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ORIGINAL PAPER

# Forecasting drought using machine learning: a systematic literature review

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**Abstract**

The number of reported drought events per year and their impacts have significantly increased in the last two decades. In addition to monitoring drought conditions, forecasting is essential for planning activities. Various Machine Learning (ML) algorithms have experienced a substantial increase in popularity in geoscience applications. This study presents a Systematic Literature Review on drought forecasting utilizing Machine Learning models. Following the PRISMA 2020 protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), the total number of papers was reduced from approximately a thousand to a hundred. The majority of the papers found study areas from Asia and Oceania. Meteorological drought was the most studied event in the articles evaluated due to the greater ease of its estimation using only rainfall data. The Standardized Precipitation Index and the Standardized Precipitation Evapotranspiration Index are the most widely used indices in research relating to drought and Machine Learning. Precipitation is the most commonly used input among the various input data used in ML models. Remote sensing has yet to be widely used in drought forecasting, with less than 20% of papers utilizing remote sensing data. What still needs to be addressed is drought forecasting in the time scale of days, which is less utilized compared to the monthly scale. The regression method is the most commonly used, with 77% of papers utilizing it. In conclusion, we formulated five recommendations based on the critical evidence and insights from our review: (1) it is essential to foster interdisciplinary collaborations among experts in ML, climatology, and hydrology while investing in initiatives that promote the sharing of data and code repositories; (2) satellite remote sensing technologies and crowd-sourced data collection methods should be considered in ML studies while enhancing existing monitoring infrastructure to increase the spatial and temporal coverage of datasets for validation of ML methods; (3) it is recommended to increase the availability of additional environmental variables, such as soil moisture and vegetation health, to promote more studies of agricultural drought and ML methods; (4) it is crucial to prioritize the integration of daily-scale climate data into drought modeling and forecasting for developing effective adaptation and mitigation measures to flash drought events; and finally (5) ethical considerations of using Artificial Intelligence (AI) for drought forecasting, emphasizing the environmental impact, issues of digital sovereignty, and the urgent need for a broader dialogue on AI's role in sustainable climate solutions.

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**Keywords** Machine learning · Drought forecasting · Climate change · Systematic literature review

**Abbreviations**

| | |
|---|---|
| ANN | Artificial Neural Network |
| ARIMA | Autoregressive Integrated Moving Average |
| AT | Oceanic/Atmospheric indices |
| EDI | Effective drought index |
| PDSI | Palmer Drought Severity Index |
| NDVI | Normalized Difference Vegetation Index |
| RU | Relative Humidity |
| SPEI | Standardized Precipitation Evapotranspiration Index |
| SRI | Standardized Runoff Index |
| SVM | Support Vector Machine |
| ANFIS | Artificial Neural Network and Fuzzy Inference System |
| AI | Artificial Intelligence |
| DT | Decision Tree |
| ET | Evapotranspiration |
| ML | Machine Learning |
| Q | Flow |
| SDI | Streamflow Drought Index |
| SPI | Standardized Precipitation Index |
| SM | Soil moisture |
| WS | Wind speed |

## 1 Introduction

Droughts have different characteristics in space and time: meteorological drought starts with persistent deficit precipitation that is less than the long-term average over a region and can evolve into agricultural drought if its condition starts affecting soil water (Mishra and Singh 2010; Wilhite and Pulwarty 2017; Loon 2015). The meteorological drought is defined by the lack of precipitation commonly quantified by using the SPI (Cunha et al. 2019) and not necessarly impacts vegetation, soil moisture or water supply. Agricultural drought arises when insufficient precipitation, evaporation, or soil moisture affects agriculture or livestock (Wilhite and Glantz 1985; Elusma et al. 2022). On the other hand, hydrological drought is characterized by deficits in surface or subsurface water levels, typically lagging behind the onset and end of meteorological drought. Prolonged precipitation deficits, usually over timescales exceeding six months, impact river levels and reservoirs, leading to hydrological drought (Loon 2015).

In the period 1970–2019, according to the World Meteorological Organization (WMO) Atlas on mortality and economic losses due to extreme meteorological, climatic, and hydrological phenomena, 11,072 disasters were attributed to risks associated with meteorological, climatic, and hydrological events, which caused 2.06 million fatalities and US 3.64 trillion in losses (Erian et al. 2021). According to WMO, only 6% of these disasters are associated with droughts, but droughts caused 34% of recorded deaths and 7% of economic losses. The number of reported disaster events per year has significantly increased in the last two decades. While there is a large year-on-year variation for droughts, current trends suggest a probable increase of more than 30% between 2001 and 2030. This means an average of 16 drought events per year during 2001–2010 could rise to 21 per year by 2030 (Disaster Reduction UNIS 2022). According to EMDAT (UNDRR 2022), there were 22 drought events registered in 2022, which is significantly higher than the average number of events (16) for 2002–2021. In 2022, the number of deaths was 2601, and 106.9 million people were affected, surpassing the average during the period 2002–2021, which was 1057 deaths and 77.5 million affected people, respectively. Economic losses were estimated at U$ 34.2 billion, a substantial increase from the previous two decades' estimate of U$ 8.5 billion.

Drought monitoring is a pressing issue all over the world, especially considering the effects of climate change on the water cycle, inducing a higher frequency of extreme events (Wilhite et al. 2014). Extremes of air temperature and precipitation are associated with impacts on several socioeconomic sectors, such as agriculture, water resources, and health (Cunha et al. 2019; Hu et al. 2023; Lima et al. 2021). Monitoring and forecasting drought are two crucial yet distinct processes for understanding and managing drought events. Drought monitoring involves continuous observation and assessment of current drought conditions, providing up-to-date information on the onset, duration, and severity of drought conditions. For this purpose, there are many indices and indicators, which are particular combinations of indicators comprising meteorological, hydrological, and other data being applied today around the world that, besides providing a historical reference, provide drought characterization, including intensity, duration, spatial extent and frequency of droughts (Narasimhan and Srinivasan 2005; Modarres 2007; Vicente-Serrano et al. 2010; Zeri et al. 2018, 2022). Effective drought monitoring helps issue alerts, inform water usage decisions, and respond to drought impacts. Drought forecasting, on the other hand, is about predicting the likelihood of drought occurrence in the future. It involves making predictions based, for instance, on historical data, current conditions, and atmospheric or hydrological models. The purpose is to predict and prepare for future drought conditions, providing better conditions for proactive planning, agricultural scheduling, water resource management, and policymaking.

The terms prediction and forecasting have distinct meanings. Prediction is a broad statement that involves inferring a value using an objective or subjective method. Predictions can also be made for the past, known as hindcasts. On the other hand, a forecast specifically refers to a prediction of the future. In this study, we will use the term "forecast" exclusively to describe future predictions. A wide range of methods and techniques have been employed during recent decades to forecast drought. However, most of the reported works have been done to forecasting drought severity (magnitude). Developing suitable techniques for forecasting droughts' onset and cessation is still challenging. Specific examples of methods already explored to predict drought aspects include regression analysis (Liu and Juárez 2001) and time series analysis (Mishra and Desai 2005).

Traditional drought assessment methods rely on precipitation data from ground-based weather stations, which are often sparse or unevenly distributed, especially in remote or under-instrumented areas. This limitation hinders the effective monitoring of drought conditions across large, diverse regions. Remote sensing, however, overcomes these constraints by providing consistent, spatially extensive, and temporally frequent observations. Using satellite-based sensors, remote sensing captures the physical characteristics of the Earth's surface through measurements of reflected and emitted radiation, covering visible and infrared (VIS/IR) spectra. Geostationary satellites equipped with multispectral radiometers, for instance, offer vital drought-related information on precipitation, soil moisture, and evapotranspiration. Since the 1980s, multispectral, thermal infrared, and microwave satellite data have been invaluable for comprehensive drought monitoring across various temporal and spatial scales (AghaKouchak et al. 2015; McCabe et al. 2017).

Machine Learning (ML) is an area of Artificial intelligence dedicated to developing methods that enable computers to solve specific tasks by learning directly and only from data (Soori et al. 2023). There are many ML methods, such as ANFIS (Jang 1993), a system that combines fuzzy logic and neural network techniques for adaptive modeling and inference, SVM (Cortes 1995), an algorithm that constructs a hyperplane in high-dimensional space to classify data points by maximizing the margin between different classes while minimizing classification error, MLP (Rumelhart et al. 1986), a neural network with multiple layers of interconnected neurons (including an input layer, one or more hidden layers, and an output layer), and Random Forest (RF) (Breiman 2001), a set of decision trees with improved accuracy and reduced overfitting through the aggregation of forecasting.

The use of Machine Learning techniques in earth sciences is already well established, mainly because systems built with these techniques contribute to reducing uncertainties and enable faster forecast times (Chen et al. 2023). One example is land use classification, which was used in the LandSat Earth observation satellite program. It began applying ML methods shortly after the launch of its first satellite, which was launched in the early 70 s. Initially, the methods applied were simple, considering isolated pixels with methods such as k-Means, evolving to more sophisticated methods that included context information, external knowledge, and object detection (Phiri and Morgenroth 2017).

Various ML algorithms have experienced a substantial increase in popularity in geoscience applications. This surge is attributed to their capacity to handle large datasets and recognize patterns at different spatial and temporal scales. As a result, ML has gained significant relevance in addressing challenges within the field of geosciences. Notable examples include Huawei's Pangu-Weather, which is operational at the European Centre for Medium-Range Weather Forecasts (ECMWF) website (Bi et al. 2023), Google's GraphCast (Lam et al. 2023), and NVIDIA's FourCastNet (Pathak et al. 2022), which are utilized for weather forecasting and monitoring conditions.

Subseasonal to seasonal (S2S) drought forecasting using Machine Learning methods can be especially beneficial in regions where complex climate models perform poorly. For decades, seasonal forecasts of drought or excessive rainfall have relied on models that couple the atmosphere's and oceans' physical systems (Johansson et al. 1998; Briggs and Wilks 1996; Goddard et al. 2001). The ability to make forecasts one to three months in advance, despite the chaotic nature of the atmosphere, stems from particular sources of predictability. The primary source at this scale is the slow variation in surface temperatures of the tropical oceans, the so-called SST. However, due to the climatological circulation of the atmosphere, this predictability due to SST is limited to a few regions of the planet. In theory, Machine Learning techniques can improve S2S forecast for those specific regions by integrating them with historical data from potential sources of predictability, such as soil moisture or the Quasi-Biennial Oscillation (Lindzen and Holton 1968; Holton and Lindzen 1972; Baldwin et al. 2001). In addition, artificial intelligence techniques have some advantages over the traditional statistical approaches. Among these is the ability to handle sparse and noisy input data (Wegmann and Jaume-Santero 2023). Artificial intelligence techniques can also model complex non-linear functions without requiring in-depth knowledge of the mapped phenomenon (Rajaee et al. 2019). In recent years, more and more research has been done using ML techniques to forecast droughts at various spatiotemporal scales. These techniques allow for training and learning using multiple long-term databases. This learning can then be applied to identify antecedent drought conditions over a region, as investigated in Zhang et al. (2023) and Yaseen et al. (2021).

We also emphasize the importance of Machine Learning in the context of climate change (Leal Filho et al. 2022). Just like seasonal meteorological forecasts, forecasting extreme events and long-term climate projections remain a challenge (Reichstein et al. 2019). Climate change disrupts historical behavior in the hydrometeorological variables (e.g., temperature rise and shifts in precipitation), increasing the variability, including more frequent extreme weather climate events. In the context of drought, climate change is shifting drought-prone regions and altering the spatial distribution of water stress (IPCC 2023), that can create feedback mechanisms (e.g., prolonged drought reducing vegetation, which in turn affects precipitation and temperature patterns) that introduce non-linear complexities. Effective drought forecasting in the context of climate change requires the integration of diverse data from disciplines such as climate and hydrology. Traditional ML algorithms can capture non-linear relationships; however, advanced techniques like deep learning are often more effective at modeling these dependencies and feedback mechanisms. They can also adapt to changes in patterns and variability. In this context, several researchers have suggested combining Artificial Intelligence (AI) and ML techniques with physical models to improve forecasts of extreme events (Reichstein et al. 2019; Huntingford et al. 2019).

Sutanto et al. (2019) presented the study that evaluates the feasibility of predicting drought impacts, using Machine Learning to relate predicted hydrometeorological drought indices to reported drought impacts. For this, the drought impact function used is derived from the Random Forest (RF) algorithm, a robust ML algorithm based on classification and regression trees. Basheer et al. (2023) uses an ML algorithm to design efficient adaptive plans for climate change based on thousands of iterations between the algorithms and integrated simulators. Among the seven decision variables, there is a drought trigger, drought output storage limit, and minimum interim water release for drought mitigation. In this way, the model analyzes the impacts of climate change on the Nile under multiple projections.

Some systematic reviews cover research in the area of droughts and ML. Santos et al. (2024) highlights the growing application of Machine Learning techniques for flash flood modeling, emphasizing the dominance of LSTM methods and the need for greater data accessibility to advance the field. Pokhariyal et al. (2023) presented an overview of methods used to monitor agricultural drought using remote sensing and Machine Learning methods. Drought monitoring based on remote sensing is a very active area of research with a significant impact on global improvement sustainability. Kikon and Deka (2022) carried out a broader review, and their studies show that drought forecasting has become significant in the field of hydrology, water resources management, and sustainable agriculture through the use of various ML techniques. Balti et al. (2020)'s systematic literature review includes several studies, research, and big data applications for drought monitoring. Challenges related to the data lifecycle include data processing challenges and data infrastructure management challenges.

This study encompasses a Systematic Literature Review (SLR), a comprehensive approach involving the identification, categorization, and analysis of pertinent literature pertaining to a specific research topic, as outlined by Page et al. (2021a, 2021b), the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) protocol. This protocol was already used in Systematic Reviews on Natural Hazards (Pérez-Gañán et al. 2023; Mls et al. 2023; Tounsi and Temimi 2023). However, our focus is on gathering studies on drought forecasting using ML models. To the best of the authors' knowledge, this constitutes the inaugural comprehensive SLR conducted on this particular subject.

**Table 1** Number of papers from each database

| Database | Papers |
|---|---|
| Web of science | 560 |
| Elsevier | 364 |
| Springer | 246 |
| Total | 1170 |

**Table 2** Query

| |
|---|
| “Drought” AND |
| “Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” |

## 2 Methods

Based on the methodology proposed by Page et al. (2021a, 2021b), this Systematic Literature Review includes articles on drought forecasting models and Machine Learning through a detailed investigation into large scientific databases.

### 2.1 Eligibility criteria

We outline the scope of the review to address different key questions related to drought forecasting while maintaining brevity. Articles that are not exclusively applied to drought forecasting or that are focused on impact, vulnerability, resilience, or sustainability were not included in this review. To make the review transparent and reproducible, this paper adopts the process suggested by Page et al. (2021a, 2021b), as well as the features of *Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020*—also known as the PRISMA 2020 protocol.

### 2.2 Information sources

This review considered articles published until August 2023 in peer-reviewed journals in the English language. The following databases were taken into consideration: Web of Science, SCOPUS/Elsevier, and Springer. No limit was set for the number of articles to be returned for this query, and we obtained 1170 articles in the broader initial search. The number of articles in each database can be seen in Table 1.

### 2.3 Search strategy

Our search strategy employed keywords relevant to the research questions using Boolean operators. We use ‘OR’ to cover synonyms and alternative spellings and ‘AND’ to connect primary terms with secondary terms. These terms have been structured into overarching concepts or levels. The combination of keywords used in the review were "drought" AND "artificial intelligence" OR "Machine Learning" OR "deep learning" (see Table 2).

In the first screening process, 231 duplicate articles were removed, leaving 939 papers. A public repository presents a table with all these 939 papers: https://github.com/Klaifer/AI_Drought_Review.

### 2.4 Selection process

The screening aimed to exclude retracted articles, corrections, reviews, and papers that were either out of scope or focused on impact, vulnerability, resilience, and non-forecasting topics. Articles were excluded based on four main categories: (1) Out-of-scope: studies related to rainfall analysis, temperature, wildfires, groundwater, soil moisture, heat waves, and climate change; (2) Not hazard-related: works addressing vulnerability, exposure, impacts, and plant tolerance to droughts; (3) Not forecasting-focused: articles involving analysis, correlation studies, and monitoring; (4) Reviews; (5) Others: retracts, duplicates, corrections, or comments. Each article was labeled under the most appropriate category. For 939 articles, 114 (12%) were selected, and 826 (88%) were not selected. For the classes/reasons of exclusion, out-of-scope (Reason 1) represents the majority of excluded papers (57%), followed by "not hazard" (Reason 2–28%), and "not forecast" (Reason 3–10%). Reason 4 is for reviews (3%), and Reason 5 is for retracts, duplicates, corrections, or comments (2%). Thus, the final set of articles in the review included 105 articles. A public repository presents a table with all papers and the screening result: https://github.com/Klaifer/AI_Drought_Review.

**Table 3** Attribute list

| Attribute | Description |
|---|---|
| Study area (country) | Country in which the research is carried out |
| Types of droughts | Meteorological, Agricultural or Hydrological |
| Index or indicator for drought | Indicators to measure and characterize some types of droughts. Drought indicators encompass hydroclimatic variables, including but not limited to precipitation, climatic water balance, soil moisture, and the levels of surface water flow and groundwater |
| Input data | Input data used in the model (precipitation, flow, stored volume, soil moisture, temperature) |
| Remote sensing | If the article used remote sensing data (radar or satellite), such as any index from satellite data, for example, Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Normalized Difference Vegetation Index (NDVI), etc |
| Spacial resolution | Spatial resolution of the input data (km) |
| Temporal resolution | Temporal resolution of the data effectively used as model input |
| Temporal domain | Total time window of data |
| Public input data available | If the input data was just public data |
| Regression or classification | The model forecasts a continuous numerical value for each entry or predicts categories or classes for each element, respectively |
| ML main method | Type of Machine Learning model used |
| Lead time forecasting (months) | Maximum forecast horizon |
| Index for ML evaluation (test) | Index used in the final test-evaluation phase of results |

The data extraction process consists of obtaining relevant information from each study and recording it in a spreadsheet. Table 3 contains all the fields used and their descriptions.

The PRISMA 2020 diagram of this systematic review can be seen in Fig. 1. The PRISMA 2020 checklist is also in the public repository: https://github.com/Klaifer/AI_Drought_Review.

# 3 Results

This section follows the third stage of the PRISMA protocol: Stage III—Reporting and Dissemination. The most relevant findings are presented in two subsections, which in turn are also subdivided into subtopics that group thematically related issues, as ilustrated in the flowchart (Fig. 2).

## 3.1 Temporal and journal distribution of the selected articles

First, it is shown how studies related to drought forecasting using ML models are distributed temporally. Thus, Fig. 3 shows the number of papers per year and the cumulative increase. The first significant increase can be observed from 2017, with high variability from 2021 to 2023. From the start of the time series of selected papers, a cumulative of 60% was reached between 2020 and 2021, with the rest in the last three years, indicating a

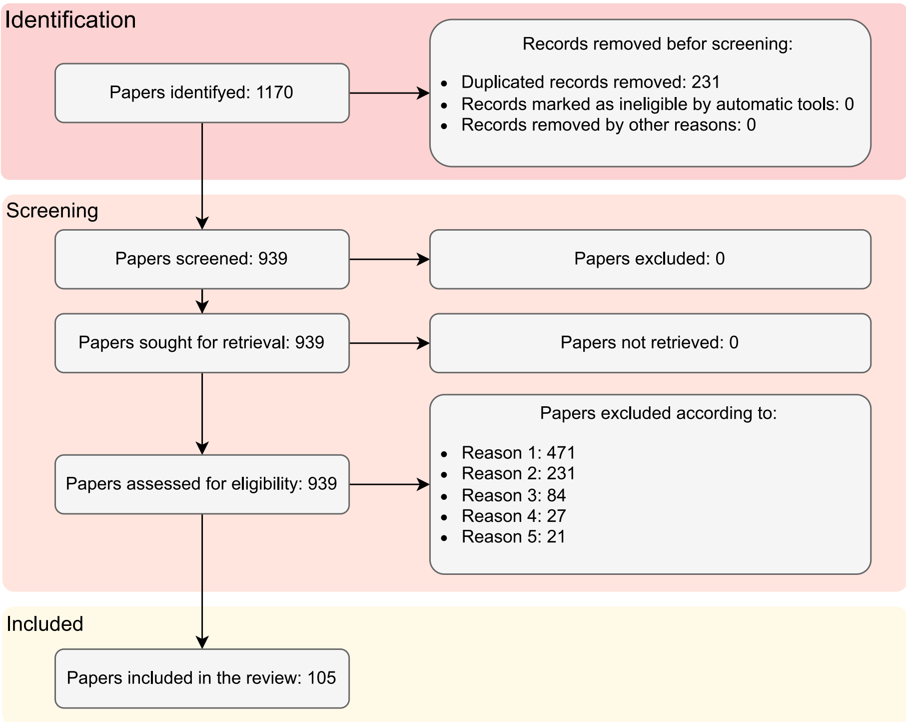


**Fig. 1** PRISMA 2020 workflow diagram

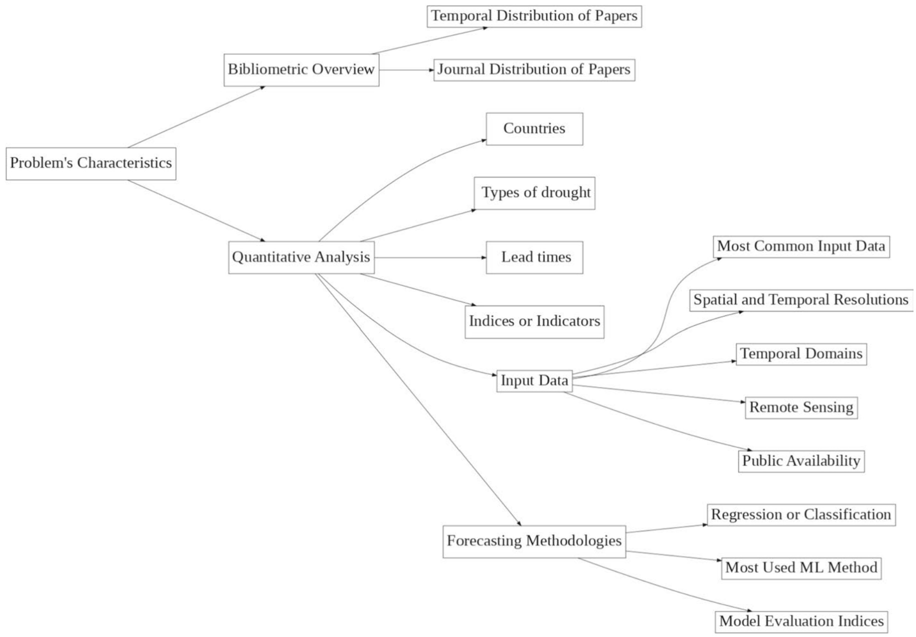


**Fig. 2** Problem's characteristics flowchart. Results of the main themes in drought forecasting research, organized into three levels: problem characteristics, input data analysis, and forecasting methodologies. Each level captures critical factors such as temporal and spatial data distribution, drought type classification, and assessment methods, illustrating the progression and interconnections within the field

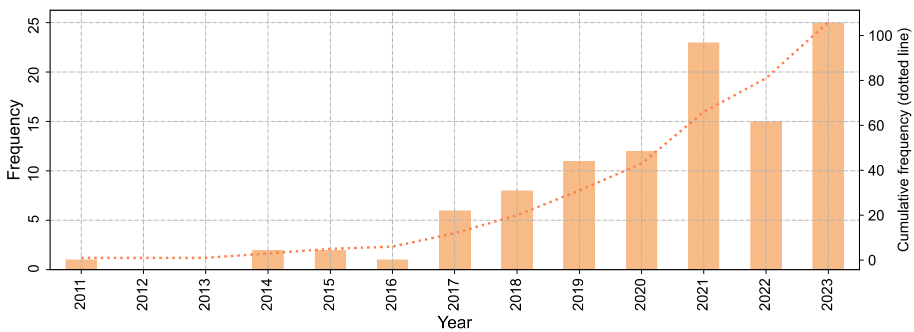


**Fig. 3** Number of publications per year (absolute and cumulative) on Machine Learning applied to drought prediction, from 2011 to 2023

growing interest in and increasing the application of these ML techniques to replace more traditional models in drought forecasting.

The increasing use of Machine Learning models in drought forecasting, such as the use of Artificial Neural Networks (ANN) and Cellular Automata (CA), in recent years, is driven by the severity in the agricultural sector and increasing food shortages for an increasingly growing world population (Kafy et al. 2023). The use of ML methods for drought forecasting has been following the trend in technological advances, allowing more accurate and comprehensive assessments of data for drought analysis and forecasting, such as methods developed for land surface temperature (LST) forecasting that include Multiple Linear Regression (MLR), Support Vector Machines (SVM), Random Forest (RF) (Al Kafy et al. 2024). Thus, it is evident that the growing use of ML models, driven between 2021 and 2023, follows a technological trend in the evaluation of data for drought forecasting, especially high-resolution remote sensing data, as well as for the evaluation of environmental changes resulting from accelerated urbanization, as demonstrated by studies carried out by Fariha et al. (2024) and Al-Ramadan et al. (2024).

The distribution of papers by journals (Fig. 4) reveals that more than 50% of the papers have been published in journals of hydrology, climatology, and natural hazards subjects, which are journals where, usually, studies on droughts are published. There is no significant difference between the most common journals, revealing a homogeneous distribution and common interests in several sectors in the application of ML to drought in water resources, agriculture, and natural hazards.

## 3.2 Quantitative analysis based on the characteristics of individual studies

This section addresses key issues related drought forecasting using ML. These issues have been divided into 3 groups, according to thematic similarity, and are presented below in separate subsections.

### 3.2.1 Key countries in drought forecasting research: common drought types, lead times, and predominant indices

Figure 5 shows in which country it is most common to find research related to Drought Forecasting. The majority of the 105 articles are located in Asia and Oceania. Iran, China, Turkey, India, and Australia had 19, 16, 12, 11, and 10 papers related to forecasting droughts, respectively. Previous SLR studies that consider several aspects of droughts also show that Asia, especially China, has led these studies (Bravo et al. 2021). It is important to emphasize that China suffered severe drought from 2009 to 2011, with intensity reaching the once-in-100-year level (Ye et al. 2012). This may be related to increased studies on droughts in the country since then Bravo et al. (2021).

It is noteworthy the low number of studies in the Americas, with none in Central America, two in North America, both in the United States, and only one in South America, in

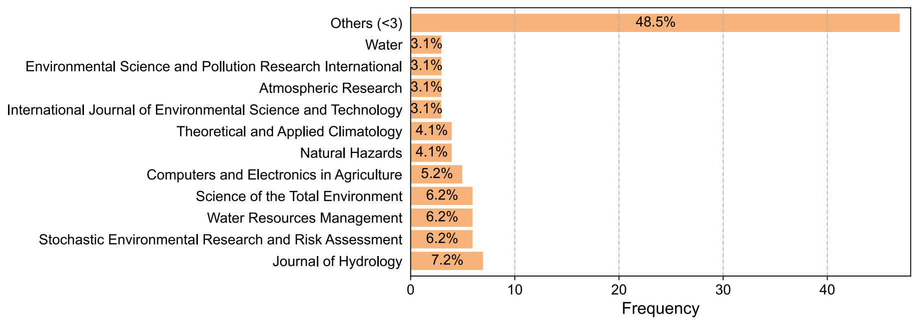


**Fig. 4** Frequency of publications by periodic

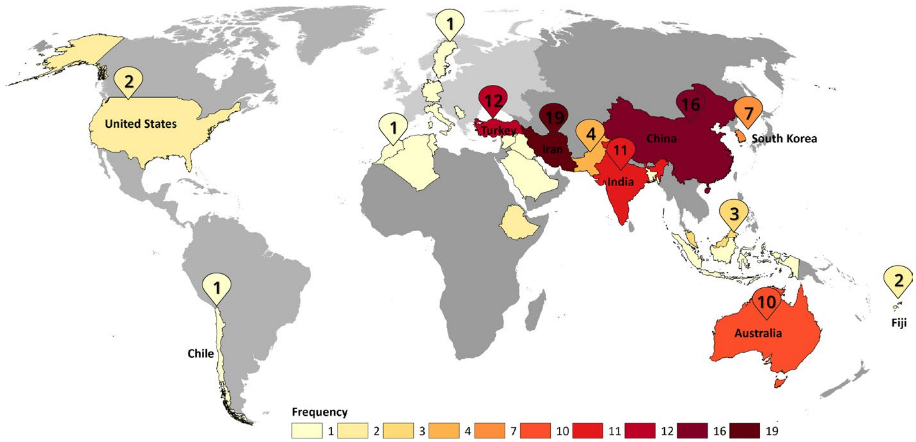


**Fig. 5** Geographical distribution of drought forecasting studies: this map highlights the frequency of studies conducted in different regions worldwide. The majority of the 105 analyzed articles are concentrated in Asia and Oceania, reflecting the significant research activity in these areas. Regions like Africa and South America are underrepresented, pointing to potential gaps and opportunities for future research

Chile. Europe and Africa had four and five articles, respectively. Additionally, there were global articles (2), East Asia (1), Central Europe (1), Australia and Cambodia (1), and Portugal (Lisbon) and Germany (Munich) (1).

Although studies providing definitions of drought typologies have been more frequent in the last decade, many studies on droughts still do not define which typology is being studied. Therefore, studies are generally characterized by the typology of meteorological drought. Meteorological drought indices are most frequently reported (70.4%), followed by hydrological (16.5%) and agricultural drought indices (13.0%) (Fig. 6). This means that, on a global basis, there were three times more studies linking drought to meteorological indices than to hydrological indices and four times more than to agricultural indices. It is clear that precipitation has been the dominant criterion used to study drought, and this can be attributed to its ease of use. For example, most of the studies used longer time scales, with monthly time scales (83.8%) dominating over daily time scales (12.4%). In addition, the majority of drought studies (44.8%) used observational data, which, in the case of precipitation, can be obtained through the use of rainfall gauge networks. Precipitation

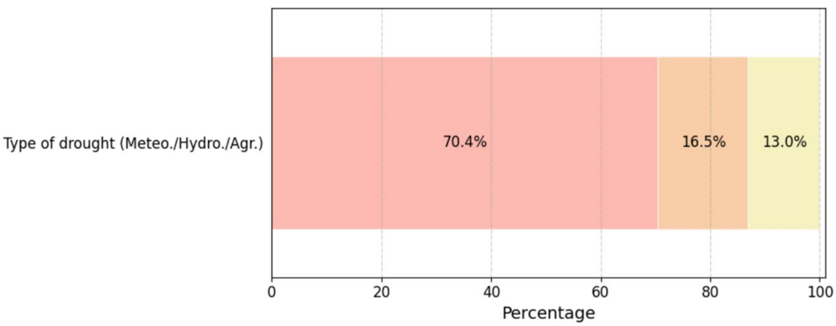


**Fig. 6** Bar-like representation of frequencies concerning the type of drought forecasting applying ML found in our systematic literature review

estimation from remote sensing information has also been a commonly used tool to supplement observed precipitation data due to the lack of sufficient rainfall gauge data for much of the Earth's surface.

Figure 7 illustrates the progression of studies focusing on different drought types over the years. While meteorological drought has historically dominated Machine Learning research in drought forecasting, recent years have seen a substantial increase in studies targeting hydrological and agricultural droughts. This shift suggests an expanding recognition of the complex, interconnected impacts of drought types, underscoring the importance of diverse predictive approaches in mitigating broader environmental and socioeconomic effects.

Lead Time Forecasting in drought forecasting refers to the ability to predict, in advance, when and where a drought will occur, allowing for the adoption of preventive measures before its impacts are felt. This approach is fundamental for early warning systems, as accuracy and timeliness in forecasts are crucial to minimize the effects of drought in vulnerable sectors such as agriculture, water supply, and natural resource management. The concept of lead time is related to the interval between the identification of conditions prone to drought and the moment it begins to impact a region, allowing governments and communities to prepare adequately. Forecasts with lead times of 1 and 12 months are widely used because they offer appropriate time windows for different types of response: short-term forecasts, such as the 1-month forecast, are useful for quick measures, such as adjustments in water management and immediate agricultural preparations; while long-term forecasts, such as the 12-month forecast, allow for strategic planning, the implementation of public policies, and the development of infrastructure to mitigate the effects of drought over time. Machine Learning has significantly improved these forecasts by processing large volumes of historical, climatic, and environmental data and identifying precursor patterns of droughts. Advanced models,

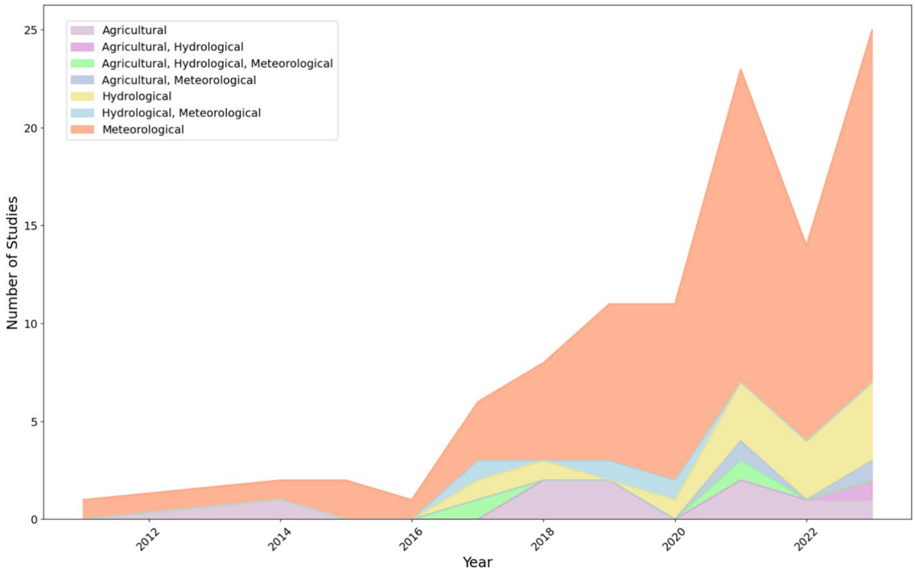


**Fig. 7** Evolution of drought types over the years in articles applying Machine Learning to drought forecasting found in our systematic literature review

such as neural networks and supervised learning, enable real-time forecasts with greater accuracy, adjusting the lead time based on local factors like soil moisture, precipitation patterns, and temperatures. The combination of short and long lead times offers a comprehensive view of imminent and future risks, enabling quick actions and long-term planning. A longer and more accurate lead time allows farmers to adjust their practices, authorities to implement effective water resource allocation policies, and at-risk populations to be alerted with sufficient advance notice. Therefore, Lead Time Forecasting, optimized by Machine Learning, becomes an essential tool for the proactive management of droughts, helping to reduce their socioeconomic and environmental impacts efficiently.

The forecast lead time in the articles ranges from 1 to 48 months. The meteorological drought category, which is present in the most number of articles (70.4%) (Fig. 6), has lead times ranging from 1 to 48 months (Fig. 8). In this category, the minimum lead time ranged from 1 to 6 months, being the 3-months the main period used, and for the maximum lead times, the main period is 12 months (Fig. 8). For the agricultural class, the most used minimum lead time is the 1-month period, while the maximum period is equally proportional to the 1, 3, and 12 months. For the hydrological category, the minimum and maximum periods utilized correspond to 1 and 12 months, respectively.

Drought indices such as the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI) are widely used inputs in ML models for drought forecasting. SPI quantifies drought severity based solely on precipitation, making it applicable across regions where precipitation is a primary drought factor, while SPEI incorporates both precipitation and temperature data, offering a more comprehensive reflection of drought conditions under varying climatic contexts. Figure 9 highlights the prevalence of these indices as critical input data, underscoring their importance in capturing diverse drought scenarios and enhancing the adaptability of ML models across different climatic zones.

The most frequently used indices in applications of ML to drought forecasting were Standardized Precipitation Index and Standardized Precipitation Evapotranspiration Index, accounting for 34.4% and 27.2% of papers, respectively.

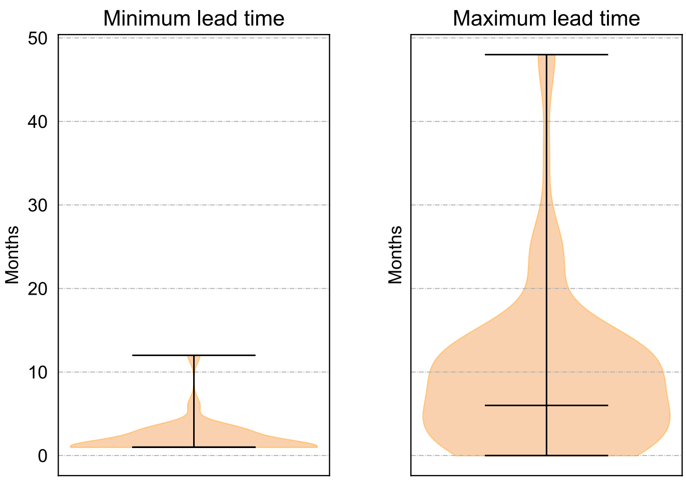


**Fig. 8** Lead time in drought forecasting applying ML found in our systematic literature review

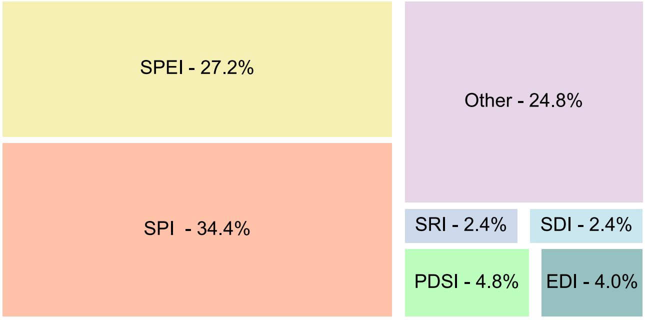


**Fig. 9** A treemap illustrating the most commonly used indices and indicators in ML applications for drought forecasting. The area of each rectangle represents the proportion of use for each index. The visualized inputs include: *SPI* Standardized Precipitation Index, *SPEI* Standardized Precipitation Evapotranspiration Index, *SDI* Streamflow Drought Index, *SRI* Standardized Reservoir Index, *PDSI* Palmer Drought Severity Index, and *EDI* Effective Drought Index. The category labeled "'Other" encompasses additional, less frequently cited indices

The treemap presented in Fig. 9 clearly illustrates the proportion of usage for the specified indices in comparison to alternative indices. These alternatives include the SRI, SDI, PDSI, EDI, and other less frequently used inputs.

Both indices are relatively easy to calculate nowadays due to the availability of packages in several languages, such as R and Python, or even because some global SPI and SPEI databases are also widely available. In addition, global gridded databases provide long-term time series of climate variables, such as precipitation, air temperature, relative humidity, and wind speed. The times series of these variables make it possible to estimate the SPI, and the evapotranspiration, for the subsequent calculation of SPEI. More complex drought indices that require streamflow or groundwater information, such as SRI (Standardized Runoff Index ) or EDI (Effective drought index), or indices that also require soil moisture, such as PDSI (Palmer Drought Severity Index ), were less common in the studies reviewed. These water-related measurements are rarely available in large areas or are not long-term for climatological studies.

### 3.2.2 Regarding the input data: types, spatial and temporal resolutions and domains most commonly used, remote sensing and public availability

Among the various input data used in ML models, precipitation is the most commonly used (Fig. 10), representing 42.9% of the total input data. To facilitate comparison, the treemap in Fig. 10 illustrates the proportion of input data typically used in the revised ML applications for drought forecasting. This includes not only precipitation and temperature but also other inputs such as Evapotranspiration, Relative Humidity, the Normalized Difference Vegetation Index, Oceanic/Atmospheric indices, Soil moisture, and Wind speed.

Emphasizing that the precipitation variable was obtained from different sources, being acquired from weather stations, from satellite products such as the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and, implicitly, from drought indices that use precipitation (SPI, PDSI, and SPEI). As it is the most used input data in ML models, it is clear that the precipitation is the driver-variable that exerts the most influence on meteorological, agricultural, and hydrological droughts. The temperature variable was the second most used in these ML models, with 23.1% of

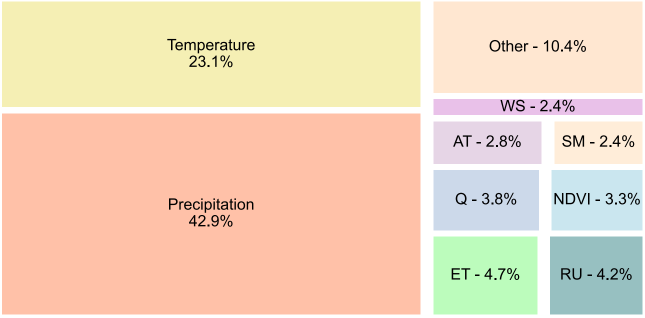


**Fig. 10** A treemap illustrating the most commonly used input data in ML applications for drought forecasting. The area of each rectangle represents the proportion of use for each input data. The visualized inputs include: *ET* Evapotranspiration, *RU* Relative Humidity, *Q* Flow, *NDVI* Normalized Difference Vegetation Index, *AT* NINO and MJO oceanic/atmospheric indices, *SM* Soil Moisture, and *WS* Wind Speed

use as input data. Like precipitation, the temperature came from weather stations and drought indices (PDSI and SPEI). Also highlighting the following variables most used as input data in Machine Learning models, in order of use: Evapotranspiration—ET (4.7%); Relative Humidity—RU (4.2%); Flow—Q (3.8%); Normalized Difference Vegetation Index—NDVI (3.3%); Oceanic/Atmospheric indices—AT (NINO, MJO) (2.8%); Soil moisture—SM (2.4%) and Wind speed—WS (2.4%). However, several other variables were also used in these ML models, represented in Fig. 10 as others, but with little use, in just one or two articles, listed below: Vapour Pressure; Sea Surface Temperature; Cloud Cover; Stored volume; Water store rate; Available water content; Catchment water storage capacity; Evaporation; Land Use; Groundwater; Solar radiation.

Temporal resolution (or time step) refers to the specific time intervals within which historical data is examined in order to detect and analyze patterns, trends, and correlations that are pertinent to the forecast of drought. The selection of temporal scope is contingent upon the distinct attributes of the geographical area, the length of historical documentation accessible, and the temporal magnitude of significance for forecasting purposes. The majority of the analyzed publications had a temporal resolution of monthly, accounting for 83.8% of the total papers (Fig. 11). The utilization of the annual resolution is restricted to the meteorological drought category, while the daily

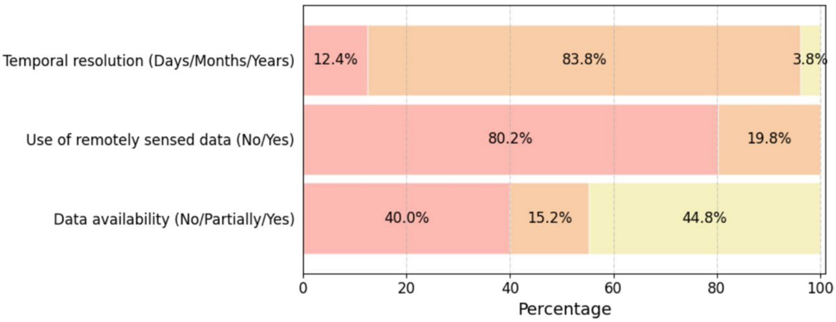


**Fig. 11** Bar-like representation of frequencies concerning the temporal resolution, using of remote sensing data and data availability

resolution is observed across all three categories and comprises 12.4% of the total documents (Fig. 11).

The articles utilize a range of time series data, referred to as the temporal domain or period. 52.7% of the studies employed a time frame exceeding 40 years; 22.6% fell within the range of 1–20 years, 16.1% fell within the 31–40 years interval, and 8.6% fell within the 21–30 years range (Fig. 12).

Spatial resolution refers to the scale of the input data used in ML models. Among the articles analyzed, the majority used in situ data obtained from weather stations, representing 61% of data. This information is related to the type of input data most used in ML models, where precipitation is the most commonly used and, therefore, is acquired mostly from meteorological stations. Input data with gridded spatial resolution, that is, coming from satellite sensors, were used in 25% of the articles, varying between 0.05° and 0.5° (5–50 km). The remaining articles analyzed did not report the spatial resolution of the input data, accounting for the remaining 14% of the articles.

The spatial domain refers to the coverage of input data in geographic terms, being classified on local, regional, national, and global scales according to the territorial dimension of the study area. Among these scales, the one most used by researchers to investigate drought events was the regional scale, used in 82% of the articles analyzed. It should be noted that the regional scale has a wide range of applications in studies in river basins, as well as data from meteorological stations distributed over a large area. The national scale was the second most used in ML model studies for drought forecasting, comprising 10% of the articles. Local and global scales were used in only 2% and 1%, respectively. The remaining articles, enclosed 5% of the 105 articles analyzed, did not specify the spatial domain of the research.

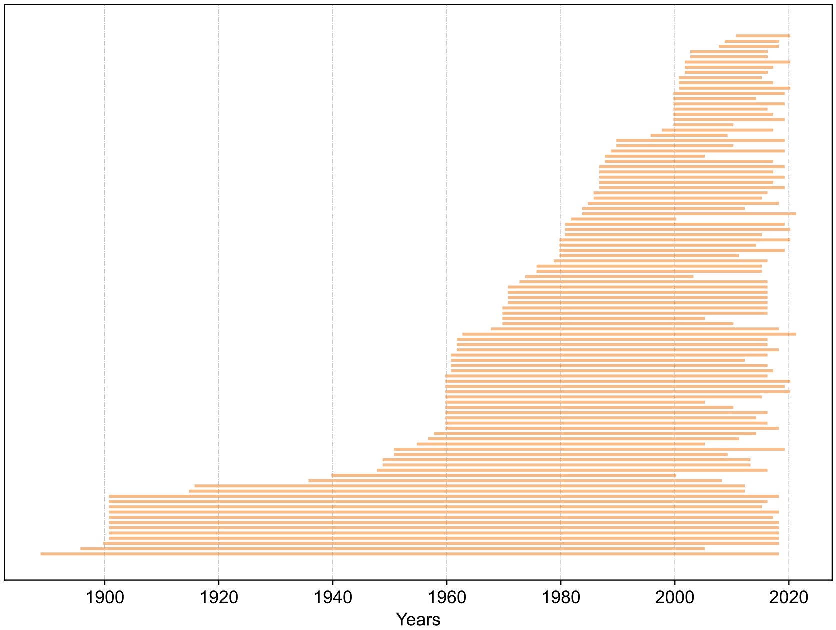


**Fig. 12** Representation of temporal domains in Machine Learning applications for drought forecasting

Remote sensing is not widely used in drought forecasting yet, with only (19.8%) (20) of the papers utilizing any type of remote sensing data (Fig. 11). It is important to highlight that meteorological drought is the most common, comprising 73 papers (70%), furthermore, some papers address more than one type of drought. Bearing this in mind, remote sensing data is mostly used in agricultural drought studies, as evidenced in eight papers, two of which focused on both agricultural and meteorological drought. Additionally, five articles related to hydrological drought and seven focused on meteorological drought also used remote sensing data. This result shows an important gap in studies regarding the use of these tools, especially considering the application of forecasting in monitoring centers and the fact that in some continental countries, the meteorological station network has low spatial density and that remote sensing data sets are extremely necessary.

Access to data used in a study is crucial for ensuring the verification of results, reproducibility, and validation of applied methods. This contributes significantly to the transparency and reliability of research findings. Moreover, data sharing enables collaboration among institutions, allowing different research groups to develop new studies from the same data without duplicating collection efforts, which can lead to faster advancements and methodological refinements in the field of drought forecasting. On the other hand, it is important to consider the confidentiality and security policies of institutions and companies, which, for various reasons, may not allow the public availability of data used in research. These restrictions, however, can affect the ability to replicate studies and hinder scientific collaboration. In drought forecasting, the availability of downloadable data is crucial for developing new forecasting methodologies. With accessible data, researchers can replicate previous studies, test new algorithms and evaluation metrics, and propose methodological advances that improve the accuracy of forecasts. This practice not only avoids duplication of efforts but also promotes scientific collaboration.

Figure 11 presents the distribution of data availability among the reviewed articles: 44.8% offer public access to the data, 15.2% provide partial access, and 40.0% do not make the data available. This indicates a relatively balanced scenario, with a slight advantage for the option of data sharing. However, the availability of downloadable data remains a challenge, with 40.0% of the articles not providing access, representing a significant limitation to collaboration and scientific progress. Therefore, data sharing is a crucial factor for advancing research in the field, as it enables the development of more robust, competitive, and accurate models.

### 3.2.3 Frequency of drought forecasting by regression or classification, the most used ML techniques and the most applied performance evaluation indices

The choice between employing regression or classification methods depends on the characteristics of the data set and the objectives of the analysis. Regression models allow for the identification of a numerical relationship between a set of input and output variables, which, in the context of droughts, can be useful for estimating climate variables and drought indices, such as SPI, SPEI, and others. On the other hand, classifiers are applied in situations where the objective is to relate input information to a set of distinct categories, which can be binary or multi-categories, and include techniques for mapping soil types or identifying drought-prone areas, for instance. Figure 13 shows the frequencies referring to the use of classification and/or regression models. It is observed from the data that the regression method is the most commonly used, accounting for

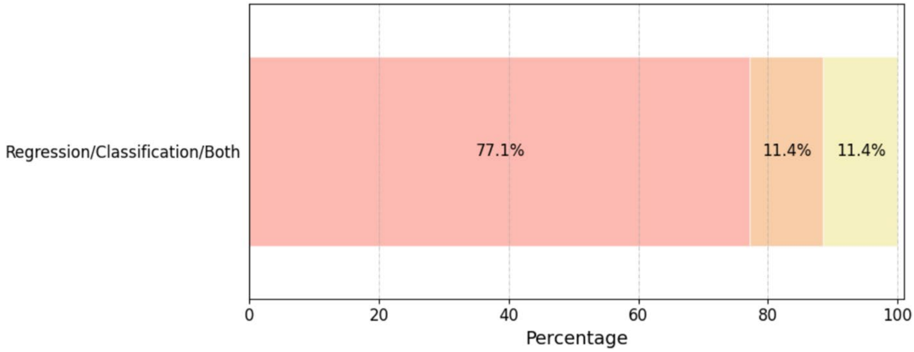


**Fig. 13** Bar-like representation of frequencies concerning the regression and/or classification models

77% of the total methods. In contrast, both the classification method and the combined approach (regression and classification) are equally employed, each representing 11.4%.

To provide a clear overview of the Machine Learning approaches and their categorization within the scope of this review, Table 4 summarizes the primary ML algorithm classes used in drought forecasting studies, including details on each class's specific techniques and whether they employ deep learning. This classification distinguishes between traditional ML methods, such as decision trees and support vector machines, and advanced deep learning architectures, such as artificial neural networks (ANNs) and their variants, which are increasingly utilized for their capacity to capture complex patterns in high-dimensional datasets.

The use of Machine Learning in drought forecasting is already well established due to its ability to reduce uncertainties and forecast on different time scales, thereby increasing the reliability and efficiency of models in this area. Figure 14 shows the ML methods considered in each publication for the study of drought. These methods are classified into seven classes based on the learning process to offer a clearer overview:

- ANN class: includes all neural network models considered for the drought study, such as Multilayer Perceptron (MLP), Bayesian Convolutional Neural Network (BCNN), Convolutional Neural Network (CNN), Deep Learning (DP), Deep Belief Network (DBN), Discrete Wavelet Transform Neural Network (DWT-ANN), Genetic Algorithm-Multilayer Perceptron (GA-MLP), General Regression Neural Network (GRNN), Gate Recurrent Unit (GRU), Long-Short Term Memory Network (LSTM), Multilayer Perceptron with Extended Kalman Filter (MLP-EKF), Radial Basis Function Neural Network (RBFNN), Recurrent Neural Network (RNN), and Wavelet Artificial Neural Networks (WANN).
- DT class: includes the decision tree algorithms M5Pruned (M5P), M5Three (M5T), Reduced Error Pruning Tree (REPT), and Decision Tree (DT).
- Ensemble class: refers to all algorithms with ensemble learning, such as Adaptive Boosting (Adaboost), Bootstrap Aggregating Trees (BAT), Bootstrap Aggregating Trees-Algorithm Optimised Extreme Learning Machine (BAT-ELM), Bootstrap Aggregating (BG), Boosted Trees (BT), Extremely Randomized Trees (ET), Gradient Boosting Machine (GBM), Gene-Random Forest (GeRF), Light Gradient Boost-

**Table 4** Summary of machine learning methods used for drought forecasting

| ML category | Method | Description | Deep learning (Y/N) |
|---|---|---|---|
| Artificial Neural Networks (ANN) | ANN, MLP, CNN, LSTM | Multilayer neural networks, including convolutional and recurrent networks, commonly used for handling complex patterns and temporal data in drought forecasting (Goodfellow 2016) | Y |
| Decision Trees (DT) | DT, M5P, REPT | Tree-based models that segment data by features; often used for interpretable drought risk predictions (Quinlan 1990) | N |
| Ensemble Methods | RF, Adaboost, XGBoost, GBM | Methods that combine multiple models (e.g., random forests, boosting) to improve prediction accuracy and reduce variance (Breiman 2001) | N |
| Adaptive Neuro-Fuzzy Inference System (ANFIS) | ANFIS, WWF, FRBS | Hybrid systems that merge neural networks with fuzzy logic for improved decision-making in uncertain environments (Jang 1993) | N |
| AutoRegressive Integrated Moving Average (ARIMA) | ARIMA, ARIMAX | Time series forecasting models capturing temporal dependencies, commonly used for drought indices predictions (Box and Jenkins 1970) | N |
| Support Vector Machines (SVM) | SVM, SVR, LSSVM | Margin-based classifiers and regressors effective in handling complex, high-dimensional data (Cortes 1995) | N |
| Deep Learning | CNN, RNN, GRU, Transformer | Advanced deep learning models for sequential and spatial-temporal data, increasingly used in climate prediction (Vaswani 2017) | Y |

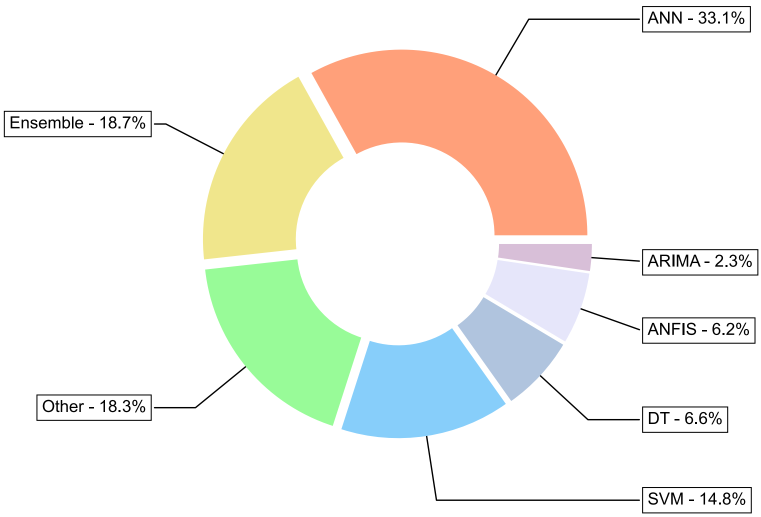


**Fig. 14** Most commonly used Machine Learning methods for drought forecasting

ing Machine (LGBM), Random Forest (RF), Random Subspace (RS), Random Tree (RT), Wavelet Boosting (WB), and Extreme Gradient Boosting (XGBoost).

- The ANFIS class refers to a category of models based on fuzzy logic, including the Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Rule-Based System (FRBS), Weighted Wavelet Fuzzy (WWF), and Wavelet Fuzzy (WF).
- ARIMA class includes the category of time series forecasting models, such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average-Long Short Term Memory (ARIMA-LSTM), Autoregressive Integrated Moving Average-Support Vector Regressor (ARIMA-SVR), and Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX).
- The SVM class refers to a supervised Machine Learning algorithm used for classification and regression tasks, which includes Support Vector Machine (SVM), Support Vector Regression (SVR), Least-Square Support Vector Machine (LSSVM), Least Square SVR (LS-SVR), Support Vector Machine Regression (SVMR), Support Vector Machine-Grey Wolf Optimizer (SVR-GWO), Support Vector Machine-Spotted Hyena Optimizer (SVR-SHO), and Wavelet Least Square SVR (WLS-SVR).
- Finally, the other class comprises a variety of models utilized in this study, including Detrended Fluctuation Analysis (DFA), Estimation of Distribution Algorithm-Extreme Learning Machine (EDA-ELM), Extreme Learning Machine (ELM), Wavelet Extreme Learning Machine (WELM), Genetic Algorithm-Extreme Learning Machine (GA-ELM), Genetic Expression Programming (GEP), Group Method of Data Handling (GMDH), Gaussian Process (GP), Gaussian Process Regression (GPR), Kernel Extreme Learning Machine (KELM), K-means, K-Nearest Neighbor (KNN), Kalman filter regression-based Online Sequential Extreme Learning Machine (KOSELM), Lasso Regression (LR), Multiple Linear Regression (MLR), Minimum Probability Machine Regression (MPMR), Nonlinear Auto-Regressive (NAR), Nonlinear Auto-Regressive with Exogenous (NARX), Naive Bayes (NB), Ordinary Least Squares (OLS), Online Sequential-ELM (OSELM), Ridge Regres-

sion (RR), and Variation Mode Decomposition Gaussian Process Regression (VMD-GPR).

Out of the 105 articles analyzed, ANN models were the most used, representing 33.1% of the methods and were applied in 42% of the works. They were followed by ensemble methods, which represented 18.7%. The ANFIS and DT methods had similar distributions, representing 6.2% and 6.6%, respectively. Additionally, ARIMA methods represented 2.3%, while other methods represented 18.3%.

The predominance of ANN over other ML methods for drought forecasting can be attributed to its capability to learn complex patterns in data, which is crucial for drought forecasting as it involves identifying non-linear relationships between climate variables. ANNs have become even more interesting after the emergence of Deep Learning, which has achieved excellent results in several applications. According to LeCun et al. (2015), deep-learning is a network capable of learning representations of input data, where it is possible to stack new layers to produce increasingly abstract representations. This ability to create representations is one of the justifications for the increased accuracy when compared to the traditional feature engineering approach.

Ensemble methods were the second most commonly type of ML method and emerged as a solution to reduce variance and bias in the forecasting process by combining multiple Machine Learning models.

Figure 15 illustrates the evolution of Machine Learning methods for drought forecasting over time. While ANN has historically been the predominant approach, recent years-particularly 2021-show a notable rise in the adoption of diverse methods, reflecting the rapid advancement of the field. This trend underscores the growing application of deep learning

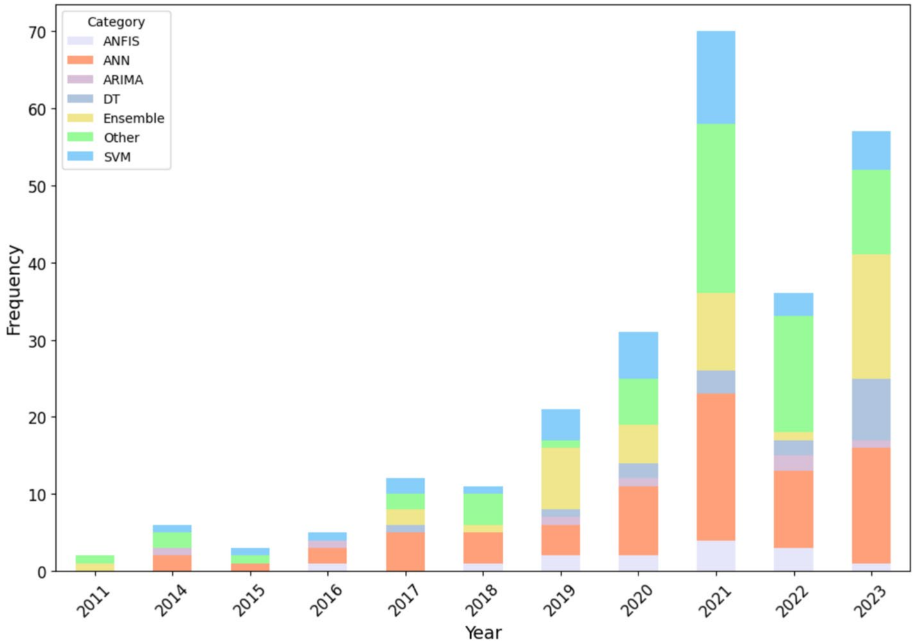


**Fig. 15** Evolution of main ML methods in drought forecasting studies over the years in the reviewed articles

techniques, which are demonstrating increasing effectiveness in capturing complex patterns for drought forecasting.

In the reviewed articles, a large number of indices were applied to evaluate the performance of the proposed forecast models. The indices' usage percentage (i.e., the number of articles that use a given index in relation to the total number of reviewed articles) is presented in Fig. 16. In line with the fact that in the vast majority of the reviewed articles, the proposed drought forecasting model performs a regression task (see Fig. 13), the 10 most recurrent indices (named in 16) are applicable for this type of modeling and, in this context, are considered as good performance evaluation indices.

It is desirable for a forecast model to be evaluated using multiple methods to have a more complete and comprehensive view of its performance, as a single coefficient may not capture all nuances of the model's performance and may be susceptible to bias. On this matter, it was noted that in 13.3% of the reviewed articles, the model is evaluated using 1 method, in 21.0% using 2 methods, in 26.7% using 3, and in 39.0% using 4 coefficient/methods or more.

## 4 Discussion

The number of scientific articles relating to drought forecasting and Machine Learning methods has increased in recent years, showing that this is a potential topic for future research. This increase brings new ways of analyzing drought patterns in space and time and innovative approaches to drought forecasting. ML methods make it possible for new drought patterns to be identified, especially when considering climate change, which has been altering the known patterns of extreme events around the world. On the other hand, the large number of options for methods and databases can generate uncertainty about the best alternative to detect drought patterns. In this sense, review articles are essential to identify the most effective methods, methods that are still little explored, and that can be suitable to be applied in centers that monitor and forecast drought.

The identification of countries and regions and their frequency of studies is essential to guide new studies on the subject for countries that are still underrepresented, such as South America and Africa. These regions have a vast territorial extension, with distinct climate patterns in different countries. Few studies have been carried out focusing on these regions, especially considering databases from remote sensors. The identification of the

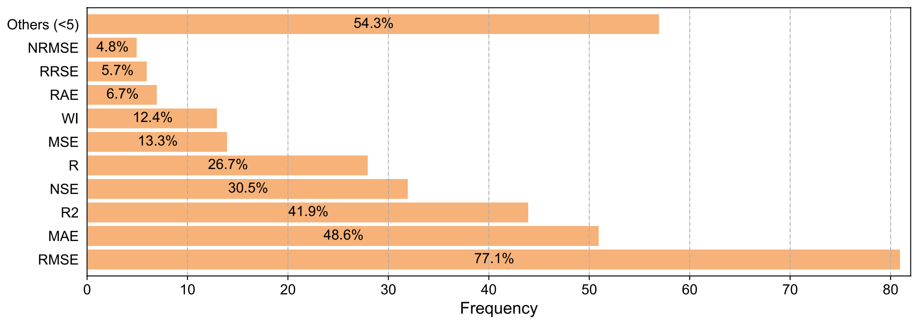


**Fig. 16** Performance evaluation indices with the highest percentage of usage in the reviewed articles

most widely used methods can handle new studies in these regions and guide public policies to promote research in areas of knowledge that are still little explored.

Meteorological drought was the most studied event in the articles evaluated due to the greater ease of estimation using only rainfall data. On the other hand, agricultural and hydrological drought are still poorly represented in ML studies. One reason is the need for additional data with high spatiotemporal resolution for their characterization, such as soil moisture or land use cover, streamflow, and ground water data.

Long-term soil moisture databases are still rare due to the complexity of their measurements. In recent years, new satellites and remote sensors have made it possible to measure soil moisture over large areas, thus creating the basis for future studies of agricultural drought. Likewise, there is still a lack of high spatial resolution databases on agricultural areas by type of crop, which is necessary for studies of the impacts of drought on agricultural production.

The SPI and SPEI are the most widely used indices in research relating to drought and ML. This knowledge can guide the formulation of future studies, the creation of new databases, and the establishment of new environmental monitoring networks. The SPI index only needs rainfall records for its formulation. However, these records need to be long-term, with minimal failures and harmonized with other spatial measurements. These characteristics require the monitoring network to be subjected to quality control and permanent maintenance to reduce the number of missing data or unrealistic records. SPEI, on the other hand, requires even more variables since it requires data on air temperature, relative humidity, wind speed, and solar radiation to calculate potential evapotranspiration, which is required in its formulation. Maintaining a monitoring network with all these variables is a challenge, especially in countries with a large territorial extension with a great variety of climates and biomes, such as Brazil or the African continent. In this sense, the need for evapotranspiration data makes it urgent to develop new compact and cheaper sensors for direct measurement of evapotranspiration. Public policies should focus on the incentives for the development of new sensors, in addition to the need for environmental monitoring by all the levels of government, with permanent support for the maintenance of existing sensors and continuing improvements on the spatial cover of the networks. Our review reveals a notable underrepresentation of drought forecasting research using Machine Learning for certain regions, particularly Africa and South America. From the selected studies in our review, this gap is clear, highlighting an urgent need for research that addresses the unique environmental and socioeconomic contexts of these areas. Targeted studies in these regions could offer valuable insights and improve global drought resilience by tailoring models to diverse geographic and climate patterns. We recommend that future ML-based drought forecasting studies consider focusing on these underrepresented areas to foster a more comprehensive and globally relevant understanding of drought dynamics.

Bias in Machine Learning models for drought forecasting poses significant challenges, as these models heavily rely on historical and environmental data, which can be influenced by factors such as regional variations, data collection density, and sensor quality. Models may exhibit bias when data is predominantly gathered from well-monitored regions, like urban or developed areas, resulting in poor generalization to rural or less-monitored regions. Additionally, reliance on historical climate patterns, without accounting for the impacts of climate change, can lead to inaccurate forecasts of future drought conditions. Temporal bias may also arise if models are trained disproportionately on data from specific seasons or extreme events, making them less effective during anomalous weather conditions or in predicting rare, severe droughts. To mitigate these biases, diverse data sources-such as satellite, in-situ, and weather station data-should be integrated to improve regional coverage. Techniques like geospatial modeling, ensemble learning, and normalization of historical data can help reduce regional and temporal biases. Periodic updates with new data and cross-regional validation should be employed to ensure that models perform well across varied geographic areas. Fairness-aware evaluation metrics can also be implemented to assess model accuracy across different regions, helping to ensure equitable forecasts, particularly for vulnerable populations in remote or socioeconomically disadvantaged areas. By addressing these potential sources of bias, drought forecasting models can provide more reliable and inclusive forecasts.

Still poorly represented is the time scale of days compared to the monthly scale. The scale of days is related to flash droughts, which have received more attention in recent years due to the greater availability of daily data on climate variables. These data come from measurements, models, or hybrid databases with homogeneous spatial coverage (global gridded datasets). Characterizing flash droughts, such as the number of events, duration, and intensity, should be a focus in future research. Climate change has altered spatial and temporal patterns of the rainy season around the world. These new standards pose challenges to established knowledge about best planting dates, appropriate areas for different species, and agrometeorological risks in each region. These new weather patterns pose risks to the food security of various regions of the globe. New studies using ML and flash drought events can contribute to producing more information that can be used to mitigate the drought impacts on different socioeconomic sectors.

Finally, discussing publication and regional bias is critical. We mitigate the limitation of publication bias in this article by selecting articles broadly and transparently. We followed a systematic review protocol (PRISMA 2020), which seeks to include all relevant studies available in the databases searched. We considered a large number of articles. We used multiple databases, such as Web of Science, SCOPUS, and Springer, which broadened the scope and increased the likelihood of including diverse studies, not limiting ourselves to the most well-known or high-impact publications. The regional bias reflects the availability of data and the concentration of research in certain regions. The inclusion criteria for articles considered their relevance to the issue of drought forecasting using ML without prejudice to geographic location. The article highlights that regions such as Africa and South America are underrepresented in the literature. This finding is not ignored but instead highlighted as an opportunity for future research and advancing studies in still underexplored regions, which can encourage more efforts in these areas. In addition, we recommend the promotion of international collaborations and data sharing.

## 5 Final remarks

We formulated five questions based on the key evidence and insights uncovered during our systematic literature review on forecasting drought using Machine Learning. Subsequently, we provide recommendations for implementing these findings into practice. Our objective is to maximize the benefits to society that can be derived from research efforts aimed at addressing challenges in drought management.

***1—How can integrating Machine Learning methods improve our understanding of drought patterns, especially considering the evolving extreme events induced by climate change? What are the critical factors to consider when selecting the most effective approach for detecting these patterns?*** To bridge the gap between research findings and practical applications, it is recommended to establish interdisciplinary collaborations among experts in AI, climatology, and hydrology. These collaborations can facilitate the development of standardized methodologies for utilizing ML in drought pattern analysis. Additionally, investing in initiatives that promote the sharing of data and code repositories can enhance collaboration and reproducibility in this field. Furthermore, creating platforms for the publication of review articles that critically evaluate existing methodologies and highlight promising avenues for future research can help guide practitioners in effectively applying ML to detect drought patterns.

*2—How to overcome the challenges of maintaining extensive monitoring networks for drought research and ML applications, especially in regions with vast territories, diverse climatic conditions, and the necessity of integrating additional variables into indices (like SPI and SPEI)?* To overcome the challenges of maintaining extensive monitoring networks in regions with diverse climates and the need to incorporate additional variables, a multi-faceted approach is recommended. This involves exploring innovative strategies, such as satellite remote sensing technologies and crowdsourced data collection methods while enhancing existing monitoring infrastructure with advanced sensor technologies. An example of the use of remote sensing information in drought monitoring is the Integrated Drought Index (IDI), developed by the National Center for Monitoring and Early Warning of Natural Disasters (Cemaden). The IDI is composed o SPI, which is calculated based on a long-term rain gauge dataset which is also fused with satellite rainfall information to fill spatial and temporal gaps. In addition, the IDI makes use of Root Zone Soil Moisture, from a NASA's Gravity Recovery and Climate Experiment (GRACE; 2002–2017) and GRACE Follow On (GRACE-FO; 2018-present) satellites. The third component in IDI is the Vegetation Health Index, based on satellite information from NOAA (National Oceanic and Atmospheric Administration). The European Drought Observatory also makes use of satellite information in its drought index, considering rainfall, soil moisture and vegetation status. These drought initiatives are interdisciplinary in nature due to the expertise required to process, integrate and interpret the products generated and potential impacts on rural and urban areas over different regions and biomes. Collaborative efforts between government agencies, research institutions, and international organizations are essential for implementing cost-effective solutions tailored to specific regional needs. Additionally, investing in capacity-building initiatives and technology transfer programs can empower local communities to actively participate in monitoring activities, thereby enhancing the coverage and accuracy of drought monitoring networks.

***3—How to overcome data limitations and enhance the accuracy and applicability of ML models for studying agricultural drought?*** To address the underrepresentation of agricultural drought in ML studies, it is recommended to explore innovative techniques for obtaining and integrating supplementary data, such as soil moisture, vegetation health, and land use cover, into existing models. Collaborative efforts between meteorologists, hydrologist, agronomists, and data scientists could facilitate the development of more comprehensive ML algorithms capable of accurately assessing agricultural drought conditions. Additionally, investing in research initiatives focused on the advancement of remote sensing technologies could provide valuable insights and data sources for improving the monitoring and forecast of agricultural drought events.

***4—How to address the inadequate representation of the daily time scale, particularly in the context of flash droughts, and what implications does this have for understanding and managing these events?*** To translate this finding into practice, it is recommended to prioritize the integration of daily-scale climate data into drought monitoring and management efforts. Collaborative initiatives between meteorological agencies, research institutions, and data providers should focus on enhancing the availability and accessibility of high-resolution daily climate data. Additionally, investing in capacity-building programs to train stakeholders in utilizing ML techniques for analyzing flash droughts can improve understanding and management strategies. Furthermore, conducting targeted research on the characteristics and impacts of flash droughts, especially under the influence of climate change, is essential for developing effective adaptation and mitigation measures to safeguard agriculture and food security.

***5—How to overcome ethical issues related to the deployment of ML models for drought prediction, such as potential misuse or overconfidence?*** For more than two decades, scientific research has warned about the increasing intensity of extreme drought events and related phenomena-such as heatwaves and wildfires-and their profound impacts on societies and ecosystems around the world (Yang et al. 2023). Alongside these challenges, there has been a sharp increase in the use of artificial intelligence (AI) technologies in drought forecasting. AI, powered by Machine Learning algorithms that process vast data sets, is increasingly controlled by large technology companies, highlighting concerns about digital sovereignty and the global imbalance in access to advanced computing power (Maslej et al. 2024).This raises crucial ethical questions related to environmental impact, as AI models require significant energy and water resources (Brockway et al. 2021). While this article does not address these complex ethical dimensions in full, it is necessary to emphasize the urgent need for a deeper conversation at the intersection of AI, sustainability, and climate change (Nordgren 2022).

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**Authors' contributions** RSO and LBLS conceived the review. All authors performed the review, analyzed the results, and reviewed the manuscript.

## Declarations

**Conflict of interest** The authors declare that there are no conflict of interest regarding the publication of this paper.

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