972, 1977, 1982, and 1992. Droughts have been seen on a regular basis since 2002, with the most extreme cold drought occurring in 2008-2009. Droughts were most recently seen in Nepal's highland regions in 2012, 2013, and 2015 [62], [63].

6) SRI LANKA

Drought occurs virtually regularly in Sri Lanka, including recurrent severe droughts, and is one of the most common calamities [64], [65]. Even the wettest districts of Sri Lanka, like Ratnapura, have lately endured severe droughts on a regular basis. According to figures supplied by Sri Lanka's Disaster Management Center [64], [65], the country experienced severe droughts in the years 2001, 2004, 2012, 2014, and 2016.

7) BHUTAN

Bhutan has had fewer droughts than other South Asian countries. Despite scant data and information, individual communities or agencies stated that the winter of 2005-2006 was extremely dry, without rain or snow [7], [10].

8) MALDIVES

Maldives, due to its tropical nature, very limited drought-related calamities have been observed. Although monthly rainfall below the first decile has been utilized as an indicator of drought, no long-term drought trends have been seen in the Maldives [10]. This has led to a very limited number of studies targeting Maldives for drought analysis, therefore, Maldives is excluded from this study.

C. KÖPPEN CLIMATE CLASSIFICATION FOR SOUTH ASIA

Figure 5 shows the map for Köppen climate classification [66] For the South Asia region. Based on Köppen climate classification, South Asia is divided into several climate zones. According to the Köppen Climate Classification map. Afghanistan mainly have warm desert (BWh) and semi-arid (BSh) climates except for the few cold desert (BWk) and cold semi-arid (BSk) areas in the north,. India's climate varies greatly, with the south and east experiencing tropical savanna (Aw) and monsoon climate (Am), the north experiencing humid subtropical conditions (Cwa, Cfa), and the foothills of the Himalayas experiencing continental conditions (Dfb, Dsb). Heavy seasonal rainfall is a feature of the monsoon (Am) and tropical savanna (Aw) climates that dominate Bangladesh and Sri Lanka. Because of the Himalayas, Nepal and Bhutan have mountainous regions with subarctic (Dwc, Dwd) and oceanic (Cfb, Cwc) climates.

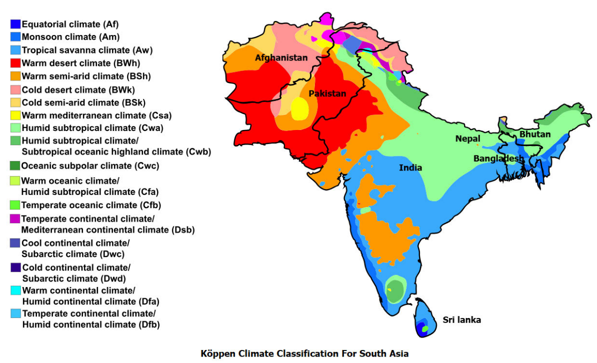

FIGURE 5. Map of Köppen climate classification for South Asia region.

D. IMPACT OF DROUGHT ON SOUTH ASIA

Drought is one of the most catastrophic natural disasters on the planet. It may cause a negative impact on the environment, industrial productivity, agricultural practices, drinkable water supplies, freshwater habitats, and water quality. According to the International Disaster Database (EM-DAT), drought caused a USD 221 billion loss from 1960 to 2016 [67]. Drought can last for weeks or longer with low precipitation. It is frequently exacerbated by a positive feedback loop in which dry soils and reduced vegetation cover suppress precipitation further through decreased evapotranspiration and increased surface temperature [68]. Drought occurrence has increased during the last 50 years, according to observations as well as model predictions [69], [70]. Considering (GHG) greenhouse gas-induced global warming, the model future forecasts indicate an increased risk of drought in most terrestrial areas in the 21st century [45], [71]. This is brought on by a decline in subtropical land precipitation and a rise in atmospheric water vapor demand worldwide [46].

Droughts have affected approximately 31% of South Asia's agricultural lands during the last two decades, posing a serious threat to the region's economic and social growth [47]. Agricultural droughts create a global annual economic damage of USD 6-8 billion, based on the WEF (World Economic Forum) [48]. Drought is recognized as being one of the least understood and most expensive natural disasters in comparison to other types of natural disasters [47]. Therefore, hydrologists, agricultural experts, ecologists, and others have become increasingly concerned about the drought [37]. The impact of drought on each of South Asian countries is summarized in Table 1.

IV. DATASETS FOR DROUGHT MODELING IN SA

This section reports literature on the use of different datasets for drought modeling. The literature demonstrates the potential of the dataset [73] for drought monitoring and assessment in different regions and at different scales. The different datasets used for drought modeling include thermal data, vegetation indices, water [74], soil moisture data [75], and image data [76]. The study in [77] discusses several types of remote sensing data used for drought monitoring such as thermal data, vegetation indices, and soil moisture data. It also covers the different methods for analyzing remote sensing data for drought modeling and assessment. The work in [78] evaluates the effectiveness of different data sources, including MODIS and Landsat, for drought monitoring in Iran. A very small number of papers are also included from Iran because it share borders with Pakistan and Afghanistan and it has very similar climate condition. The performance of different vegetation indices and soil moisture indices in detecting drought conditions is also reported.

The study [79] focused on the use of vegetation indices for drought monitoring such as NDVI, EVI, and SAVI. The effectiveness and limitations of vegetation indices in monitoring drought are also presented. Likewise, the work in [80] covers the different types of remote sensing data used for drought monitoring, including thermal data, vegetation indices, and soil moisture data. It also discussed the several methods in analyzing remote sensing data for drought

TABLE 1. Summary of impact of drought on South Asian countries.

Country	Impact	Reference(s)
Afghanistan	The drought of 1998-2002 resulted in significant losses in livestock and agricultural production. Inadequate rainfall ruined 50-75% of each farmer's orchard. Furthermore, the 2008-2010 drought killed thousands of livestock due to pasture dryness and a lack of water resources. About 1,400,000 livestock were given at very low prices in Samangan Province, whereas 30% of them died due to drought. Around 3 million people experienced food insecurity, with 80% of rainfed wheat harvests lost across the country.	[49]
India	Disaster Statistical Review (2016) revealed that drought has affected nearly 0.33 billion people and caused damage at the cost of US$ 1.5 billion in India. In 2002, severe drought decreased both the harvested area and food grain production to 112 million hectares and 174 million tons, respectively, in comparison to a normal year. According to Gadgil and Gadgil (2006), in recent decades, drought has inflicted significant impacts on the agricultural sector and economy of India, by at least 5% of the GDP	[50] [72]
Pakistan	Precipitation in Sindh province fell by 12 to 30% during 1999 and 2000, affecting over 3.3 million people. Drought has harmed the country's agriculture, with major crops showing negative growth. Agriculture as a whole experienced deep recession of 2.6% between 2000 and 2001. The 1998-2002 drought, one of the harshest in the last 50 years, harmed 1.2 million people, killed 2 million livestock, and resulted in significant agricultural loss.	[52] [53]
Nepal	The summer drought of 2015 had a significant impact on crop yield, affecting almost 80% of the inhabitants in the western part of the country. Drought caused a large crop loss of 56,000 metric tonnes in 2013, and 300,000 people were food insecure in 2015 and 2016.	[54]
Bhutan	Crop loss ranges from 1 to 19% due to changes in the beginning of rainfall, dryness, and windstorms.	[55] [10]
Sri Lanka	Drought was responsible for around 52% of agricultural destruction from 1974 to 2013. A persistent drought observed in 2001 and 2002 had a significant impact on the country's hydropower production and agriculture sectors, lowering GDP by around 1%.	[55] [56] [57]
Bangladesh	Approximately 2.18 million tons of rice were damaged owing to drought between 1973 and 1987, whereas 2.38 million tons were lost due to flood during the same time. The region's groundwater depth level climbed from 3.7 m in 1981 to 7.3 m in 2016, with a growing trend. Droughts have already impacted 47% of the region's total land and 53% of its people.	[58]

modeling, for instance, machine learning and statistical methods.

Table 2 reports different studies representing datasets and their respective regions. These studies are, especially, focused on the South Asian region, which is the scope of this study. It can be observed in Table 2 that precipitation data is most commonly used for drought modeling, which is evidence of the relationship between precipitation and drought. The countries reported in Table 1 heavily rely on agriculture as a primary source of income. Thus, the impact of drought is considered severe, and it affects a large population. Besides, there are a few studies focused on tropical countries like Sri Lanka where high amounts of precipitation are observed.

The SPI (Standardized Precipitation Index) was primarily utilized in Nepal to quantify drought. The study in [93] used SPI-12 to evaluate the monthly precipitation data for the period between 1971 and 2003. It found moderate droughts afflicted 9% of the land and severe droughts hit 5% of the territory in Nepal. Also, the central and northeastern portions of Nepal were considered likely to have long-term drought danger, whilst, the western and northwestern regions were considered likely to experience short-term drought risk. A few stations of high mountains in Nepal displayed a distinct declining trend in SPI, which depicts an escalating drought [94]. It is interesting to note that droughts in Afghanistan were studied using a variety of drought indexes. However, less number of studies discussed droughts in Afghanistan, while several studies focused on determining if the index was appropriate for capturing drought. A land surface phenology in Afghanistan for a dry year (2001) and a rainy year (2003) was compared in [95], which used the MODIS (Moderate Resolution Imaging Spectroradiometer) and NDVI (Normalized difference vegetation index). In order to determine the most appropriate monitoring index for the basin, [96] implemented the SPI alongside three statistical distributions (namely, normal, log-normal, and gamma

TABLE 2. Dataset, type of dataset, parameters, indicator or indexes for SA region.

Paper	Dataset Type	Parameters	Region
[81]	Precipitation Dataset	SPI	Kansabati River basin in India
[82]	Gridded Dataset	SPI	East Asia
[83]	Gridded Dataset	Unified rain gauge data	India
[84]	Precipitation Dataset	Daily Precipitation Dataset	Iran
[16]	Hydrological Drought Index	SSI (Standard Streamflow Index)	Iran
[85]	Drought Index	Composite Drought Index (CDI)	Pakistan
[86]	Precipitation, Temperature and Drought Index Dataset	Standard precipitation temperature index (SPTI) and Reconnaissance Drought Index (RDI)	Pakistan
[87]	Precipitation dataset	Standard Precipitation Evapotranspiration Index (SPEI)	Bangladesh
[88]	Precipitation dataset	Standard Precipitation Index (SPI)	Bangladesh
[89]	Precipitation dataset	Standard Precipitation Evapotranspiration Index (SPEI)	Afghanistan, Italy and Russia
[90]	Image Dataset	Raw Satellite Image Dataset	Pakistan
[91]	Precipitation Index	SPI	Sri Lanka
[92]	Rainfall	daily index of antecedent rainfall (ARI)	Nepal

distributions), the Percent of Normal Precipitation Index (PNPI), the Deciles Index (DI), and the China-Z Index (CZI) for the first on KRB (Kabul River Basin) in Afghanistan.

The SPI was mostly used in Pakistan for drought assessments. To analyze the variations in the Pakistani drought, both geographically and temporally, [97] calculated several SPI time intervals (i.e., 3, 6, and 12 months) using the gridded rainfall data from 1960 to 2007. The SPI's PCA revealed that Pakistan's drought mostly affected a major portion of the afflicted region and has a 16-year recurrence interval. The SPI was examined across Sindh in Pakistan by [98], where periodic dryness was noted. Nine meteorological stations' monthly rainfall data from 1951 to 2010 was used to calculate SPI at various time ranges. According to an analysis study [99] of NDVI and SPI across the Thar Desert for five years (2002, 2005, 2008, 2011, and 2014) resulted that vegetation rose from 2002 to 2011 and subsequently decreased from 2011 to 2014. The construction of drought severity-area-frequency curves for the SPI indices over various seasons in Pakistan revealed that 10.33% of the region remained impacted by the drought and witnessed once in 50 years [100], and 25.76% of the area would encounter the drought once within 100 years [100].

Several indicators were used to identify the droughts in India, and intriguingly, a brand-new index was also developed to measure the severity of the droughts. The benefits and drawbacks of the drought indicators used in India have been discussed in the literature. A historical series of the SPI-1 across India was created by [101] using daily rainfall data from the years 1951 to 2007. The findings showed that at the start of the twenty-first century in India, the range of the regions susceptible to medium drought frequency increased. According to [102], the Vegetation Temperature Condition Index (VTCI), which measures drought based on the link between crop water status, accurately captured the severity and geographic scope of drought stress in India in 2000, 2002, and 2004. In order to create a drought severity map, [103] used the SPI to analyze daily gridded data for the Puruliya District in West Bengal, India, between 1971 and 2005. Mild droughts were seen more frequently than that of severe or moderate droughts [104]. Table 2 shows Dataset types, Parameters, Indicators or Indexes, and regions used in this study for South Asia region.

Table 3 shows the utilization of remote sensing indexes across South Asia. It shows that based on the studies included in this study there is unever usage of these categories of indexes. Most commonly used category is precipitation indexes such as SPI or SPIE. Some countries like Pakistan, India, and Bangladesh shows the studies with large variety of indexes and countries like Nepal and Srilanka exhibit significant gaps. This uneqaulity show the need for standardized methodologies, broader data integration across the region to improve the performance of drought modeling system so that effective regional collaboration and policy-making can be done.

TABLE 3. Comparison of remote sensing Indexes for drought modeling for different countries.

Indexes	Pakistan	India	Bangladesh	Nepal	Srilanka	Afghanistan
Precipiation Indexes	✓	✓	✓	✓	✓	✓
Soil Indexes	✓	✓	✓	✓	✓	✓
Temperature Indexes	✓		✓			✓
Vegetation Indexes		✓	✓			✓
Water Indexes						
Drought Indexes	✓					
Raw Satelite Images	✓					

V. DROUGHT MODELING AND EVALUATION INDEXES

Machine learning (ML) and deep learning (DL) techniques have shown great promise in drought modeling [105], providing accurate and reliable predictions of drought conditions [106]. These techniques can integrate multiple data sources, including remote sensing data [107], climate data [108], and social and economic data, to improve the accuracy and reliability of the models. Besides, these techniques can provide near-to real-time monitoring and forecasting of drought conditions [8], enabling more effective drought modeling.

In the context of drought modeling, machine learning techniques are typically used to develop statistical models [109] that can predict the occurrence and severity of droughts based on historical data. Commonly used machine learning techniques for drought modeling include artificial neural networks (ANNs) [110], support vector machines (SVMs) [111], decision trees, and random forests [112]. Whilst, Deep learning, a subset of machine learning, has also been applied to drought modeling. Deep learning models can learn hierarchical representations of input data and can capture complex nonlinear relationships between the input and output variables. Commonly used deep learning models for drought modeling include convolutional neural networks (CNNs), recurrent neural networks (RNNs) [89], and long-short term memory networks (LSTMs) [17]. One of the main advantages of machine learning and deep learning techniques for drought modeling is their ability to integrate multiple data sources and model complex interactions between environmental and human factors. For example, remote sensing data can be used to capture the spatial and temporal variation of soil moisture [112], while climate data can be used to capture the long-term trends and patterns of drought. Table 4 shows the different ML and DL techniques applied for drought modeling over the South Asian region.

The most essential aspect of machine learning and deep learning is the performance of the developed model in predicting given data. This section discusses several evaluation indexes (i.e., performance indicators) of the drought modeling models. Table 4 represents the evaluation indexes used in the literature for drought modeling models. It can be observed in Table 4 that RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and R-squared are the most commonly used indexes [83], [88] [117]. RMSE calculates the square root of the average squared differences between the predicted and actual values; MAE shows the average absolute differences between the predicted and actual values and R-squared measures the proportion of the variance in the dependent variable that is predictable from the independent variable(s) representing Coefficient of determination. These indexes are used with continuous data. However, a few other indexes such as NMSE [116], PRMSE [122], MD [117], PE [91], Pbias [117] were also observed in evaluating drought modeling models. These indexes, nonetheless, are found less commonly used; but are still useful in evaluating the performance of ML and DL models for drought modeling.

Accuracy, Precision, Recall, and F1-Score [90], [118] are classification indexes, i.e., metrics that measure the performance of classification models. AUC ROC [89] measures the performance of binary classifiers at several threshold settings. These classification metrics are observed in the studies where either drought level (i.e. Extreme Drought, Moderate Drought etc.) or drought occurrence is predicted. TNR measures the proportion of actual negative cases that are correctly identified as negative [85]. TPR measures the proportion of actual positive cases that are correctly identified as positive [92]. Table 5 represents the evaluation parameters used in studies for the SA region.

Table 6 represents the machine learning model categories for drought modeling across the SA region. The key observation from Table 6 is that Supervised Learning, Ensemble Learning, and Deep Learning are the most widely adopted machine learning techniques. However, modern machine learning techniques like Hybrid modeling is underutilized in some countries, such as Nepal and Sri Lanka. Particularly, machine learning approaches such as Unsupervised Learning, Distributed Machine Learning, and Explainable Machine Learning are not applied in SA region, this show the opportunity for future research in these domain (Unsupervised Learning, Distributed Machine Learning, and Explainable Machine Learning) for drought modeling.

VI. RESEARCH TRENDS

Over the past decade, there has been a growing interest in the application of machine learning and deep learning techniques to drought modeling [123], [124] [125], [126] [127]. Initially, drought modeling was performed with the help of statistical modeling. As in [128], linear mixed models for drought forecasting using SPI have been used. There have been other studies, whose focus was statistical models [129], [130] [131] such as ARMA [132] and ARIMA [132].

The advancement in the field of Machine learning has taken great attention and the focus of model development is observed from statistical modeling to machine learning modeling. In machine learning modeling both classical machine learning algorithms such as SVM, KNN [117], and several others as well as deep learning architecture such as RNN, CNN, and transformers are used. SVR for drought forecasting using SPI is reported in [115]. Apart from classical modeling, ensemble approaches have also been employed such as bagging and boosting [112], [118].

Another major trend in drought modeling is the use of DL models. This trend started from the use of simple ANN [91], [110], [116], [117] for drought modeling to more complex techniques such DFNN [112], ANFIS [114], DENFIS [119], and HRNN [89]. A recent addition to this trend is RNN architecture such as LSTM [17] for drought forecasting. Besides ML and DL techniques, there are few trends in terms of data used for the development of drought Modeling model. The most commonly used data for drought modeling is the precipitation data in the form of SPI [87] and SPEI [17]. Numerous studies used only precipitation data for drought modeling. Another trend in terms of data is several remote sensing indexes, which are being applied for drought modeling and are later fed to ML and DL models. The commonly used indexes are EVI, NDVI NDWI, VCI, VHI, SSI, [110], [114] [113].

Certain drought indexes are also created, for instance, CDI [85] and RDI [86] for drought modeling. Apart from single data modality, multimodal data is also used for drought modeling [9]. Most of the Studies focused on either non-real-time or near-to-real-time prediction [8] for the drought model in South Asia. Precisely, Fig. 6 reports major research trends and their sub-trends. it can be concluded from Fig. 6

TABLE 4. ML and DL techniques applied for drought modeling.

Paper	Drought Type	Data	Algorithm/s	Modeling Approach	Region
[112]	Agricultural Drought	Soil Moisture Deficit Index (SMDI)	Deep Forwarded Neural Network, Distributed Random Forest, Gradient Boosting Machine	Forecasting	South Asia
[89]	Hydro Meteorological Drought	Standardized Precipitation Evapotranspiration Index (SPEI)	Hybrid Recurrent Neural Network	Drought Monitoring	Russia, Afghanistan, Italy
[113]	Agricultural Drought	Normalized Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI) Land Surface Temperature (LST)	Linear Regression	Drought Impact Analysis	Afghanistan
[91]	Drought	SPI and Rainfall	ANN	Drought Forecasting	Sri Lanka
[87]	Drought	SPI	random forest (RF), minimum probability machine regression (MPMR), M5 Tree (M5tree), extreme learning machine (ELM) and online sequential-ELM (OS-ELM)	Drought Forecasting	Bangladesh
[110]	Agricultural Drought	Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), Soil Moisture Content (SMC), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI)	ANN	Drought Assessment	Bangladesh
[111]	Hydrological Drought	SPI	Support Vector Regression (SVR), ANN, Wavelet Packet Transform (WP), WP-SVR and WP-ANN	Drought Forecasting	India
[114]	Drought	SPI, and NDVI	Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	Drought Forecasting	India
[115]	Meteorological Droughts	SPI	SVR	Drought Forecast	India
[116]	Meteorological Drought	SPI	SVM and ANN	Drought Forecast	Iran
[117]	Drought	SPEI	SVM, ANN and k-Nearest Neighbour (KNN)	Drought	Pakistan
[118]	Drought	Raw satellite imagery	Bagging and Boosting ML Algorithms	Drought Prediction	Pakistan
[119]	Drought	SPI	extreme learning machine (OP-ELM) and dynamic evolving neural-fuzzy inference system (DENFIS)	Drought Prediction	Pakistan
[120]	Drought	SPI	Mann–Kendall test and PCA	Drought Assessment (SpatioTemporal Analysis)	Nepal
[93]	Drought	SPI	PCA	Drought Assessment (SpatioTemporal Analysis)	Nepal

TABLE 5. Evaluation parameters used in studies for SA region.

Paper/s	Parameters
[83] [87] [88] [91] [121] [131] [111] [114] [119]	RMSE
[88] [91] [121] [111] [114]	MAE
[87] [88] [91] [112] [121] [122] [111] [116] [117]	R-Squared
[116]	NMSE
[122]	PRMSE
[90] [118]	Accuracy
[90] [118]	Precision
[90]	Recall
[90] [118]	F1-Score
[89] [90] [118]	AUC ROC
[117]	MD (Modified index of agreement)
[117]	Percentage of bias (Pbias)
[85] [92]	TNR
[91]	Percentage Error (PE)
[92]	TPR
[117]	NRMSE

TABLE 6. Machine learning model categories and their application across regions for drought modeling.

Model Categories	Pakistan	India	Bangladesh	Nepal	Sri Lanka	Afghanistan
Supervised Learning	✓	✓	✓	✓	✓	✓
Ensemble Learning	✓	✓	✓		✓	✓
Deep Learning	✓	✓	✓	✓		✓
Time Series Analysis	✓	✓		✓	✓	
Hybrid Models	✓	✓				✓
Unsupervised Learning						
Distributed Machine Learning						
Explainable Machine Learning						

that drought modeling with the help of machine learning and deep learning techniques is focused on developing more accurate, robust, models, which can integrate a wide range of data with single and multiple modalities. These trends have significant implications for drought management and adaptation, as they can enable more effective and efficient strategies for mitigating the impacts of drought.

VII. RESEARCH CHALLENGES

Despite the significant progress made in the application of machine learning and deep learning techniques for drought modeling [133], [134] [135], several challenges still, remain unaddressed for more effective and reliable model development. The major challenge is the limited availability of high-quality data, especially in developing countries [136], such as in South Asian countries. Furthermore, the data collected from different sources is inherently inconsistent or incomplete for South Asia regions (i.e. coverage of data products may vary from region to region). It is observed that usually, lesser coverage is available for developing regions, which can affect the accuracy and reliability of the models.

Another challenge is the lack of standardization in data collection, processing, and modeling techniques, for example, the unavailability of benchmarking makes it more difficult to compare and integrate the results from different studies and models. The uncertainty and variability associated with various physical, biological, and socio-economic factors [137] that cause drought can pose significant challenges for developing accurate and reliable models. Thus, a diverse set of features need to be integrated. Overfitting is a common problem in machine learning and deep learning models, where the model performs well on the training data but fails to generalize to new data. This can lead to inaccurate and unreliable predictions. In detecting overfitting, usually a benchmarked dataset is used, which is unavailable.

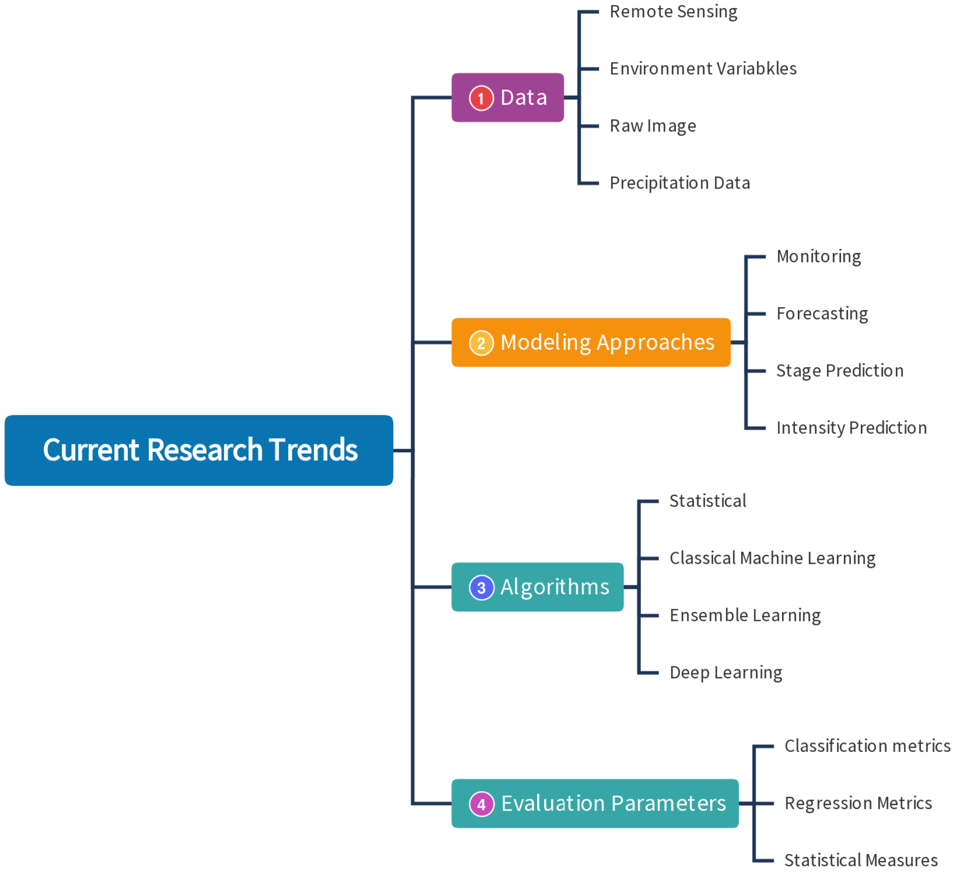

FIGURE 6. Current research trends for ML and DL based drought modeling for SA Region.

Deep learning models, in particular, are often observed as black boxes that are difficult to interpret and explain; thus, making it challenging to gain insights into the underlying mechanisms of drought. A few studies are carried out in this regard [138]. Furthermore, several machine learning and deep learning models require significant computational resources, which can limit their applicability in resource-constrained environments [139]. Addressing these challenges will require a concerted effort from researchers, policymakers, and practitioners. A possible solution, for instance, may be improving data collection and standardization, developing more robust and interpretable models, and integrating multiple sources of information to reduce uncertainty and variability. In case, these challenges are effectively dealt with; machine learning and deep learning models can become powerful tools for improving our understanding of drought. Fig. 7 shows the overall research challenges that are observed in this study for the South Asian region.

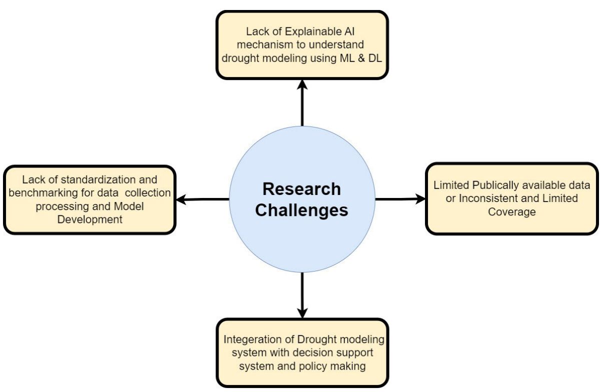

FIGURE 7. Research challenges for ML and DL based drought modeling for SA region.

VIII. FUTURE DIRECTIONS

Future directions for drought modeling proposed in this study are extracted from the research challenges section VII. Fig. 8 depicts potentially possible research directions for drought modeling, especially, in the South Asia region. Based on the observation from research challenges there are four key areas for identified for future research. These 4 areas are 1) Data Integration, 2) Distributed Learning 3) Explainable Machine Learning and 4) Real Time Drought Modeling. Lets discuss each of these one by one.

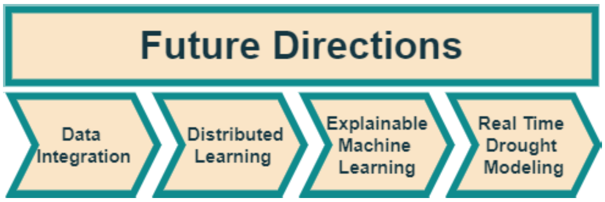

FIGURE 8. Future research direction for ML and DL based drought modeling for SA region.

The first potential research direction is data integration that addresses the challenge of varying the coverage of data products across different regions. Integrating multiple data sources, such as remote sensing, climate, social, and economic data can improve the accuracy and reliability of drought modeling systems and provide wide coverage of data across the region. It is represented in Fig. 9. There are 4 layers to proposed data integration methodology. In Data layer data from diverse source will be collected in data integration layer data will be preprocessed so that data from different source can be integrated. This integration or fusion can be done in number of ways such as vertical fusion [140], horizontal fusion [140], etc. These fusion techniques [141] [142] will provide better data coverage, hence more complete and consistent datasets across the region. This proposed integration technique increases dataset size in terms of feature and instances, hence bigger and complete dataset are generated. Once data from diverse source is integrated machine learning modeling and evaluation will be performed and trained model will be made available on output layer where end user can use them.

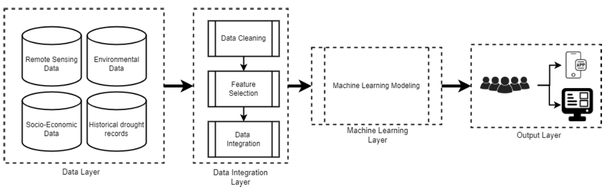

FIGURE 9. Proposed data integration methodology.

To deal with challenges such as limited or inconsistent data coverage lack of benchmarking dataset resulting either unreliable or overfitting machine learning model for drought modeling, this paper has recognized distributed ML. With distributed machine learning more robust, consistent and accurate drought modeling can be performed. One such way to do that is federated learning. Fig. 10 shows scheme of prospective distributed machine learning which can result can better drought modeling [143]. Federated learning [144] address the issue of data benchmarking by training model on diverse dataset hence the model does not overfit on singular dataset hence a more generalizable model is developed. Fig. 10 shows how individual models are aggregated in single model using aggregation algorithms such as FedAvg [145]. Models in this scheme can be trained using transfer learning for better performance [146].

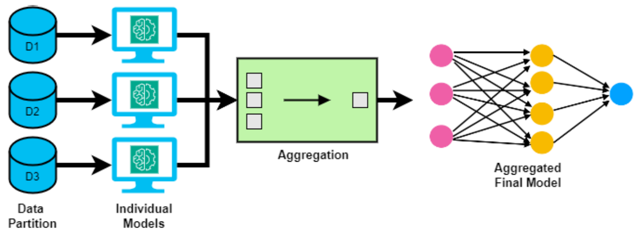

FIGURE 10. Proposed distributed machine learning scheme.

Drought modeling is high stakes applications, it is very important to understand why a model predicts something, so reason of outcome would provide a clear picture for decision making. Explainable Artificial Intelligence (XAI) makes sure that predictions produced by the model are transparent so that the stake holders can take informed decisions. Explainable Artificial Intelligence [147] is essential for creating black-box deep learning models [139] interpretable models so that stakeholder can gain better insights into the underlying mechanisms of drought. (XAI) improves drought modeling by interpreting model predictions using SHAP [148] and LIME [149]. While LIME [150] explains individual predictions by locally approximating model behavior, SHAP [149] values offer a global perspective of how characteristics such as temperature, vegetation indices, and soil moisture contribute to drought risk. These strategies ensure transparent decision making for drought modeling. Fig. 11 shows the flow of XAI for drought modeling with model prediction and explanation will be shown on user interface and user will be able to make decision.

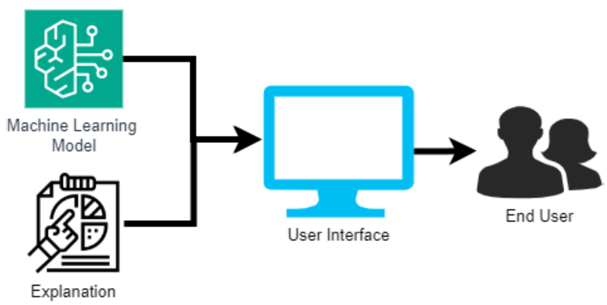

FIGURE 11. Proposed explainable machine learning scheme.

The most important research challenge is having constant update in drought modeling system. Mostly, studies focused on non-real-time or near-real-time drought modeling in South Asia. Because real-time integration of data streams into ML/DL models for drought modeling posses challenges such as handling high frequency data streams, managing inconsistencies in spatial and temporal resolutions, and model retraining strategies. Thus, to address this challenge future research should envision leveraging real-time data sources such as remote sensing (e.g., MODIS, Sentinel). Real-time monitoring and forecasting using machine learning and deep learning could enable more effective drought modeling as most of these types of systems are available in developed countries such as the USA [151].

Finally, integrating future innovation into decision-making processes could provide actionable insights to support decision-making in agriculture, water management, and disaster management.

IX. CONCLUSION

This study examined ML and DL techniques for drought modeling focusing on the South Asia region. It is concluded that ML and DL techniques have great potential in forecasting, predicting, monitoring, and tracking drought conditions. These techniques are effective in comparison with conventional statistical models. Classical supervised learning, ensemble learning are the most common machine learning approaches being used for drought modeling in SA. DL and Hybrid also show some promise in drought modeling but these models need to more widely adopted for drought modeling SA. Besides, these techniques may incorporate a variety of data sources such as remote sensing data, climatic data, and social and economic data in predicting accurate and precise outcomes. The incorporation of diverse data modalities, including soil and vegetation indexes, precipitation indexes, and remote sensing data, highlights the significance of comprehensive datasets in augmenting the accuracy and resilience of models.

The study also identified a number of challenges in existing practices, including the requirement for larger and more consistent datasets, incorporation of uncertainty analysis into the models need attention, under utilization of real-time data and the lack of research into sophisticated techniques like explainable and distributed machine learning. Nonetheless, these challenges highlight future areas where research is anticipated in machine learning and deep learning techniques for drought modeling.

The potential future directions in drought modeling for the South Asia region would be applying data integration to enhance number of indexes, apply distributed machine learning for creating more consistent and reliable drought modeling systems, develop explainable machine learning models so that stakeholder can not only know the outcome but also the reason behind the outcome and do all this in real time so constant update can be gathered by stakeholder and end users of a drought modeling system. Overall this paper discuss existing ML and DL infrastructure for drought modeling, current trends, challenges and how to improve upon these challenges and develop better drought modeling system so that better decision making can be done.

DECLARATION OF COMPETING INTEREST

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

DATA AVAILABILITY

All the data is available within the manuscript.

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