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Characterizing drought prediction with deep learning: A literature review

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REVIEW HIGHLIGHTS

- This review shows the drought prediction research through deep learning techniques.
- Moreover, this review presents the countries that have published efforts to implement deep learning techniques in drought prediction.
- Finally, this review highlights the drought index most used to be predicted using a deep learning technique.

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ABSTRACT

Drought prediction is a complex phenomenon that impacts human activities and the environment. For this reason, predicting its behavior is crucial to mitigating such effects. Deep learning techniques are emerging as a powerful tool for this task. The main goal of this work is to review the state-of-the-art for characterizing the deep learning techniques used in the drought prediction task. The results suggest that the most widely used climate indexes were the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). Regarding the multispectral index, the Normalized Difference Vegetation Index (NDVI) is the indicator most utilized. On the other hand, countries with a higher production of scientific knowledge in this area are located in Asia and Oceania; meanwhile, America and Africa are the regions with few publications. Concerning deep learning methods, the Long-Short Term Memory network (LSTM) is the algorithm most implemented for this task, either implemented canonically or together with other deep learning techniques (hybrid methods). In conclusion, this review reveals a need for more scientific knowledge about drought prediction using multispectral indices and deep learning techniques in America and Africa; therefore, it is an opportunity to characterize the phenomenon in developing countries.

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Subject area:	*Computer Sciences*
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Name of your method	*Characterizing drought prediction with deep learning: A literature review*
Name of the reviewed methodology:	*Drought prediction with deep learning*
Keywords:	*Drought; deep learning; prediction; remote sensing and climate index*
Resource availability:	*Not applicable*
Review question:	*Where is drought prediction research being conducted, and in what areas of study has it been applied?* *What indices have been used with artificial intelligence algorithms to predict drought?* *Which deep learning algorithms are used for drought prediction?*

Background

Due to several factors, drought is a nonlinear, nonstationary, and complex phenomenon [1,2]. Researchers have recently focused on developing warning systems and predicting drought occurrence using mathematical and computational models to minimize its impact.

Models based on deep learning have revealed a significant potential in drought event prediction [3], taking advantage of its ability to find and learn the nonlinear relationships in the data. Its success in this field is due to its capacity to classify and process complex patterns and nonlinear relationships in the information, which is crucial for a proper phenomenon prediction [4]. Therefore, this review aims to characterize drought prediction using deep learning methods worldwide.

In the literature, there are systematic reviews of the advances in drought prediction from a general overview. Notably, in [5–15], some stochastics or statistics techniques, general circulation models, machine learning approaches, and deep learning algorithms are studied. However, only some reviews are entirely focused on the last one. For example, in [9,11,13], the deep learning techniques implemented for drought prediction are mentioned in a single and short section of the document, with no deepening of the elements of each approach or inclusion of more methods. Consequently, this review contains a characterization of deep learning methods for drought prediction in a detailed form and with a particular approach, highlighting the study areas where they are applied, the countries with interest in the phenomenon study, and the drought indices employed. We aim to highlight the areas of research opportunity by identifying the study areas where deep learning techniques have been applied to drought prediction and their methodologies.

Table 1 shows the list of acronyms used in this manuscript.

Method details

Distribution of study areas for predicting drought using Artificial Intelligence (AI) approaches

One particular aspect of this analysis is the worldwide distribution of drought prediction research. This section aims to highlight the countries where the use of artificial intelligence (AI) techniques for drought prediction has been intensely researched, as well as those with the most interest in the problem. This analysis answers the research question: ***Where is drought prediction research being conducted, and in what areas of study has it been applied?*** The inclusion criteria employed were *drought, prediction or forecast*, and *artificial* intelligence.

Analyzed study areas

Regarding the distribution of study regions where drought prediction was performed using AI techniques, the countries with the highest quantity of research are located in Asia and Oceania, with Iran [16–2817], India [1,12,29–36], and Australia [37–42,] standing out. It is essential to mention that such countries present arid climate regions where drought is a constant problem. In contrast, Africa, Europe, and America are the continents with the lowest number of publications on drought prediction using AI techniques. These publications focused on small, arid regions in each country. The United States of America has the highest number of drought prediction research studies on the American continent [43–45], while Latin American countries have the fewest publications on the subject. Fig. 1 shows this distribution, and Table 2 shows the country's name and the number of publications in each.

Various studies employ simulations to attempt to predict the future behavior of drought. These simulations utilize a range of Global Circulation Models (GCMs). They are based on scenarios such as Shared Socioeconomic Pathways (SSP) in phase 5-8.5 (SSP5-8.5) and Representative Concentration Pathways (RCP) in phases 4.5 (RCP4.5) and 8.5 (RCP8.5).

In the first case (See Fig. 2 in [46]), the SSP5-8.5 scenarios and nine circulation models belonging to the Coupled Model Intercomparison Project (CMIP) in phase 6 (CMIP6) were considered. Four climate indices, SPI, SPEI, Standardized Runoff Index (SRI), and Standardized Streamflow Index (SSI), were calculated to describe the trends in drought conditions for 1901-2100. The analysis revealed that the regions exhibiting an increased likelihood of experiencing intensified drought conditions are concentrated in the United States and Mexico, Latin America, Europe, the Middle East, North and South Africa, Australia, and parts of China [46].

In scenarios RCP4.5 and RCP8.5 with 16 GCMs (See Fig. 5 in [47]), the frequency and severity of drought would be more significant in areas throughout the Americas, Africa, Europe, Asia, and Australia [47].

The preceding analysis highlights the importance of conducting studies in various areas worldwide where drought conditions could intensify. Compared with the studies found where AI is applied to predict the phenomenon (Fig. 1), we can highlight that the countries with the most extensive studies (Iran and Australia) are located where the phenomenon could intensify. In contrast, India is an example of a country where simulations indicate a reduction in drought conditions, yet many studies employ AI.

Table 1
List of used acronyms.

Acronym	Definition
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
NDVI	Normalized Difference Vegetation Index
LSTM	Normalized Difference Vegetation Index
AI	Artificial Intelligence
GCMs	Global Circulation Models
SSP	Shared Socioeconomics Pathways
RCP	Representative Concentration Pathway
CMIP	Coupled Model Intercomparison Project
SRI	Standardized Runoff Index
SSI	Standardized Streamflow Index
DF	Drought Frequency
DS	Drought Severity
MCI	Meteorological-drought Composite Index
SDI	Standardized Drought Index
SAPEI	Standardized Antecedent Precipitation Evapotranspiration Index
SWDI	Soil Wetness Deficit Index
MSSI	Multivariate Standardized Streamflow Index
EDI	Multivariate Standardized Streamflow Index
SSAI	Standardized Streamflow Anomaly Index
WBC	Water Bearing Coefficient
CDD	Consecutive Dry Days
SHDI	Standardized Hydrological Drought Index
nSPI	non-parametric SPI
NDI	Natural Drought Index
MSPI	Multivariate Standardized Precipitation Index
SMI	Soil Moisture Index
SMAI	Soil Moisture Anomaly Index
LST	Land Surface Temperature
NMDI	Normalized Multiband Drought Index
ET	Evotranspiration
SSM	Surface Soil Moisture
SUSM	Subsurface Soil Moisture
MEI	Multivariate El Niño Southern Oscilation
SOI	Southern Oscilation Index
ONI	Oceanic Niño Index
RDI	Reconnaissance Drought Index
WMO	World Meteorological Organization
SAVI	Soil Adjusted Vegetation Index
ARVI	Atmospherically Resistant Vegetation Index
EVI	Enhanced Vegetation Index
VHI	Vegetation Health Index
NDWI	Normalized Difference Water Index
SMDI	Soil Moisture Deficit Index
SDCI	Scaled Drought Condition Index
MNDWI	Modified Normalized Difference Water Index
VCI	Vegetation Condition Index
NDVI	Normalized Difference Vegetation Index
ANN	Artificial Neural Network
DFNN	Deep Feedforward Neural Network
DRF	Distributed Random Forest
GBM	Gradient Booster Machine
PAI	Precipitation Anomaly Index
PCI	Precipitation Condition Index
TCI	Temperature Condition Index
GAM	Generalized Additive Models
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
MERRA	Modern Era Retrospective-Analysis for Research and Applications
NAR	Nonlinear Autoregressive
MSE	Mean Square Error
ARIMA	Autoregressive Integrated Moving Average
EA-LSTM	Entity-Aware LSTM
MLP	Multi-Layer Perceptron Neural Network
RMSE	Root Mean Square Error
ConvLSTM	Convolutional Long- and Short-Term Memory
RF	Random Forest

(*continued on next page*)

Table 1 (*continued*)

Acronym	Definition
GAN	Generative Adversarial Network
AE-CNN-LSTM	Autoencoder Convolutional Neural Network model for Long Short-Term Memory
TD-CNN	Time-Distributed Convolutional Neural Network
CNN-LSTM	Convolutional Neural Network Model for Short-Term Memory
TWSA	Terrestrial Water Storage Anomaly
GWSC	Groundwater Storage Changes
MD-to-AD	Meteorological Drought to Agricultural Drought
MD-to-GD	Meteorological Drought to Groundwater Drought
SGI	Standardized Groundwater Index
MRA-WT-LSTM	Multi-Resolution Analysis Wavelet Transform and LSTM
RFR	Random Forest Regression
MODIS	Moderate-Resolution Imaging Spectroradiometer
TRMM	Tropical Rainfall Measuring Missionhttps://gpm.nasa.gov/missions/trmm
GLDAS	Global Land Data Assimilation System
GRACE	Gravity Recovery and Climate Experiment
GRACE-FO	Gravity Recovery And Climate Experiment - Follow-On
SRTM	Shuttle Radar Topography Mission
GFS	Global Forecast System
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
AVHRR	Advanced Very High Resolution Radiometer
IRIMO	Islamic Republic of Iran Meteorological Organization
MAE	Mean Absolute Error
ERA5	ECMWF Reanalysis version 5
TAMSAT	Tropical Applications of Meteorology using SATellite
NDDI	Normalized Difference Drought Index

Table 2
Number of publications per country where a region study was performed.

Country	Frequency
Iran	13
India	10
Australia	6
Turkey, China	5
USA	4
Malaysia	3
Ethiopia, Algeria	2
Vietnam, Cambodia, Laos, Italy, Morocco, Nigeria, Colombia, South Korea, Pakistan, Slovakia, Peru, Bangladesh, Indonesia, Mexico, Ecuador	1

In most countries of the American continent, drought conditions tend to increase and become more severe. However, studies attempting to predict these conditions with AI techniques have not been conducted, except in the United States of America, where the most significant number of studies can be found. Similarly, the same conditions prevail in Africa as in America, where the phenomenon is predicted with high intensity, and there is not sufficient research for forecasting with AI (see Fig. 1).

Regions where drought analysis is produced

One curious aspect of drought prediction publications is that they are often generated in regions where the analysis is not applied. This issue has been increasing in recent years. This study suggests the need to establish collaborative networks within the country where the study area is located and with experts from other countries to investigate this phenomenon. This distribution suggests the need for a collaborative approach [26,48,49]. According to Fig. 2, the distribution of countries involved in the issue is lowest in the Americas and Africa, while Europe and Asia have more countries involved. It is worth noting that authors such as [11,50] conduct research in countries where the phenomenon is a constant problem despite being elsewhere.

Anurag Malik has produced five research papers on using AI to predict drought in various regions of India, making him one of the most prolific researchers in this field [31–35].

Drought indices used as input of the deep learning techniques

Several indices estimate drought intensity based on information captured by local warning networks or remote sensors 51[51,52]. These indices can be categorized into two groups: climate indices and multispectral indices. Climate indices are calculated using data from local meteorological warning network sensors that capture climate variables at specific locations and time intervals. In contrast, multispectral indices are computed from satellite images that capture the earth's surface conditions [51].

Both indices can predict drought behavior over time. However, maintaining a local meteorological monitoring network that provides information to calculate climate indices can be challenging in some regions due to financial constraints. Consequently, it can

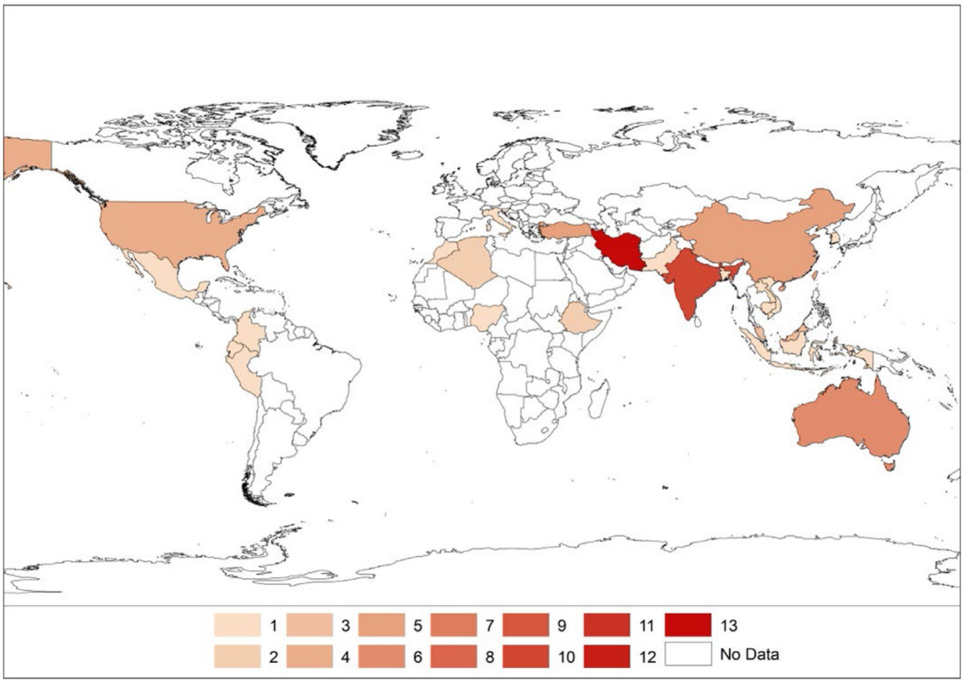

Fig. 1. Countries where AI has been used for drought prediction. The intensity of the red color indicates the number of papers published on the topic, with the darkest red indicating the most published. Conversely, lighter shades of red indicate countries with fewer publications.

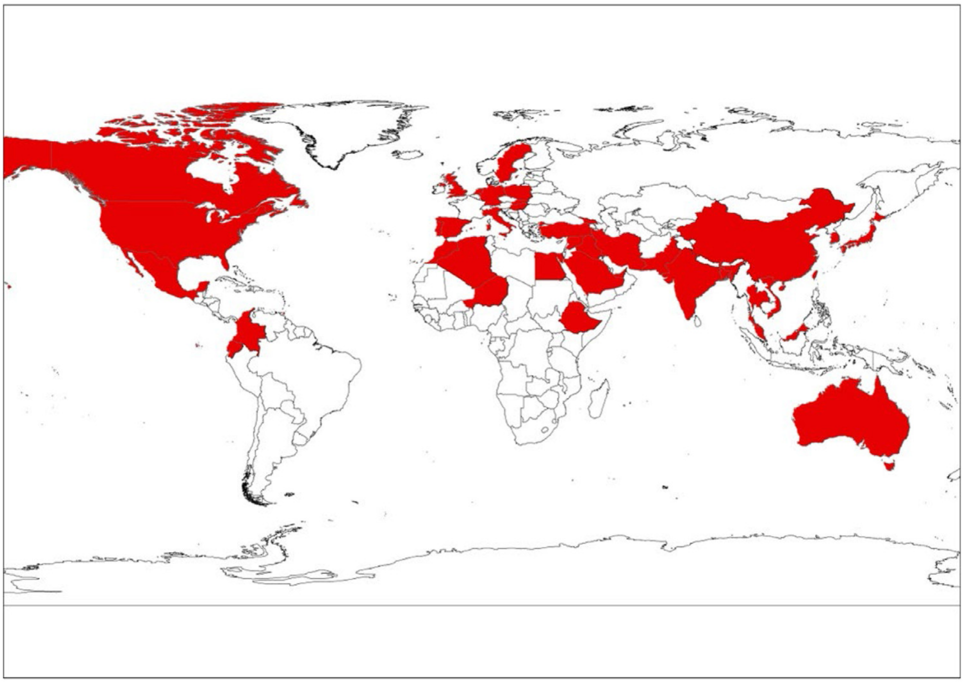

Fig. 2. Distribution of countries where research on drought prediction using artificial intelligence techniques is being carried out. The red color indicates the presence of a study or research center related to the search.

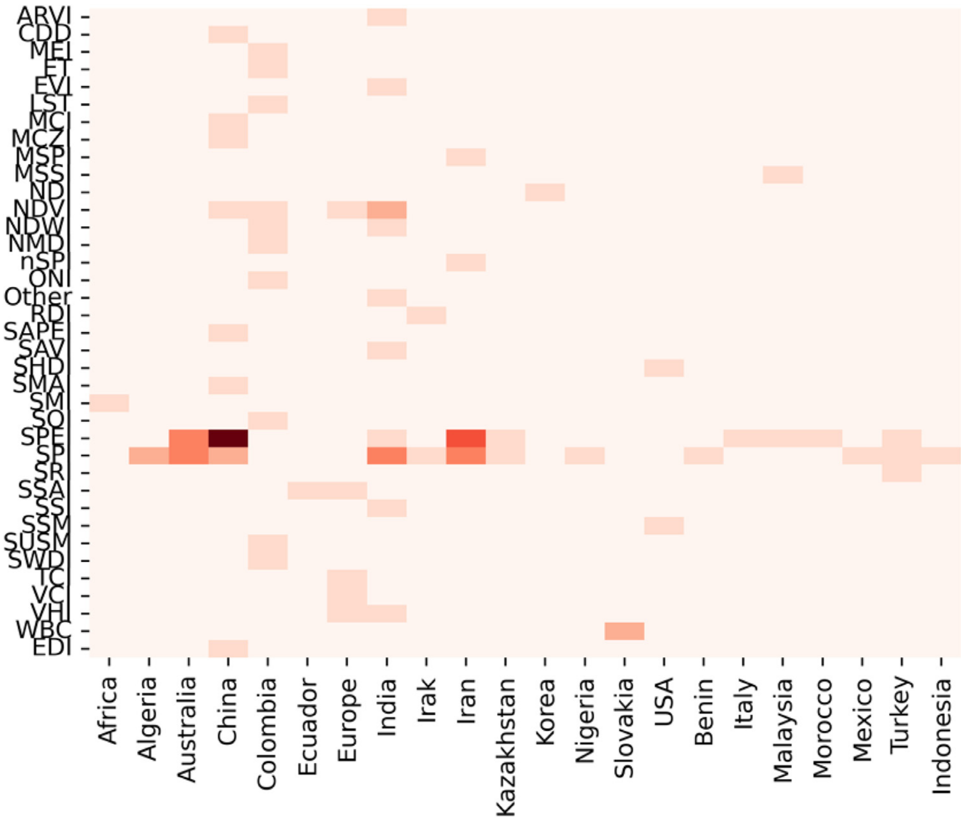

Fig. 3. Heat map of the publications number where each index was used and which region was implemented.

result in missing information over extended periods, complicating the study of the phenomenon [51]. Multispectral indices are commonly used to address this issue. However, it is essential to note that these indices are derived from high-resolution satellite images and only reflect the land surface conditions, such as bodies of water and vegetation, without providing contextual information. Therefore, caution should be exercised when interpreting these indices, as they may indicate drought conditions where the phenomenon does not occur.

This section aims to answer the research question: ***What indices have been used with artificial intelligence algorithms to predict drought?*** The goal is to identify the most effective indices for describing the phenomenon's behavior in different contexts. The inclusion criteria employed to answer this question were *drought, prediction or forecast, artificial intelligence*, and *remote sensing or satellite images*.

Table 3 and Fig. 3 display the correlation between the study region and the index utilized in predicting drought behavior. The climatic indexes discovered include the SSI, Meteorological-drought Composite Index (MCI), Standardized Drought Index (SDI), SPI, SPEI, Standardized Antecedent Precipitation Evapotranspiration Index (SAPEI), Soil Wetness Deficit Index (SWDI), Multivariate Standardized Streamflow Index (MSSI), Effective Drought Index (EDI), Standardized Streamflow Anomaly Index (SSAI), SRI, Water Bearing Coefficient (WBC), Consecutive Dry Days (CDD), Standardized Hydrological Drought Index (SHDI), non-parametric SPI (nSPI), Natural Drought Index (NDI), Multivariate Standardized Precipitation Index (MSPI), Soil Moisture Index (SMI), Soil Moisture Anomaly Index (SMAI), Land Surface Temperature (LST), Normalized Multiband Drought Index (NMDI), Evotranspiration (ET), Surface Soil Moisture (SSM), Subsurface Soil Moisture (SUSM), Multivariate El Niño Southern Oscilation (MEI), Southern Oscilation Index (SOI), Oceanic Niño Index (ONI) and Reconnaissance Drought Index (RDI). SPEI is the most commonly used set for prediction as it establishes a relationship between precipitation and evapotranspiration [4]. SPEI has been used in drought prediction with AI in various regions, including China [53–63], Australia [38,41,42], and Iran [9,18,64,65]. These regions are known for their hot and arid weather conditions.

On the other hand, SPI is another frequently used climatic index. It is used to observe the deviation of accumulated precipitation from the climatological mean. It is worth mentioning that the World Meteorological Organization (WMO) recommends using SPI to describe the phenomenon [66]. This index has been utilized to forecast drought using AI tools in different parts of the world, such as Turkey [67], Nigeria [68], India [12,32,57], Indonesia [69], and Mexico [70].

Regarding multispectral indices, the following multispectral indices are reported: Soil Adjusted Vegetation Index (SAVI), Atmospherically Resistant Vegetation Index (ARVI), Enhanced Vegetation Index (EVI), Vegetation Health Index (VHI), Normalized Difference Water Index (NDWI), Soil Moisture Deficit Index (SMDI), Scaled Drought Condition Index (SDCI), Modified Normalized

Table 3
Number of publications per country and employed index.

Index	Africa	Algeria	Australia	China	Colombia	Ecuador	Europe	India	Irak	Iran	Kazakhstan	Korea	Nigeria	Slovakia	USA	Benin	Italy	Malaysia	Morocco	Mexico	Turkey	Indonesia
ARVI	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CDD	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MEI	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ET	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EVI	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LST	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MCI	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MCZI	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSPI	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
MSSI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
NDI	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
NDVI	0	0	0	1	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NDWI	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NMDI	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
nSPI	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
ONI	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Other	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RDI	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
SAPEI	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SAVI	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SHDI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
SMAI	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SMI	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOI	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SPEI	0	0	3	7	0	0	0	1	0	4	1	0	0	0	0	0	1	1	1	0	1	0
SPI	0	2	3	2	0	0	0	3	1	3	1	0	1	0	0	1	0	0	0	1	1	1
SRI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
SSAI	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SSI	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SSM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
SUSM	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SWDI	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TCI	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VCI	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VHI	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WBC	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
EDI	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Difference Water Index (MNDWI), Vegetation Condition Index (VCI), and Normalized Difference Vegetation Index (NDVI). For this type of index, NDVI is the most commonly used worldwide, especially in regions of India [71–74], where its geophysical characteristics and topology strongly influence climate changes [75].

Deep learning techniques for drought prediction

This section analyzes deep learning implementations for drought prediction, particularly papers that use multivariate remote sensing data in different case studies. This analysis answers the question: ***Which deep learning algorithms are used for drought prediction?*** Moreover, the inclusion criteria search used were *drought* and *prediction or forecasting* and *deep learning* and *neural networks* and *remote sensing* or *satellite images*.

The reviewed documents include several deep learning algorithms, from conventional implementations and their variants to hybrid models. The different models are described below.

Artificial Neural Networks (ANN)

Recently, Artificial Neural Networks (ANN) have gained popularity among data-driven models for drought prediction. They provide superior prediction results to models based on physical principles. Given droughts' inherent nonlinearity, neural networks have proven practical tools for analyzing the relationship between indices and variables that influence drought [76].

For example, Prodhan et al. [72], present a deep learning technique for monitoring agricultural drought in South Asia using remotely sensed data, specifically for predicting SMDI behavior. In this work, a Deep Feedforward Neural Network (DFNN) was used, and the results were compared with two machine learning models: the Distributed Random Forest (DRF) and the Gradient Booster Machine (GBM). The constructed model considers the SMDI as a function of the prediction and soil factors, as presented in Eq. (1), where Y is the SMDI value, precipitation is Precipitation Anomaly Index (PAI), Precipitation Condition Index (PCI), SPI-3, SPI-6, SPEI-3, SPEI-6, vegetation is VCI, VHI, Temperature Condition Index (TCI), and soil is EDI.

$$Y = f(precipitation, vegetation, soil) \tag{1}$$

This study used a raster image dimension of 7818 (row) × 8859 (column) with a total pixel cell of 69259662 for each input variable. The DFNN model was implemented with one input layer, four hidden layers, and one output layer connected. The output is achieved by linear summation through a nonlinear activation function that passes through the layers with neurons, where each neuron receives one or more input signals. As a result, DFNN outperforms the compared models regarding prediction accuracy. Analysis of the importance of variables showed that precipitation factors had the most significant influence on SMDI variability. The study highlighted the spatio-temporal trends of drought and evaluated the stability of the DFNN model through cross-validation, demonstrating its effectiveness for agricultural drought monitoring in South Asia.

Furthermore, due to its multi-layer approach, the DFNN has the advantage of finding an optimal output in high-dimensional data. By increasing the model parameters (hidden layers with neurons, adaptive learning rates, among others), the calculations become more practical, relevant, and precise in prediction. However, this model depends on the input parameters and the size of the training set.

On the other hand, Adede et al. [77] introduce a multivariate model to predict drought conditions up to three months in advance using VCI. This work uses an integrated approach combining Generalized Additive Models (GAM) and ANNs. Initially, GAM reduces the variable space from rainfall and vegetation cover data, thus optimizing the selection of variables. The GAM models are expressed as Eq. (2), where a is an intersection, f are soft functions, Y is the response function, and $x_1 \dots x_n$ are the n predictors variable.

$$Y = a + f_1(x_1) + f_2(x_2) + \cdots + f_n(x_n) + \varepsilon \tag{2}$$

The model space for the study is approximately 2.15 billion, which renders it impractical to navigate the search for the optimal predictor model. By applying a two-variable plus a third sufficiency assumption for seasonality, the model space is reduced to 496 models. Additional reduction is achieved by ensuring that no two variables of the same type (precipitation and vegetation) are used and that only one level of lag variables is used in the same model. This process reduces the model space to 102. After that, a brute force method is applied with ANNs using the backpropagation algorithm for the final model, benefiting from the previous simplification to improve training efficiency. Moreover, the network architecture was defined with two hidden layers followed by a 2-5-3-1 configuration aimed at limiting the complexity of the model and allowing the representation of arbitrary functions.

Consequently, integrating GAM with ANN enables a reduction in the model space, thereby reducing the training time. However, this approach employs a brute force methodology to obtain the prediction results, which is inefficient in high-dimensional data.

Convolutional Neural Networks (CNNs)

In the case of Convolutional Neural Networks (CNN), Chaudhari et al. [78] compare three deep learning approaches: CNN, AlexNet, and VGGNet. These models were complemented with ANN for agricultural drought prediction using satellite images and vegetative indices (NDVI, SAVI, EVI, and ARVI). CNN model is based on convolutional layers to process images identifying relevant features through filters and max-pool operations to reduce the data dimensionality. Moreover, a dropout layer is used before the last one to prevent model overfitting. The output of this model is added to the other indices calculated from the image and serves as training for the neural network. On the other hand, AlexNet follows a similar methodology but changes the sequence of convolutional and pooling layers. AlexNet and VGGNet are used instead of CNN to train the images, and ANN to train the index data. The results showed that the customized CNN model outperforms the AlexNet and VGGNet models, highlighting its effectiveness in integrating satellite imagery and vegetative data for agricultural drought prediction. Furthermore, the CNN model has a structure that necessitates a smaller number of trainable parameters, in contrast to AlexNet and VGGNet, which implies a lower computational complexity. Nevertheless, this model cannot detect temporal patterns within images, as it solely considers the spatial component.

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are designed to process sequential data. Consequently, they are considered highly suitable for time series analysis, which encompasses drought indices, among other things. RNNs maintain a hidden state that preserves information from past sequences, enabling them to recognize and learn from long-term patterns in the data [4]. A LSTM network inherits the memory feature of a RNN. The primary innovation in LSTM is its memory cell c_t, which serves as a repository of state information. This cell is operable through multiple self-parameterized access, modification, and clearance control gates. Each time a new input arrives, its information will be stored in the cell if the input gate is active.

Furthermore, the previous cell state c_{t-1} can be erased if the forget gate f_t is engaged. The transfer of the most recent output from cell c_t to the final state h_t is managed by the output gate o_t. One significant benefit of employing the memory cell and gates to manage information flow is the containment of the gradient within the cell, which helps prevent it from dissipating too rapidly. Eq. (3) expresses LSTM element calculation, where σ represents the sigmoid function, and $\circ$ represents the Hadamard product [79].

$$\begin{aligned} i_t &= \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}\circ c_{t-1} + b_i\right) \\ f_t &= \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}\circ c_{t-1} + b_f\right) \\ C_t &= f_t\circ c_{t-1} + i_t\circ tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \\ O_t &= \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}\circ c_t + b_o\right) \\ \mathrm{H_t} &= \mathrm{o_t}\circ tanh\left(\mathrm{c_t}\right) \end{aligned} \tag{3}$$

Zhang et al. [80], propose a deep learning method based on LSTM networks for predicting historical monthly time series data of soil moisture based on Modern Era Retrospective-analysis for Research and Applications (MERRA)-Land from 1980 to 2012. This approach involves using lagged values as training sequences, relying on a nonlinear autoregressive (NAR) model to predict future values, and relying on historical data. Mathematically, this model predicts future sequence values, denoted by the hat symbol, $\hat{y}(t)$, based on past data points of the series, $y(t-1), \dots, y(t-d)$. Training sequences consist of the time series data, excluding the final time step. Eq. (4) expresses the predictive model, represented by the function f. This function is designed to grasp temporal dependencies within the data and embodies the LSTM model.

$$\hat{y}(t) = f(y(t-1), \dots, y(t-d)) \tag{4}$$

In this model, the LSTM layer matrix contains 200 hidden units, and the Adam optimization algorithm with an adjustable learning rate was used to train the dynamic neural networks for 600 epochs. The proposed method showed a much lower Mean Square Error (MSE) than the Autoregressive Integrated Moving Average (ARIMA) model and NAR.

Another work that implements LSTM networks from remotely sensed data is developed by Lees et al. [81], who propose two types of LSTMs to predict VCI. This approach uses a standard LSTM network and an Entity-Aware LSTM (EA-LSTM) network, which modifies the input gate where only static (pixel-specific) attributes are used to determine what information is passed from the input data to the state vector. As a result, the number of weights in the model is reduced, acting as a regularization technique and potentially improving the model's generalization. Data from the last three months served as input for both models. The models utilized data from times $t-3$, $t-2$, and $t-1$ to forecast the VCI at time t. The models were trained using the smooth $L1$ loss function, which has been observed to exhibit reduced sensitivity to outliers in comparison to the root mean square error loss. The training was halted after 100 epochs due to a lack of performance enhancement over ten successive epochs. The loss function can be referred to as Eq. (5).

The proposals were trained on the same input data from 2002 to 2005, and their performance was evaluated on the exclusion test set for all months from 2016 to 2018. The models were trained over the period 2002-2015 and tested over the period 2016-2018. In addition, the results were compared with a Multi-Layer Perceptron Neural Network (MLP), consisting of a single hidden layer (fully connected), which has as an activation function the ReLu function and generates a vector of the same size as that generated by the LSTM hidden layer (i.e., 64 values). The performances of LSTM and EA-LSTM were very similar, with significantly better results than the fully connected neural network in terms of Root Mean Square Error (RMSE) and R^2. The principal advantage of employing EA-LSTM is that it rectifies the gateway promptly, utilizing solely static attributes to ascertain the data flow to the state vector. This approach enables the reduction of the model's weightings, thereby regulating the computational cost.

$$\begin{aligned} loss(x,y) &= \frac{1}{n}\sum_i z_i \\ z_i &= \begin{cases} 0.5\left(x_i - y_i\right)^2 & if\ \left|x_i - y_i\right| < 1 \\ \left|x_i - y_i\right| - 0.5 & otherwise \end{cases} \end{aligned} \tag{5}$$

The methods presented above address medium and long-term drought prediction. However, Park et al. [82] propose a short-term (eight-day) drought prediction model that takes into account temporal patterns of satellite-based drought indices, numerical model results using Convolutional Long- and Short-Term Memory (ConvLSTM), and Random Forest (RF) approaches in a part of East Asia. The proposed approach consists of two steps. First, ConvLSTM, which combines CNN and LSTM, is used to obtain temporal patterns from historical drought conditions (SPI and SDCI) over a study period from 2003 to 2018. Unlike a standard LSTM, ConvLSTM replaces internal matrix multiplications with convolutional operations. As a result, ConvLSTM can produce a 2-D output, while the LSTM result is only a one-dimensional vector. In Eq. (6), the components of ConvLSTM are specified, where the symbol $*$ denotes the convolution operator. Besides, in the second step, RF is used to incorporate static variables (i.e., land cover, elevation, and climate zone) and predicted climate factors (temperature and precipitation) provided by the numerical model into the output of the previous step.

$$\begin{aligned} i_t &= \sigma\left(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} \circ c_{t-1} + b_i\right) \\ f_t &= \sigma\left(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} \circ c_{t-1} + b_f\right) \\ C_t &= f_t \circ c_{t-1} + i_t \circ tanh\left(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c\right) \\ O_t &= \sigma\left(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{co} \circ c_t + b_o\right) \\ H_t &= o_t \circ tanh\left(c_t\right) \end{aligned} \tag{6}$$

ConvLSTM offers a distinct advantage over traditional LSTM methods. By integrating convolutional operations into the mathematical equations of the LSTM, ConvLSTM enables the prediction of time series while considering spatial characteristics. This approach allows for the maintenance of the complexity inherent to LSTM cells while accounting for spatial characteristics.

Generative Adversarial Networks (GANs)

Ferchichi et al. [8], recently proposed a model that uses Generative Adversarial Networks (GAN) to predict drought in Africa. This architecture comprises two components, a generator G and a discriminator D, represented as $f = (G, D)$, which integrates both CNN and LSTM technologies. The model focuses on how future spatio-temporal variations in drought change under the effects of climate change. The study uses multivariate remote sensing data over the continent from 1999 to 2022. The study evaluates agricultural drought using the SMI as a response parameter. The input variables for the GAN model include hydrological, meteorological, and vegetation spectral factors.

Given a time series data set in the latent space vector Z_t, which is encoded by the multivariate time series X_t, the generator G is capable of defining a distribution of the generated time series to match the distribution of the actual time series by fitting Z_t to the generated time series $G(z)$. The discriminator then takes $G(Z_t)$ and X_t as inputs to differentiate between them. The optimization process can be regarded as a minimax game problem. The optimization function for the proposed GAN model is expressed in Eq. (7), where $x \sim p_g$ represents the temporal series from the generated data distribution and $E_{x\sim p_g}[\log(1 - D(G(Z_t)))]$ denotes the expectation that the discriminator will identify the generated time series as false. Conversely, $x \sim p_{real}$ represents the time series from the distribution of actual data, and $E_{x\sim p_{real}}[\log D(X_t)]$ denotes the expectation that the original time series will be found to be authentic by the discriminator.

$$\min_{G} \max_{G} L(G, D) = \mathrm{E}_{\mathrm{x\sim p_{real}}} \left[\log D\left(X_t\right)\right] + \mathrm{E}_{\mathrm{x\sim p_g}} \left[log(1 - D(G(Zt)))\right] \tag{7}$$

The proposed model's structure includes a convolution layer with 16 filters, a kernel size of 2, and a ReLU activation function. It also has a max-pooling layer with a pool size and stride of 2, a fully connected layer with a unit and sigmoid activation, an LSTM layer with 100 cells, and a dropout layer of 0.2. The optimization is performed using the Adam algorithm, experimenting with two different values of batch size, learning rate, and epoch size. The experimental results confirmed the reliability of the proposed model for forecasting agricultural drought. It was superior to the deep learning techniques, Autoencoder Convolutional Neural Network model for Long Short-Term Memory (AE-CNN-LSTM), Convolutional Neural Network model for Long Short-Term Memory (CNN-LSTM), CNN, and LSTM.

Furthermore, the GAN model's structure enables it to identify spatio-temporal data characteristics using CNN and LSTM. However, the model's limitations primarily stem from its structure, which, although it reflects the relationships between time series and drought events and can accurately capture the complex relationships between climate and RS indices, remains opaque. Understanding the model's results and how they were obtained is challenging. Furthermore, this proposal is unable to predict uncertain data. Finally, as a deep learning algorithm, its computational time is competitive due to the time series generation component, which requires iterative debugging to achieve better-than-real results.

Hybrid models

Dhyani et al. [83] proposed a methodology that analyzes how meteorological droughts, characterized by prolonged periods of low precipitation, affect water availability by increasing evaporation and transpiration. This phenomenon can lead to agricultural droughts due to the reduced water accumulation necessary for crops. This approach uses a recurrent LSTM network to learn the sequential characteristics of SPEI data from 1901 to 2018. In a drought, agricultural prediction is made using the NDVI index calculated from Landsat 8 images as input to the Time-Distributed Convolutional Neural Network (TD-CNN) to classify the subsequent sequential output. If a drought is predicted, the authors will develop anti-drought strategies based on the proposed model output and SMI analysis.

Consequently, TD-CNN with LSTM has the advantage of predicting an image sequence using distributed CNNs, which allows for identifying the sequential relationships of the image sequence. By utilizing different CNNs in parallel and with individual parameters, TD-CNN can extract the relevant and essential features independently for each image of the input sequence. However, it still maintains a high computational cost by using LSTM as part of its methodology.

On the other hand, Seo and Lee [59] developed a probabilistic framework to analyze drought propagation in South Korea using satellite data. They implemented a CNN-LSTM with data from 2003 to 2019. The predictor variables included precipitation, temperature, NDVI, MNDWI, soil moisture content, and Terrestrial Water Storage Anomaly (TWSA), while the response variable was the Groundwater Storage Changes (GWSC). The model was trained using the Adam optimizer and the ReLU activation function to minimize the mean square error. Hyperparameters such as delay time, epochs, nodes, filters, hidden layers, and batch size were optimized using Bayesian techniques. The mean propagation times were also estimated, with the propagation time from Meteorological Drought to Agricultural Drought (MD-to-AD) estimated at 2.83 months and the propagation time from Meteorological Drought to Groundwater Drought (MD-to-GD) estimated at 4.34 months. The results indicate that the probability of drought occurrence increases with the severity of previous meteorological conditions. It highlights the importance of using models to characterize the relationship between meteorological, agricultural, and groundwater droughts under different conditions for effective management. Subsequently, a joint distribution between three drought types was constructed using the most appropriate copula functions. Conditional probabilities of drought occurrence at different temporal and spatial scales were calculated. Given the joint probability distribution of SPI, SSMI, and Standardized Groundwater Index (SGI), the conditional probability of droughts under preceding drought conditions can be obtained using Eq. (8). For example, the transition probabilities from MD-to-GD for light, moderate, severe, and extreme meteorological drought scenarios are 38%, 43%, 48%, and 53%, respectively.

$$\begin{aligned} P(Y \leq y \mid X \leq x) &= \frac{P(X \leq x, Y \leq y)}{P(X \leq x)} = \frac{F_{X,Y}(x,y)}{F_X(x)} \\ P(Y \leq y \mid x_1 < X \leq x_2) &= \frac{P\left(x_1 < X \leq x_2, Y \leq y\right)}{P\left(x_1 < X \leq x_2\right)} = \frac{F_{X,Y}\left(x_2, y\right) - F_{X,Y}\left(x_1, y\right)}{F_X\left(x_2\right) - F_X\left(x_1\right)} \end{aligned} \tag{8}$$

The principal advantage of this method is the utilization of conditional probabilities of drought occurrence, calculated by the copula function, which permits the description of intricate dependencies between variables. Nevertheless, it is computationally complex as a method that employs LSTM cells due to the mathematical operations involved.

Finally, Abbes et al. [64] propose a hybrid model, MRA-WT-LSTM, combining LSTM and Multi-Resolution Analysis Wavelet Transform (MRA-WT) to predict drought in the Sarab region of Iran. This model is called MRA-WT-LSTM. The model utilizes station data, including precipitation, temperature, humidity, pressure, and evaporation, and the NDVI index derived from satellite images from 1988 to 2016 to predict the SPEI. The initial phase of the analysis involves examining the evaporation data using the MRA-WT technique. This method, referred to as WT, partitions nonstationary time series across both the time and frequency domains. It is represented by Eq. (9), where $\psi_{a,b}$ is known as the mother wavelet, a denotes the scale parameter, and b indicates the position of the wavelet. The discrete wavelet transform (DWT) is a signal decomposition method that creates a discrete set of wavelets. This process decomposes the signal into orthogonal parts. It is computed as Eq. (10).

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{9}$$

$$\psi_{j,k} = 2^{-\frac{j}{2}}\,\psi\left(2^{-j}t - k\right) \tag{10}$$

The level of Wavelet decomposition for the MRA-WT method is determined by the equation $L = int[\log(N)]$, where N represents the number of the data set, L is the decomposition level, and int expresses the integer part function. The trend and seasonal components obtained are scaled to the range of (0, 1) according to the nature of the feature. The LSTM network was implemented using hyperparameters adjusted to the model's objectives, with the MSE used as loss function. The methodology was trained using the Adam optimizer with an initial learning rate of 0.001 for 200 epochs. This approach utilizes the benefits of LSTM for time series analysis and MRA-WT for nonstationary data analysis, resulting in precise long-term predictions. MRA-WT-LSTM outperformed three other machine learning models, ANN, SVR, and Random Forest Regression (RFR), including the LSTM network.

Furthermore, using the wavelet transformation, MRA-WT decomposes nonstationary time series in both the time and frequency domains. This process enables the MRA-WT-LSTM to reduce training time compared to LSTM. Finally, the MRA-WT-LSTM can handle nonstationary features in the data, a capability that is not shared by most prediction methods.

Table 4 presents a comparative summary of the methods discussed, emphasizing using Moderate-Resolution Imaging Spectroradiometer (MODIS) and Landsat as input data for drought prediction. This preference may be attributed to these sources providing freely accessible information with constant temporality [84]. The most commonly used evaluation metrics are RMSE and R^2. RMSE assesses model performance in meteorology, climate, and geosciences. For the second, it is used to measure the reliability of the prediction model about the observed values. A value close to or equal to one indicates a good prediction of the model, while values close to zero indicate the opposite case [58,13]. Moreover, LSTM is the most widely used method for drought prediction, individually or in combination with other methods, due to its ability to process sequential data and long-term retention of data behavior. However, as aforementioned, LSTM presents a high computational complexity, which results in high hardware costs and energy consumption due to the mathematical operations used for the prediction [85–87].

New research areas for drought prediction

Based on the findings in this review, the following research opportunity are detected.

Table 4
Deep learning models where satellite data and climate indices were used as input. Performance metrics presented were those corresponding to the best results obtained.

	Model	Type Data	Data source	Drought Index	Performance Metrics	Case Study
[59]	CNN-LSTM	Remote sensing data	TRMM, Landsat 5 and 8, GLDAS, GRACE and GRACE-FO	GWSC	r = 0.72, RMSE = 42.92 mm/month	South Korea
[82]	1st stage: ConvLSTM 2nd stage: Random Forest	Remote sensing data	MODIS, TRMM MODIS, SRTM, GFS	SDCI, SPI	SDCI: r = 0.90, RMSE = 0.11 SPI: r = 0.93, RMSE = 0.08	East Asia, including east China, southeast Russia, Korea, and part of Japan
[72]	DFNN	Remote sensing data	GLDAS-02), MODIS, CHIRPS	SMDI	R2 = 52 to 0.94, RMSE = 0.486, MAE = 0.359, MSE = 0.237	South Asia (India, Nepal, Bhutan, Bangladesh, Pakistan, Afghanistan, Sri Lanka, and the Maldives)
		Station Data	Department of meteorology for each country			
[64]	LSTM	Remote sensing data	(AVHRR) instrument on-board the Landsat series 7	SPEI	LSTM: R2 = 0.92, RMSE = 0.03, Bias =0.00512, MAPE = 9.246	Sarab, Iran
	Hybrid model MRA-WT-LSTM	Station Data	Islamic Republic of Iran Meteorological Organization (IRIMO)		MRA-WT-LSTM: R2 = 0.93, RMSE = 0.02, Bias = 0.00735, MAPE = -1.955	
[83]	1st stage: LSTM	-	-	SPEI	Cosine similarity = 0.74, loss = 0.33	Northern Karnataka
	2nd stage: Hybrid TD-CNN	Remote sensing data	Landsat 8	NDVI	Accuracy = 95%, loss = 0.08	
[8]	GAN based on hybrid CNN-LSTM	Remote sensing data	GLDAS, MODIS, CHRISPS, Landsat 5 and 8	SMI	RMSE = 1.008, MAPE = 0.009, MAE = 0.739	African continent
[78]	CNN	Remote sensing data	_	NDVI, SAVI, EVI and ARVI	Accuracy CNN: NDVI=0.94, SAVI=0.91, EVI=0.88, ARVI=0.88	_
	AlexNet				Accuracy AlexNet: NDVI=0.76, SAVI=0.67, EVI=0.73, ARVI=0.67	
	VGGNet				Accuracy VGGNet: NDVI=0.91, SAVI=0.91, EVI=0.94, ARVI=0.97	
[81]	LSTM	Remote sensing data	CHIRPS, ERA5, NASA SRTM, MODIS (BOKU)	VCI	LSTM: RMSE = 6.46, R2 = 0.95	Kenya
	Aware LSTM (EA LSTM)				EA LSTM: RMSE = 6.46, R2 = 0.95	
[77]	ANN	Remote sensing data	TAMSAT, BOKU	VCI	R2 = 0.78	Kenya: Turkana, Marsabit, Mandera and Wajir.
[80]	LSTM	Remote sensing data	MERRA-Land	SMI	RMSE = 0.088	_

1. ***Use of combined multispectral drought indices.*** The analysis presented in this work determines the need to employ multispectral indices combining two or more features for predicting drought, such as the Normalized Difference Drought Index (NDDI). NDDI takes advantage of two indices used to determine the vegetation conditions (NDVI) and surface moisture (NDWI) [56]. Works worldwide demonstrate that NDDI is a complementary and powerful tool for efficiently determining drought conditions. It is worth noting that deep learning techniques have yet to be used to predict drought using NDDI.
2. **Drought Prediction in Latin America**. According to the works analyzed in this study, only four studies have been conducted in Latin American countries using deep learning techniques to predict drought: Mexico [70], Colombia [88], Ecuador [89], and Peru [11]. It may be due to the prevalent use of meteorological models or stochastic and statistical techniques to predict this phenomenon. Furthermore, Latin American countries still need to utilize multispectral indices to predict drought with deep learning models. This document highlights a research opportunity in this region, which contains distinct features compared to the study areas analyzed.
3. ***Neuroevolution***. Most of the deep learning techniques discussed in this review use architectures proposed by their respective authors. However, proposing an architecture is a complex task that requires prior knowledge of the problem and expertise in designing the structure of a deep neural network. Therefore, a previously unexplored research direction, until this study, is using methods to find a suitable deep neural network architecture for predicting drought. This method is called neuroevolution. Neuroevolution uses evolutionary optimization algorithms to efficiently determine the neural network structure for solving a specific problem. Therefore, neuroevolution has not been utilized to determine the number of hidden layers and the number of LSTM or GRU units, among others, to predict drought in a particular study area.

Conclusion

Drought is a complex phenomenon with significant human impacts. Therefore, the scientific community aims to mitigate its impacts by predicting it. Deep learning has emerged as a valuable tool for achieving this goal.

This review differs from other reviews on drought prediction in that it is more specific in its focus. Rather than examining a range of statistical and artificial intelligence techniques, it concentrates on deep learning techniques and the data indices used for drought prediction on an international scale. Furthermore, the countries most interested in studying the phenomenon and the regions most studied were identified. Consequently, this review employs a comprehensive approach that enables the identification of pertinent issues about the utilization of deep learning tools and the global research interest in this field. This approach facilitates the identification of potential avenues for future research. The points above are described in greater detail below.

AI techniques are primarily utilized in Asia and Oceania, with most institutions dedicated to studying the phenomenon in these regions. In contrast, America and Africa have fewer areas of study and institutions. It is important to note that experts from various countries, even those outside the analysis area, are involved in studying the phenomenon. The most commonly used indices for studying the phenomenon are climatic, specifically SPI and SPEI. However, the use of these indices is restricted by the need for long-term climate data, which is only accessible in countries with a reliable climate monitoring network. Regarding remote sensing indices, NDVI is the most commonly used indicator for analyzing vegetation conditions. The text primarily discusses MODIS and Landsat data, which have consistent periodicity and cover extended periods.

As a result, the LSTM network is the most frequently used deep learning technique, individually or combined with other models (hybrid techniques), even with its high computational cost. Moreover, the most commonly used metric to evaluate model performance is RMSE, which ranges between values of [0.02, 42.92] and [0.78, 0.96], respectively. Finally, this literature review highlighted the lack of work on drought prediction using machine learning techniques in Latin America, even though the problem is a priority and high incidence. Therefore, we propose applying Deep Learning with remote sensing indices to address the lack of reliable monitoring networks.

Ethics statements

Not applicable

Credit author statement

Aldo Márquez-Grajales: Conceptualization, Methodology, Writing - Original Draft **Ramiro Villegas-Vega**: Conceptualization, Methodology, Writing - Original Draft **Fernando Salas-Martínez**: Conceptualization, Methodology, Writing - Original Draft **Héctor-Gabriel Acosta-Mesa**: Supervision, Writing - Review & Editing **Efrén Mezura-Montes**: Supervision, Writing - Review & Editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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