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AGRICULTURAL DROUGHT AND MACHINE LEARNING: A SYSTEMATIC REVIEW AND BIBLIOMETRIC ANALYSIS

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Abstract: Agriculture drought is a recurrent catastrophe affecting people, food, and livestock. Hence, it is crucial to have precise and up-to-date drought monitoring, as this helps decision-makers to respond effectively to drought-related losses. This review systematically highlights the advancement of machine learning in agricultural drought assessment and forecasting. Moreover, a bibliometric analysis is conducted to assist subsequent research and collaboration in the field by identifying the most cited articles, journals, and leading countries. A systematic search was conducted on WoS and Scopus for the timeframe 2014-2023 following the PRISMA-guideline, utilising Bibliometrix R-package and VOSviewer. A dataset of publications were retrieved, and applying the inclusion and exclusion criteria, 43 articles were included for the final analysis. The analysis results showed a significant yearly increase in publications with 34.59%. This indicates that machine learning has recently played a vital role in agricultural drought assessment. Random forest was the most widely used algorithm by researchers due to its strengths in dealing with non-linear remote sensing data and its performance in selecting the most influential variables. However, considering the fact that the model performs differently in different geographical regions, more studies need to be conducted in different areas to build the appropriate assessment model.

Keywords: Sustainability, drought, machine learning, food security.

Introduction

Drought has been considered as one of the most recurrent natural disasters in the world (Schwalm *et al*., 2017). In contrast to other natural catastrophes, drought typically covers extensive areas over prolonged durations and exerts substantial influence on hydrology and ecosystems (Rousta *et al*., 2017; Orth & Destouni, 2018; Deng *et al*., 2022). In the context of global warming and climate change, droughts are growing more frequent, extending their duration and impacting larger geographical regions (Syed *et al*., 2021; Wang *et al*., 2022; Wang *et al*., 2023). Drought primarily arises from meteorological irregularities, during which periods of reduced precipitation led to deficiencies in water supply at different stages of the hydrological cycle or throughout the entire cycle (McKee *et al*., 1993; Mohammed *et al*., 2022). Drought is a multidimensional concept that can be categorised into meteorological, agricultural, hydrological, and socio-economic droughts (Gyamfi *et al*., 2019; Singh *et al*., 2021).

Agricultural drought for instance can be defined as a disruption in the soil moisture balance resulting from prolonged, severe weather conditions that interfere with the typical growth of crops (Wang *et al*., 2023). Agricultural Drought pertains to the circumstance in which, during the crop's growth phase, the farming soil lacks water from rainfall, groundwater, or irrigation. Consequently, the soil's water supply continually depletes, resulting in insufficient water for plants' usual physiological requirements, which leads to constrained growth (Hassan *et al.*, 2019). The frequent incidence of drought significantly affects agricultural output. Throughout history, humanity has endured the consequences of drought calamities. Given its high occurrence, the effects include prolonged duration, the inevitable impact to large areas, and substantial delayed consequences (Li & Xu, 2021).

Reliable drought monitoring is essential for assessing their risk and minimising potential agricultural losses (Liu *et al.*, 2020). Therefore, different approaches have been adopted to assess agricultural drought. The most widely adopted and efficient method for monitoring agricultural drought involves the creation of appropriate drought indices. These indices serve as variables employed to characterise the physical aspects of drought, including its severity, geographical extent, and duration (Hao & Singh, 2015). In the past, conventional drought indices relied on data from ground-based monitoring stations, primarily involving the fixed-point monitoring in the field and random investigation techniques (Wang *et al.*, 2022). The majority of single-variable indices primarily represent a singular aspect of drought and lack the capacity to discern the intricate characteristics of agricultural drought (Liu *et al.*, 2020). Nonetheless, agricultural drought tends to occur regionally and the distribution of monitoring stations is often uneven and fragmented, making it a daunting task to accurately capture the intricate spatial patterns of drought in a region (Beck *et al.*, 2017). In addition, agricultural drought does not arise solely from the interactions among precipitation, temperature, and vegetation. Other factors such as evaporation, topography, and soil characteristics also play a crucial role in its development (Leng & Hall, 2019). Therefore, using a single index is not suitable to adequately depict drought conditions (Li & Xu, 2021).

With the increasing abundance of remotely acquired data, there has been a development of comprehensive agricultural drought monitoring indices. This integrated approach to monitoring agricultural drought leverages a combination of remote sensing, ground station data, and geographic context information. This combination allows for a more thorough depiction of agricultural drought characteristics and enhances the precision of drought monitoring (Jiao *et al.*, 2021).

The methodology for merging multiple variables and indices plays a pivotal role in the formulation of integrated drought indices. Typically, the development of these integrated drought indices can be classified into three main categories: Linear combinations (Rhee *et al.*, 2010), copula-based approaches (Hao & AghaKouchak, 2014), and machine learning techniques (Brown *et al.*, 2008). The majority of existing integrated drought indices have been created using the first two methods, which could potentially encounter challenges due to the assumption of linearity when assigning weights or parameters to various variables and indices (Liu *et al.*, 2020). Indeed, to address the challenge of the nonlinear nature of drought variables, numerous non-binary composite models have recently been developed globally with the utilisation of ML algorithms. These models aim to provide objective evaluations of drought conditions (Hanadé Houmma *et al.*, 2022) by utilising the diverse array of comprehensive surface data derived from real-time meteorological observations collected at meteorological stations and via satellite remote sensing (Tian *et al.*, 2022).

Machine learning, a subset of artificial intelligence has distinct capabilities for unravelling intricate patterns, examining varied datasets, and constructing predictive models. It holds the potential to enhance drought prediction, refine drought monitoring, and provide data-driven decision support systems for individuals involved in agriculture. Moreover, recent advancements in geospatial technologies, ML algorithm, and the utilisation of cloud computing platforms like Google Earth Engine have quickened the pace of drought research (Mokhtar *et al.*, 2021). Leveraging remote sensing in conjunction with data-driven integrated agricultural drought indices offers a powerful means for monitoring, assessing, and forecasting agricultural drought effectively (Aghelpour *et al.*, 2021). As a result, various studies have demonstrated that ML algorithms surpass traditional methods in terms of performance. In the past few years, ML has been extensively used in forecasting natural disasters, including drought, by taking advantage of the recent, significant growth in the availability of open data, computing power, and advanced algorithms (Panahi *et al.*, 2022; Kan *et al.*, 2023). Among the most widely employed machine-learning algorithms for modelling the relationships between various variables in the context of agricultural drought are ANN, SVM, and RF. As noted in the literature, several studies revealed that agricultural drought is influenced by different variables in different locations and subsequently different machine learning algorithms perform differently in different locations (Benítez *et al.*, 1997).

The objective of this systematic review and bibliometric analysis is to comprehensively explore the dynamic and evolving landscape of agricultural drought using machine learning by summarising the extant literature in the field. In an era characterised by rapid environmental changes, it is not only relevant but also imperative to understand how machine learning can strengthen our capacity to address agricultural drought. Researchers employ the bibliometric analysis for multiple reasons, including the identification of emerging patterns in article and journal performance, the examination of collaboration patterns and research contributors, and the exploration of the intellectual framework within a particular area as presented in the existing literature (Donthu *et al.*, 2021a). This descriptive analysis is a fundamental characteristic of bibliometric studies (Donthu *et al.*, 2021b; 2021c).

Although previous researchers (Adisa *et al.*, 2020; Hanadé Houmma *et al.*, 2022; Nandgude *et al.*, 2023) have reviewed papers in the field of drought and machine learning, this paper systematically focuses on agricultural drought and ML while incorporating bibliometric analysis. Additionally, this review can offer valuable information on publication patterns, including the volume of publications, their rate of increase, and their influence in terms of citations. By scrutinising the citation trends, it becomes feasible to recognise influential papers, highly cited authors, and prominent journals in the field. This evaluation aids in the grasp of the way in which knowledge is disseminated and the impact of this dissemination on the research community. This visual representation can facilitate an understanding of the evolution of the research themes, emerging trends, and potential changes in the emphasis across various timeframes.

Methodology

This research blends quantitative and qualitative synthesis methods to assess the utilisation of machine learning in the context of agricultural drought within the existing literature. While a systematic review represents a crucial initial stage prior to any study, it is important to acknowledge that it could potentially introduce bias in outcome reporting, and subjective interpretations may arise during manual reviews (Tlili *et al.*, 2022a). Hence, there is a requirement for a comprehensive systematic review that employs a mixed-methods approach, integrating bibliometric analysis and content analysis to systematically ascertain the knowledge foundation and development of a specific subject (Tlili *et al.*, 2022b). Systematic reviews focus on well-defined and specific research inquiries, as opposed to a broad topic or general issue of interest. These reviews also establish precise guidelines regarding the studies used to address the research questions, commonly referred to as the inclusion criteria or eligibility criteria.

On the other hand, bibliometric analysis is a popular and rigorous method used for examining the patterns of the large number of published documents in order to illustrate the history and current status of a field (Yang *et al.*, 2023). It enables us to delve into the intricate developments and illuminate the emerging trends within a particular field (Donthu *et* *al.*, 2021b). With the aid of this methodology, researchers can examine a wide range of concerns within a research field, their trends, and the associations between them in the literature (Zhang *et al.*, 2022). In this study, we employed a comprehensive range of analytical methods to explore the intersection of machine learning and agricultural drought. Utilising descriptive publication data on citations, journals, authors, keywords, disciplines, and institutions, we conducted Performance Analysis, Publication Trend Analysis, Institutions' and Countries' Influence Analysis, Science Mapping, Citation Analysis, Keyword Co-occurrence Analysis, Co-citation Analysis, and specific analyses on machine learning applications. These methodologies, in combination with advanced text mining techniques have produced networking knowledge maps and identified research themes and promising future research directions. This has provided a comprehensive and multifaceted understanding of the research landscape. This review focuses on traditional machine learning methods in agricultural drought research. Deep learning algorithms were not included in this review due to their complexity and recent advancements, which warrant a separate review. This approach ensures a focused and coherent examination of established methods while recognising the need for future studies on deep learning.

Database and Search Strategy

In September 2023, in order to accomplish the objectives of this review, a systematic and bibliometric analysis approach was adopted. Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach, Bibliometrix package tool in R environment, and VOSviewer were used to conduct the systematic literature and bibliometric analyses. In accordance with the PRISMA guidelines, the scoping process was employed to identify the articles most pertinent to agricultural drought and machine learning. This approach has become an aid in defining the essential characteristics of crucial insights and categorising potential search keywords (Shu *et al.*, 2019; Qureshi *et al.*, 2020). Relevant documents and scientific journals were searched thoroughly in two multi-disciplinary databases, namely WoS and Scopus. These databases are recognised as the most considerable cross-disciplinary repository of scientific literature and are extensively employed by researchers worldwide (Zhang *et al.*, 2022). The process of the literature search selection adheres to the PRISMA concept and it is conducted as illustrated in Figure 1.

Identification

Documents were identified by conducting the search for documents that are likely to be relevant to the review. Two main data sources named Web of Science (WoS) and Scopus were used as a reference database for searching the relevant documents for this review. As it is crucial in systematic review, the research question was identified clearly, and the search keywords were subsequently discovered. The Boolean search that combines two parts of the search string was applied. The particular search formula is shown in Table 1.

At first, a total of 275 documents were displayed: 87 from WoS and 187 from Scopus. This encompassed all document types (e.g., research article, review, book chapters, and others). Next, we refined the documents' search results for each individual database considering the following criteria (Time frame: 2014-2023, Language: English, Documents type: Article, Proceeding Paper, Early Access, and Conference Paper). At this stage, 203 articles were obtained and the data file was exported in different formats to be used for further analysis.

Screening and Eligibility

WoS and Scopus articles were merged and 74 duplicate documents were removed in this step by using the Microsoft Excel tools. Furthermore, titles and abstracts for 129 publications were screened by three authors independently and one out of two labels (I = Included or E = Excluded) was assigned to each article. For the purpose of reducing the risk of bias, the authors checked

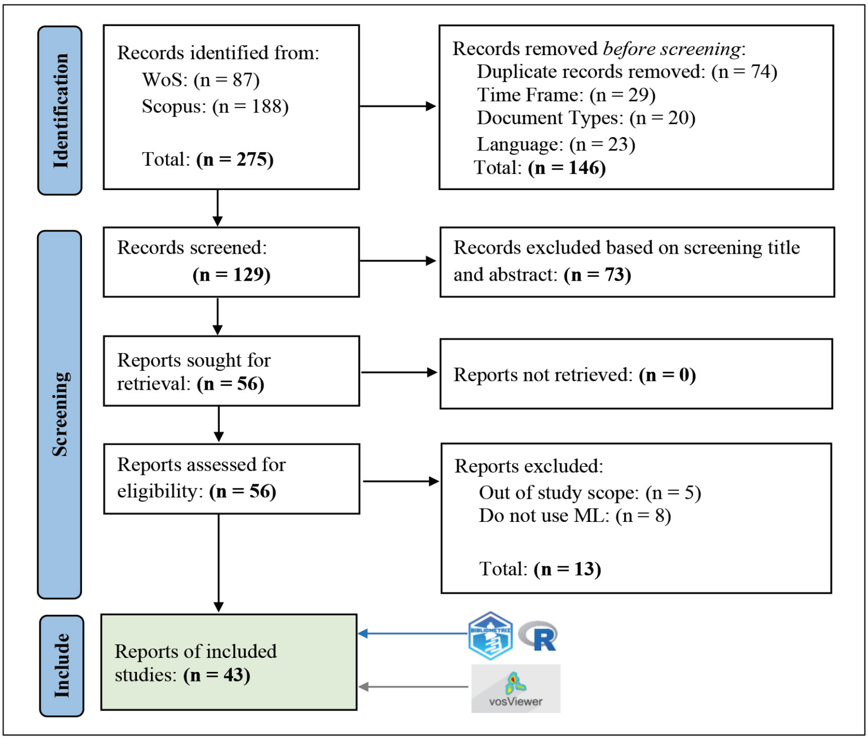

Figure 1: Flow diagram of the systematic review following (PRISMA-2020)

Table 1: Boolean search in WoS and Scopus

Database	Search Within	Boolean string	Date
Web of Science	Title or Abstract or Author Keywords	(“agricultur* drought”) AND (“machine learning” OR “algorithm” OR “artificial neural networks” OR “support vector machine” OR “random forest” OR “decision trees” OR “xgbr” OR “supervised classification”)	15/09/2023
Scopus	Article title Abstract keywords	(“agricultur* drought”) AND (“machine learning” OR “algorithm” OR “artificial neural networks” OR “support vector machine” OR “random forest” OR “decision trees” OR “xgbr” OR “supervised classification”)	15/09/2023

whether the article contained relevant text to the “Agricultural Drought” AND “Machine Learning”. For each article to be included, *I* must be equal to 2 or 3 to decrease the bias. In view of this, 56 articles matched the criteria and were included to be analysed in the next step, and 73 articles that were deemed irrelevant to this review were excluded.

Inclusion

To ensure accurate selection, in this final step, full-text articles were downloaded and reviewed to determine their eligibility for the final included phase. Articles were considered suitable for inclusion if they met the following criteria: (1) Assessing, predicting agricultural drought, (2) using multi-source data, and

(3) applying machine learning algorithms. In contrast, articles were excluded if they: (1) Focused on other types of droughts (e.g., Meteorological, Hydrological), and (2) used conventional or pure statistical methods. Subsequently, two authors independently collected the relevant information employing a predefined data extraction form, and if there were any disparities, they were settled through discussion between the reviewers. Subsequently, the extracted data were re-evaluated by a third party for confirmation. Forty-three articles were included for bibliometric and systematic analyses.

Results

Bibliometric research has witnessed significant expansion over the last 20 years (Mukherjee *et al.*, 2022). This analysis technique can be classified into two main categories: (1) Performance analysis, which evaluates the contributions of research elements, and (2) science mapping, which delves into the connections between these research elements (Donthu *et al.*, 2021b). The performance analysis and scientific mapping of the research field were carried out using the Bibliomatrex package in R environment and VOSviewer as a bibliometric appraisal tool. Subsequently, the findings were deliberated upon, addressing potential research gaps and outlining research prospects. Utilising software was allowed for the delineation of the current trends in the study of relevant machine learning approaches in agricultural drought. This, in turn, offered researchers a clear comprehension to assist them in future studies and collaborative efforts.

Performance Analysis

The performance analysis assesses the contributions of research components within a specific field (e.g., authors, institutions, countries, and journals) (Mukherjee *et al.*, 2022; Yalcinkaya *et al.*, 2023). In our review, we utilised the performance analysis to identify the most productive countries, articles, institutions, and authors that have contributed significantly to the field of agricultural drought and machine learning. Additionally, we aim to uncover the evolving trends in this domain.

Publication Trend Analysis

Employing graphs to evaluate the publication years of the acquired literature provides a straightforward insight into the evolution of the field (Yang *et al.*, 2023). In its early stages, the field of agricultural drought and machine learning typically witnessed a limited number of published studies, primarily because most researchers relied on statistical methods for assessing agricultural drought (which have limitations) with only a few authors utilising the machine learning approach. For instance, linear combination, Bayesian approach, PCA, and the entropy method make the assumption that there is a linear relationship between the various factors contributing to drought (Hao & Singh, 2015; Deng *et al.*, 2018). Nonetheless, these techniques have demonstrated constraints when it comes to addressing non-linear patterns or non-stationary elements in drought predictions. Machine learning approaches on the other hand, can untangle the influences of co-linear variables and examine both hierarchical and nonlinear associations between independent and dependent variables, typically yielding superior performance in comparison to the traditional linear methods (Guzmán *et al.*, 2018; Feng *et al.*, 2019). In this view, as the field develops gradually, an increasing number of authors become involved in research and collaborative efforts, leading to a gradual rise in the number of published studies. For instance, the quantity of yearly publications in the field was rather limited with just two articles in 2016. However, there had been a gradual rise in the volume of published literature, reaching a total of 16 publications in 2023, signifying an annual growth rate of 34.59%. Due to climate change and the adoption of advanced machine learning methods, an expanding group of researchers and institutions is giving greater focus on this area. As a result, a continued rise in the volume of research papers in this field in the years ahead is anticipated. Utilising Bibliometrix package (version 4.1.3), Figure 2 shows the number of publications per year.

Institutions and Countries Influence Analysis

Novice researchers in a field initially explore the literature authored by respected scholars and institutions to acquire the most reliable and accurate information, helping them to enhance their understanding of the field (Yang *et al.*, 2023). Hence, we have conducted an analysis of productive institutions and countries within the field to assess the most significant and influential contributors in the application of machine learning to agricultural drought research. Table 2 shows that Chinese affiliations are the largest contributors in the field due to the fact that the country is considered to be one of the most profoundly impacted by droughts. According to a Chinese government report, between 1956 and 2016, the yearly average of drought-affected land area exceeded 200,000 square kilometres, and the annual average economic losses linked to droughts surpassed tens of billions of dollars (Deng *et al.*, 2018). Likewise, the USA, Iran, and India have made important contributions to the field over time. Figure 3 shows the concept of "Country Scientific Production," which quantifies the frequency of author affiliations by country. In practical terms, if an article involves authors from the USA, China, and Iran, each of these three countries' counts would increase by 1. Suffice to say that China, followed by India are the most productive countries in the last few years. However, the research output of influenced countries is developing over time, indicating that studies in this area will increase continuously.

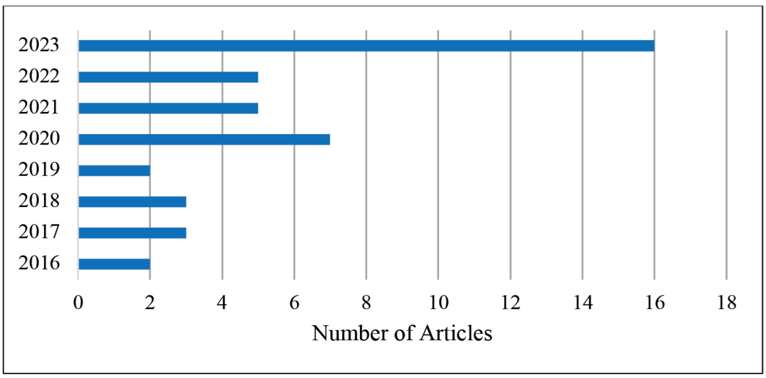

Figure 2: Annual scientific production

Table 2: Most Relevant Affiliations

Affiliation	Articles
Beijing Normal University	7
China University of Geosciences	4
University Of Chinese Academy of Sciences	4
Fasa University	3
Hohai University	3
Mansoura University	3
Northeast Institute of Geography and Agroecology	3
Yarmouk University	3
Bangabandhu Sheikh Mujibur Rahman Agricultural University	2
Chinese Academy of Sciences	2

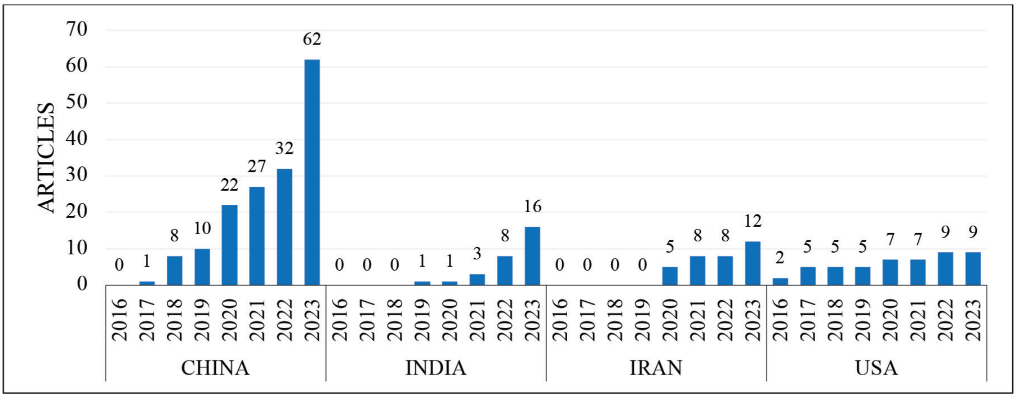

Figure 3: Countries' production over time

Science Mapping

Science mapping scrutinises the connections among research elements (Baker *et al.*, 2021). The analysis concerns the intellectual interactions and structural connections between the research constituents (citation, co-citation, bibliographic coupling, co-word, and co-authorship) (Baker *et al.*, 2020).

Citation Analysis

Citation analysis reveals multiple insights into a specific research field. Firstly, it uncovers the most influential publications, authors, and countries that contribute to the field and exert a significant effect (Rejeb *et al.*, 2022). Secondly, authors' knowledge flow and communication relationships can be revealed. Finally, by citing works' linkage, one can trace the evolution of a knowledge field over time (Pournader *et al.*, 2020). Citations also serve as indicators of the significance and liveliness of a paper's contributions to the literature on a particular subject (Rejeb *et al.*, 2022). Table 3 shows the most cited articles, Figure 4 and Figure 5 show the most cited authors, and countries respectively. These articles were reviewed and analysed in the next sections.

Keyword Co-occurrence Analysis

Keywords serve as a concise representation of an article's content and by analysing them, we can promptly identify the current focal points of research in a specific field. Keyword co-occurrence analysis represents the most straightforward and efficient approach for encapsulating research trends within a particular field, aiding researchers in promptly recognising these trends (Lyu *et al.*, 2024).

In our review, the 43 articles contain 146 keywords. The threshold was set to a minimum of 5 co-occurrences to determine the keywords that exemplify the content most effectively. This led to the identification of the top eight keywords that are most pertinent. The node size on the map corresponds to the frequency of keyword appearances and the proximity of nodes as well as the thickness of the connecting lines signify the robustness of their association, indicating how often they appear together. Figure 6 shows the strong link from the "agricultural drought" keyword to the "machine learning" and "remote sensing" keywords, revealing that the connection between these fields is strong. Likewise, the strong link from the "drought monitoring" keyword to the "random forest" keyword explains the dominance of the RF algorithm in agricultural drought assessment as it will be discussed in the following sections.

Co-citation Analysis

We employed the co-citation analysis to uncover the intellectual framework underpinning the field of agricultural drought and machine learning.

Table 3: Most Cited Articles

Article	Total Citations
Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions	220
Machine learning-based integration of remotely-sensed drought factors can improve the estimation of agricultural drought in South-Eastern Australia	120
Machine learning approaches for spatial modelling of agricultural droughts in the south-east region of Queensland Australia	91
Agricultural drought prediction using climate indices based on Support Vector Regression in Xiangjiang River basin	83
Development and evaluation of a comprehensive drought index	80

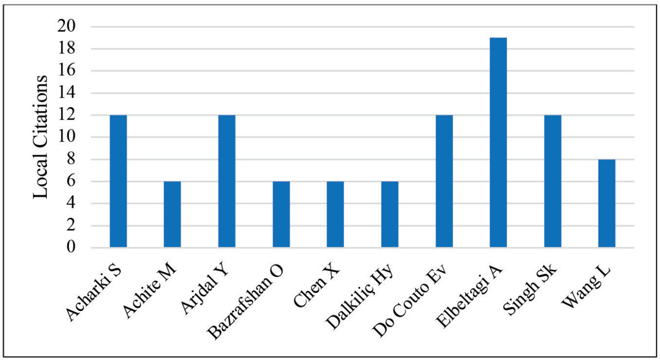

Figure 4: Most local cited authors

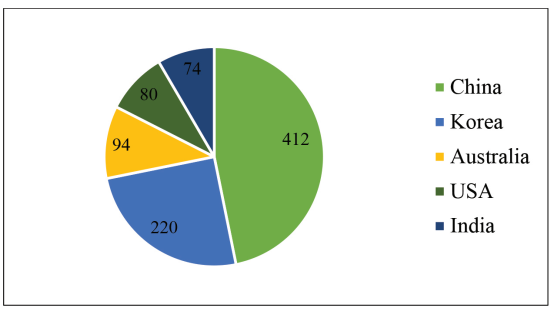

Figure 5:Most cited countries

The co-citation analysis entails monitoring pairs of papers that are referenced together in source articles (Khare & Jain, 2022). As numerous authors co-cite the same pairs of papers, clusters of research start to emerge. These clusters of co-cited papers often revolve around a common theme (Rejeb *et al.*, 2022). Figures 7 to 9 shows the co-citation network. The larger node size indicates the higher importance of author, literature, and source. In other words, through the identification of highly cited publications and their associations, the publications are grouped into specific research clusters where publications within a cluster consistently share similar concepts (Small, 1973; McCain, 1990). Figure 7 shows the reference-based co-citation analysis, setting the citation threshold to 3, while the two references with the most robust

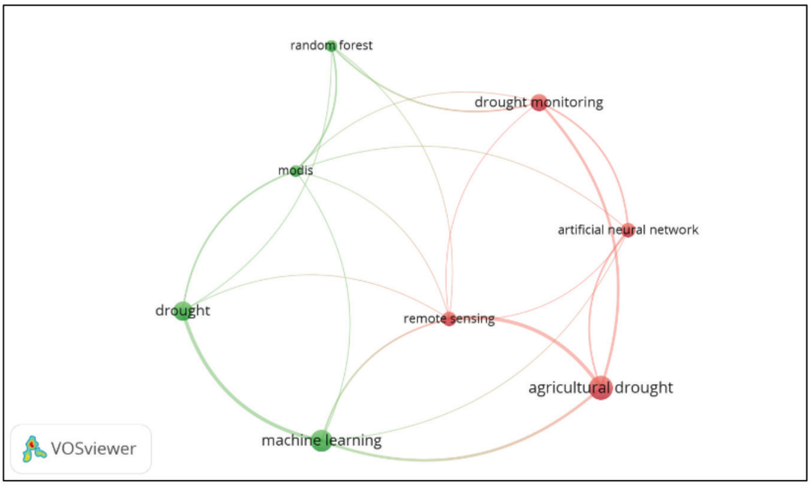

Figure 6: Keyword co-occurrence map

connections to other references were with Rhee *et al.* (2010) (links strength: 17) and Zhang and Jia (2013) (links strength: 14). Figure 8 shows the source-based co-citation analysis, setting the citation threshold to 15, where the two sources with the strongest connections to other sources were the Journal of Hydrology (links strength: 1,162) and Remote Sensing of Environment (links strength: 1,040). Figure 9 shows the author-based co-citation analysis, setting the citation threshold to 20 with the two authors most prominently connected to other authors were Singh (links strength: 1,327) and Vicente (links strength: 1,315).

Machine Learning and Agricultural Drought

Due to the intricate and nonlinear characteristics of the agricultural drought phenomenon, it is essential to conduct simulations using the nonlinear time series data. This has led to significant attention being directed towards the utilisation of machine learning for drought prediction due to its robustness in dealing with non-linear variables. In this review, we discussed different articles that studied agricultural drought using different ML algorithms in different locations and time scales to deal with the non-linear relationship among agricultural drought drivers. Artificial Neural Network is

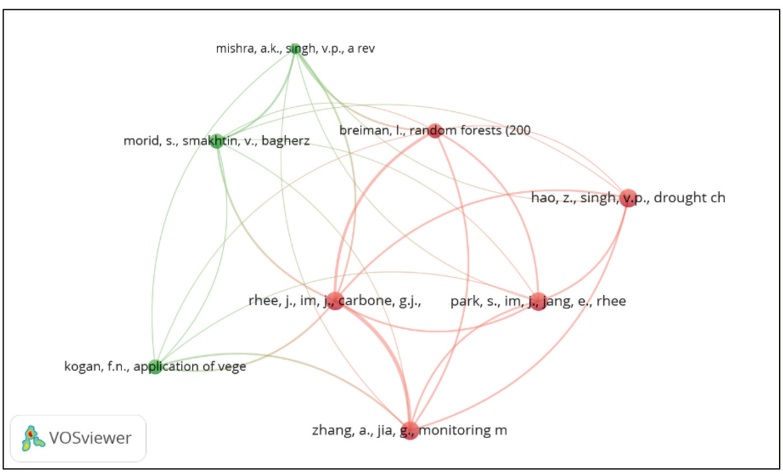

Figure 7: Co-citation analysis (reference-based)

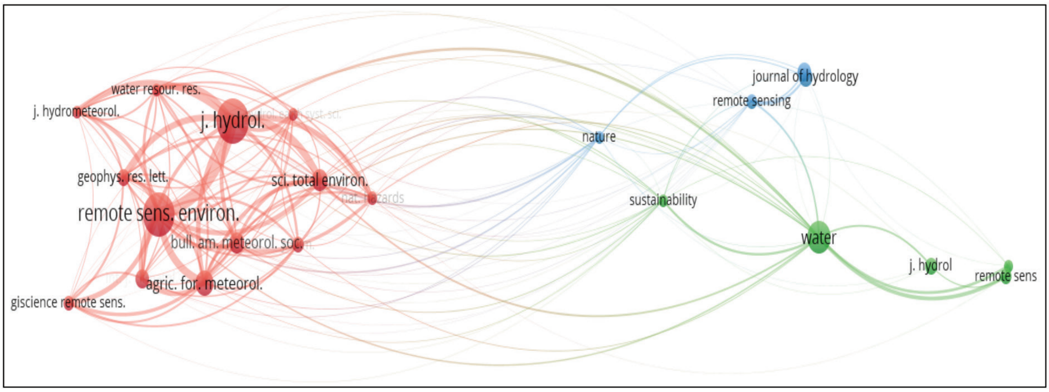

Figure 8: Co-citation analysis (source-based)

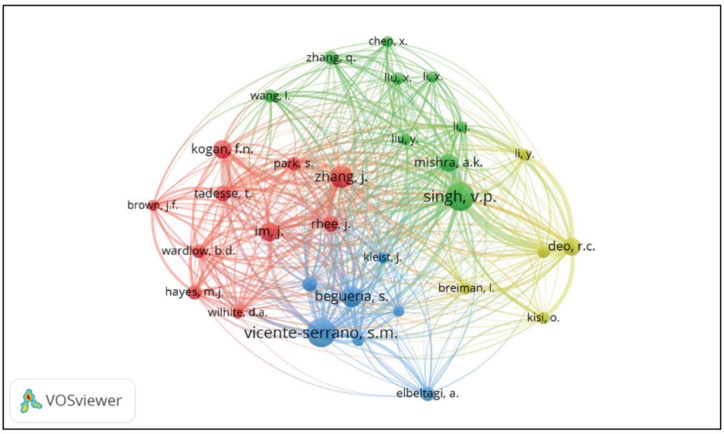

Figure 9: Co-citation analysis (author-based)

one of the algorithms used to assess and predict agricultural drought. The concept of an ANN was inspired by the structure of neural networks found in the human brain (Singh *et al.*, 2021). It is a construct of three layers (input, hidden, and output). In 2016, a study led by Lingjun Kang and backed by a grant from the NASA Applied Science Program, an ANN-powered predictive model was introduced. This model aims to forecast the normalised difference vegetation index (NDVI) of grasslands in the U.S. Great Plains region. The foundation of this forecasting model is rooted in historical trends, specifically the delayed correlations between the vegetation index and meteorological variables, which can be used for monitoring agricultural drought (Kang *et al.*, 2016). A few years later, in 2020, a decade's worth of multi-source data for Sangli district, India was examined using K-means Clustering and the Naive Bayes classification algorithm (utilising the backpropagation Artificial Neural Networks) to enhance the accuracy of drought assessment and prediction. Since the Naive Bayes algorithm achieved an impressive 97% accuracy rate, it was employed as a classifier for categorising predicted drought images (Singh *et al.*, 2021).

However, 10 years is considered a short time to train the ANN model and thus, a longer period needs to be considered. In the same year, Xianfeng Liu introduced a novel drought indicator called the Integrated Agricultural Drought Index (IDI) to address the challenge of identifying the non-stationary relationship of drought conditions. The IDI incorporates meteo-hydrological variables and utilises the remote sensing data and back propagation neural networks to describe the connection between various factors and agricultural drought conditions. Furthermore, this index can capture the delayed influence of NDVI concerning the precipitation and land surface temperature (LST) changes. In this study, IDI exhibits a correlation with soil moisture across all the stations assessed with correlation coefficients ranging from 0.52 to 0.73. However, it is important to note that the current version of the IDI is unable to monitor drought events at temporal scales finer than one month. Additionally, this study exclusively involves the meteo-hydrological variables, limiting the IDIs ability to distinguish the differential impacts of drought on various crops, such as winter wheat and summer maize, as well as the associated effects of IDI-based drought assessments on crops at different growth stages (Liu *et al.*, 2020). In 2023, in order to compute the 1-month Standardised Precipitation Evapotranspiration Index (SPEI) at all monitoring stations, Ayoub Nafii employed on-site measurements of rainfall and temperature. The results served a dual purpose: first, to characterise the drought conditions in the region, and secondly, to construct an ANN machine learning model capable of forecasting the annual SPEI, which is valuable for predicting agricultural drought.

Consequently, the ANN model demonstrates a reasonably high level of accuracy in predicting SPEI', with $R^2 = 0.99$, making it a valuable tool for early agricultural drought prediction (Nafii *et al.*, 2023). Artificial neural networks have significantly advanced the understanding and measurement of non-linear connections between input factors and target variables across various domains. The flexibility and adaptability of the ANN model have proven to be valuable tools in predicting droughts' occurrence, which can vary in terms of the duration, severity, and occurrence throughout the growing season. As a result, many scholars have utilised these benefits in their studies. To make use of the distribution patterns of precipitation and temperature, an ANN model was created to forecast the rate of agricultural drought losses throughout China (Yang *et al.*, 2020). Mokhtari R (2020) stated that the ANN approach provided higher accuracy than the other three algorithms (SVR, DT, and RF) for agricultural drought prediction (Mokhtari & Akhoondzadeh, 2020). In contrast, in 2022, Paramita Roy asserted that MaxEnt (maximum entropy) is more effective than ANN in identifying drought vulnerability in India (Roy *et al.*, 2022). This verifies the fact that different ML algorithms perform differently in different locations. Nevertheless, a primary criticism of ANN revolves around its status as "black boxes" due to the absence of a sufficient explanation for how it functions (Benítez *et al.*, 1997) and its sensitivity to the outliers.

Support Vector Machine (SVM) is a supervised learning algorithm employed in machine learning for addressing classification and regression tasks. SVMs excel in handling binary classification problems, where the goal is to categorise elements in a dataset into two distinct groups. Several studies have applied this technique in the field of agricultural drought. In his research, Ye Tian (2018) explored the connection between soil moisture and various timescale drought indices within the Xiangjiang River basin. Drought indices were carefully chosen for subsequent predictive modelling. By analysing the impacts of the western Pacific subtropical high (WPSH) and El Nino southern oscillation (ENSO) on drought, a Support Vector Regression (SVR) model was constructed to forecast agricultural drought. The findings suggested that integrating climate indices into the SVR model enhances the prediction accuracy when compared to using drought indices alone (Tian *et al.*, 2018). In 2017, Di Liu observed that SVMs or SVM-DA (data assimilation) with limited meteorological variables as inputs was able to forecast the soil water deficit index for agricultural drought monitoring (Liu *et al.*, 2017).

To overcome the limitations caused by outliers on different ML algorithms, scholars utilised the robustness of the Decision Tree technique. The Random Forest algorithm is found to be one of the most used algorithms in the area of agricultural drought due to the revised literature. The accuracy of the Random Forest algorithm's results primarily relies on three key parameters: (a) Trees number to grow in the forest, (b) maximum count of randomly chosen features at each node, and (c) maximum extent to which each tree is allowed to grow (Deng *et al.*, 2022). Many scholars have used the RF algorithm in their studies (Park *et al.*, 2016; Deng *et al.*, 2018; Son *et al.*, 2018; Montaud, 2019; Rahmati *et al.*, 2020; Zhu *et al.*, 2020; Chen *et al.*, 2023; Hanadé Houmma *et al.*, 2023; Kan *et al.*, 2023; Zarei *et al.*, 2023). In 2022, Xiyuan Deng opted to utilise the "drought-affected area" and "drought-suffering area" as the indicators for assessing agricultural drought disasters. Random Forest algorithm, based on four datasets, was employed for training and testing to uncover the intricate connections between 22 factors and agricultural drought disasters (Deng *et al.*, 2022). Even though the study did not consider the vegetation biophysical information directly, it is revealed that the longest time length dataset had the best model performance with $R^2 = 0.65$, which supports the principle of machine learning. Likewise, a Comprehensive Remote Sensing-based Agricultural Drought Conditions Index (CADCI) was created using the Random Forest algorithm to monitor agricultural drought in semi-arid regions characterised by diverse rain-fed agricultural landscapes in Jordan and Syria. CADCI relies on the time series data obtained from multiple satellite systems. The model has demonstrated its effectiveness in assessing agricultural drought with validation results ranging from R^2 values of 0.407 to 0.974 (Alkaraki & Hazaymeh, 2023). To overcome the bias in RF, in 2023, Yihao Wang, based on the bias-corrected random forest mode, introduced a novel index called the Random Forest Synthesised Drought Index, designed for monitoring agricultural drought in the NEC region of China. The research found that the BCRF model exhibited superior accuracy and stability compared to the traditional random forest model, with R^2 values ranging from 0.86 to 0.89 (Wang *et al.*, 2023). Likewise, the bias-corrected RF model effectively generated the agricultural SPEI maps that are aligned with SEI drought maps derived from station-based data (Feng *et al.*, 2019). A sophisticated Decision Tree algorithm needs to be applied and validated in the field to improve the accuracy of the model.

In the same context, for the purpose of improving accuracy, many researchers employed an alternative version of the decision tree. For instance, in 2020, Foyez employed the fast-and-frugal decision tree (FFT) within a classification framework (Prodhan *et al.*, 2020). In 2022, Ahmed Elbeltagi employed the Random Subspace Method (RSM) as an ensemble learning approach to predict SPI (Standardised Precipitation Index) at various time intervals to assess agricultural drought in India (Elbeltagi *et al.*, 2023). Needless to say, the RF algorithm is considered a "White Box" as it can deal with data from different sources. In addition, it confirms its performance with the common issues of remote sensing and in situ sources, like missing data and outliers.

Conclusions

In conclusion, this systematic review and bibliometric analysis of the retrieved documents published from 2014 to 2023 shed light on the evolving field of agricultural drought research. The present comprehensive study highlights several key findings and trends.

Performance analysis revealed that China, India, and the USA are leading contributors with significant involvement from key institutions and prominent authors. The publication trend analysis demonstrated a notable increase in research output with the number of publications escalating from two in 2016 to 16 in 2023, reflecting the growing relevance and advancement of machine learning techniques in this field. Furthermore, the institutions and countries influence analysis highlighted China's central role, attributable to its significant exposure to drought, while also recognising substantial contributions from the USA, Iran, and India. Citation analysis identified pivotal publications and influential scholars such as Singh and Vicente, underscoring their critical impact. Additionally, keyword co-occurrence analysis elucidated prevailing research trends, emphasising strong connections between terms like "agricultural drought," "machine learning," and "remote sensing." Co-citation analysis further delineated thematic clusters, pinpointing key references and influential journals, including the Journal of Hydrology and Remote Sensing of Environment. Collectively, these analyses enhance our understanding of the research landscape, illustrating its development, current focus, and future research directions.

As a result of the availability of the number of algorithms with the improvement in the computing functions of the machines, scholars have explored a wide range of machine learning techniques and algorithms (e.g., ANN, RF, and SVM) for agricultural drought monitoring, prediction, and mitigation. These applications range from forecasting crop yield to predicting droughts, demonstrating the adaptability of machine learning in agriculture. Random forest was the most used algorithm due to its performance in dealing with data variability and outliers. Nevertheless, agricultural drought directly impacts food security, making the application of machine learning in this area of research not only scientifically significant but also vital for addressing global challenges.

It is thus acknowledged that data is the backbone of any ML technique. In this view, machine learning effectiveness in the field of agriculture largely relies on the availability and quality of data. As evident in the analysis, the integration of diverse data sources, including remote sensing, climate, and soil data is a common practice in this field. It is worth to say that there is no "one-size-fits-all" ML model that suits all geographical locations. Moreover, it is important to emphasise that the climate change impact on crop growth differs from one region to another (Wang *et al.*, 2023). In light of this, the geographic distribution of research in agricultural drought using machine learning is distinguishable. Different areas face distinct drought challenges, leading to localised studies and models tailored to specific agricultural contexts. In addition, choosing agricultural drought assessment indicators forms the fundamental framework for conducting agricultural drought analysis (Deng *et al.*, 2022). For that, researchers applied the ML algorithms for "variable importance selection," where this method advances the accuracy and computation cost of algorithms by selecting the most important factors that influence drought in different regions depending on characteristics of the climate, topography, and human activities.

In terms of cooperation, the review reveals many collaborations between scholars from various fields, for instance, computer science, agronomy, and environmental science. This interdisciplinary approach is crucial for advancing the field and addressing complex agricultural drought issues effectively. However, while ML has been shown to be promising, challenges such as data scarcity, model interpretability, and scalability persist. Nonetheless, a thorough analysis of the most efficient machine learning techniques to create a comprehensive data-driven integrated agricultural drought index using remote sensing is still lacking (Xu *et al.*, 2023). These challenges present opportunities for further research and innovation in the agricultural drought field. As we take a step further, future research, innovation, and data-driven solutions will be instrumental in tackling this pressing issue and ultimately protect our agricultural systems.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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