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Drought Forecasting: A Bibliometric Analysis and Future Research Directions

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Abstract

Droughts represent one of the most dangerous natural disasters in the world, due to their ability to progressively spread over large areas up to continental scale, as well as their adverse environmental, human and socio-economic effects. Unfortunately, these effects are increasingly accentuated under the influence of climate change. One of the main challenges today is to mitigate the damage associated with droughts by developing tools capable of predicting the occurrence of such events in advance. Many solutions have been implemented for this purpose. But with the great progress in artificial intelligence, many scientists propose the use of Machine Learning to provide more optimal solutions to the problem related to droughts. In the present study, a bibliometric analysis was conducted to assess the current level of research on forecasting and monitoring of droughts in the world in general, particularly in West Africa through different methods based on the artificial intelligence. A search for articles on the topic was performed in the Web of Science (WoS) database, which is a global, publisher-independent citation database. The search identified a total of 3284 documents and the collected data was analyzed using a bibliometric tool called Bibliometrix. The main results are presented and discussed, followed by some potential avenues for research.

Keywords

Droughts, Forecasting, Climate Change, Bibliometric, Web of Science (WoS)

1. Introduction

Droughts are one of the most devastating natural disasters affecting various regions of the world. The phenomenon starts with a deficit of precipitation and impacts various aspects such as river flow and soil moisture [1]. According to the report of the COP15 of the United Nations Convention to Combat Desertification (UNCCD), drought is the second most dangerous disaster after floods. Indeed, the number and duration of droughts have increased by 29% since 2000, compared to the two previous decades [2]. These statistics revealed by organizations dealing with climate-related problems prove that this is obviously a global crisis that is important to monitor. It affects mainly the agricultural sector, the energy sector and the water resources causing heavy economic losses [3] as well as food insecurity and famine [4]. According to a publication by [5], climate change is believed to be a factor that accentuates droughts due to the increase in evaporation associated with rising temperatures. Moreover, [6] reveals that gravity and the spatial coverage of climatic droughts has increased over the past few decades because of climate change. A recent study by the World Weather Attribution consortium found that climate change has increased the risk of drought 20 times in the hemisphere [7]. It can be said that humanity is only suffering the consequences of its misuse of the environment because climate change is mostly caused by the abusive exploitation of natural resources causing a slow destruction of the ecosystem and a strong climatic instability [8]. According to the report of the COP15 of the United Nations Convention to Combat Desertification (UNCCD), severe drought affects Africa more than any other continent, with more than 300 events recorded in the last 100 years, representing 44% of the world total. Faced with these alarming figures, one wonders what fate will be reserved for the African continent in the years to come as well as the types of droughts that will occur there. An analysis made in [9] shows that several factors would be the basis of drought conditions in Africa, in particular: El Nino and SST being considered as major impact factors. According to [1], droughts can be categorized as follows: meteorological, characterized by the scarcity of precipitation below a certain threshold; hydrological drought, which refers to the decrease in the flow of rivers; agricultural drought, which causes a reduction in soil moisture and consequently, crop yields; and socio-economic drought, which is the economic difficulty encountered by people as a result of all the above types of drought. However, due to the large-scale evolution of drought, there is a need for efficient climate monitoring tools. Advanced drought warning and prediction systems are crucial to limit the damage of drought through proper planning, adaptation strategies as well as the implementation of mitigation programs [10]. It is therefore important to note that during the last two decades, the number of studies aimed at establishing drought warning and forecasting systems has increased considerably. Most of these studies are increasingly based on artificial intelligence approaches [11] and [12].

This study aims to contribute to the debate on drought forecasting. For this purpose, it seeks to answer the following research questions:

- What is the current state of research in drought forecasting around the world?
- Who are the most productive and influential authors in the field of drought forecasting?

- What are the most dynamic publication sources in this field?
- What are the potential research avenues for drought forecasting?
- What are the most used index and algorithms for drought forecasting?

In order to provide answers to these research questions, this paper is based on a bibliometric analysis of drought forecasting data extracted from the Web of Science (WoS) database. The rest of the paper is structured as follows: Section 2 presents the research methodology. Section 3 presents the results followed by a discussion. Sections 4, 5 and 6 deal respectively with the contributions, limitations, conclusion and future research directions.

2. Methodology

The main objective of this work being to evaluate the current level of knowledge development on drought forecasting, we opted for a bibliometric approach. This research approach is recommended to assess the status or level of advancement of a discipline through various indicators, such as: most influential and most cited publications, journals, authors, institutions and countries. It also allows to evaluate the level of network collaboration between authors, institutions and countries. More broadly, this research approach is useful because it serves to analyze considerable amounts of publication data. This method of document synthesis has been successfully exploited in previous studies to analyze many fields and areas of research [13] and [14].

Database Selection, Data Extraction and Analysis

To achieve the above objectives, the Web of Science (WoS) database was used. It is indeed a multidisciplinary bibliographic database platform allowing access to a multitude of references of scientific articles, conference proceedings and books using its search engine. A search was performed on May 11, 2022 in the WoS database using a set of keywords: "droughts" and "forecasting". This search retrieved 3284 relevant documents. These documents were then selected for further analysis using a dedicated bibliometric tool called Bibliometrix. Specifically, we used the bibliometrix's shiny interface better known as biblioshiny. Bibliometrix is an open source R tool dedicated to quantitative research in scientometrics and bibliometrics and which brings together all the main methods of bibliometric analysis.

3. Results and Discussion

In the sections below, we present and discuss the results of our bibliometric analysis.

3.1. Main Information on the Collected Documents

Table 1 presents the main information on a dataset extracted from the Web of Science containing articles dealing with drought forecasting. Several interesting information can be drawn from this table. For example, our search allowed us to retrieve 3284 documents among which we have: articles, reviews, procedural documents, editorial materials, data papers, to name a few.

These documents were published over a period of time ranging from 2000 to 2022. The sources (journals, books, etc.) in which the identified documents were published number 686, which shows that many journals and publishing houses are very interested in the subject of drought forecasting.

3.2. Annual Scientific Production and Main Sources of Annual Scientific Production

Figure 1 shows the annual scientific production of papers on drought forecasting. From this figure, it can be seen that the first 28 papers written on this subject date back to 2000. It is easy to see that from the year 2000 until 2021, the trend in the production of documents has only increased year after year, thus showing the interest of the scientific world in the problem of droughts. Let's remember that the number and duration of droughts have increased by 29% since 2000 [2]. In addition, more than 1.4 billion people have been affected by droughts from 2000 to 2019. These figures make droughts the second most common natural disasters affecting the greatest number of people after floods. This has undoubtedly attracted the attention of scientists and would probably explain why from 2000, the production of documents relating to droughts increased. However, from 2012 to 2021, there is a much faster increase in the publication of papers dealing with drought forecasting. Several facts may justify this growing trend. Indeed, this period was marked by large sequences of droughts around the world including: North America (in 2011-2017); South America (in 2010-2019); Central America (in 2016-2019); Europe (in 2015-2020); Africa (in 2010-2012, 2018-2022); Asia (in 2010-2011, 2015-2018) [2] *(voir* **Figure 3**). During these periods of crisis, scientists have published a lot on the subject of droughts, especially drought forecasting, which explains this strong growth in the production of documents between 2012 and 2021. In 2022, there is a slight decrease in document production (147 documents). This is probably due to the fact that we are only at the beginning of the second quarter of 2022. This trend could change by the end of 2022.

The distribution of the 20 most relevant sources in the dataset from WoS is shown in **Figure 2**. It is clear that the JOURNAL OF HYDROLOGY tops the list with 119 published papers on drought forecasting. HYDROLOGY AND EARTH SYSTEM SCIENCES comes second with 98 papers, then comes the JOURNAL OF HYDROMETEOROLOGY with 91 papers, followed by the INTERNATIONAL JOURNAL OF CLIMATOLOGY WATER with 89 papers published. The JOURNAL OF CLIMATE ranks fifth with 75 documents.

3.3. Source Growth Dynamics

The evolution of sources in relation to the topic of drought forecasting is illustrated by **Figure 3**. The three sources with significant growth are: Journal of Hydrology, Hydrology and Earth System Sciences, Journal of Hydrometeorology. A

Table 1. Main information about the collection of published drought forecasting papers in WoS.

Description	Results
Timespan	2000-2022
Sources (journals, books, etc.)	686
Documents	3284
Average years from publication	5.89
Average citations per documents	26.79
Average citations per year and per doc	3.445
References	1
DOCUMENT TYPES	
article	3042
article; data paper	6
article; early access	37
article; proceedings paper	46
article; retracted publication	1
correction	4
editorial material	14
letter	3
news item	3
review	123
review, book chapter	1
review, early access	4
DOCUMENT CONTENTS	
Keywords Plus (ID)	5695
Author's Keywords (DE)	7601
AUTHORS	
Authors	10,294
Author appearances	15,023
Authors of single-authored documents	176
Authors of multi-author documents	10,118
AUTHORS COLLABORATION	
Single-authored documents	186
Documents per Author	0.319
Authors per Document	3.13
Co-Authors per Documents	4.57
Collaboration Index	3.27

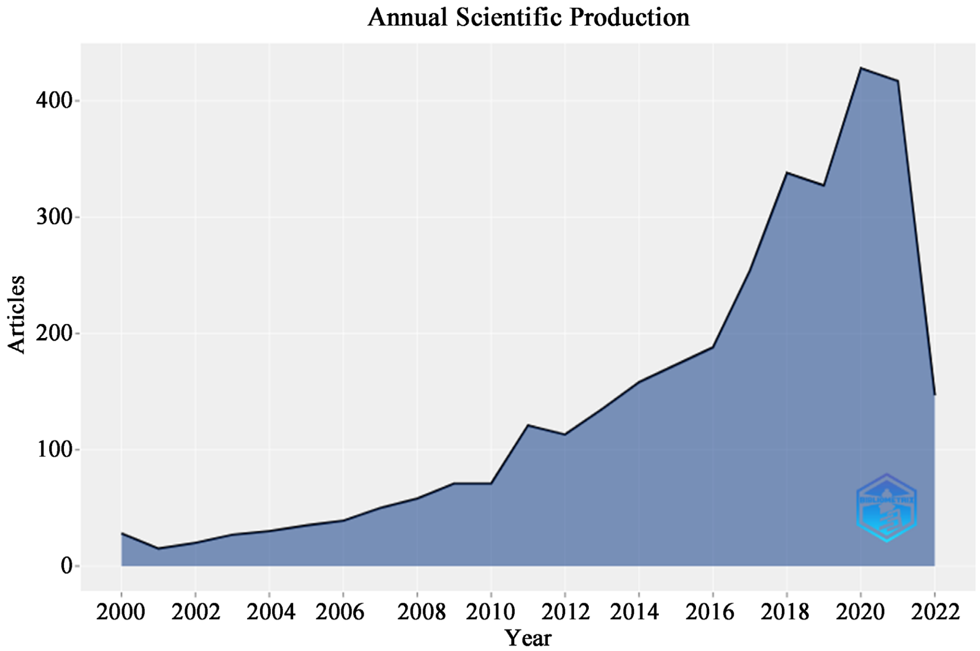

Figure 1. Annual scientific production.

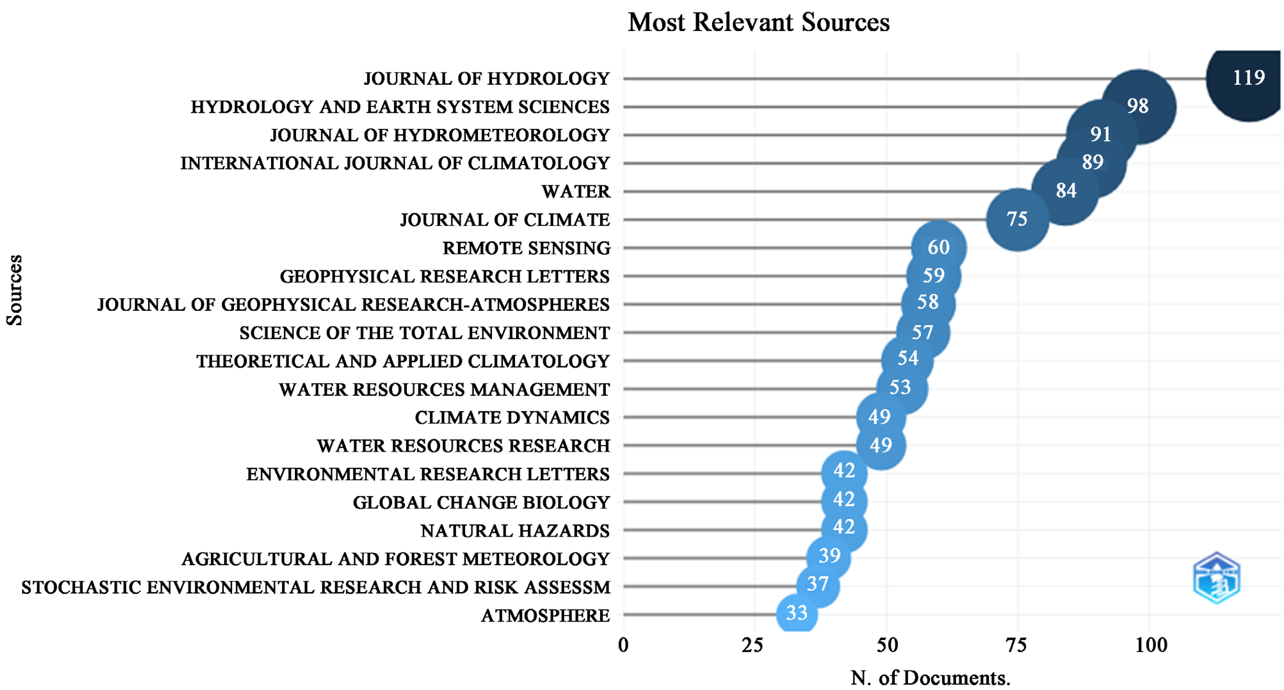

Figure 2. Top 20 most relevant sources.

total of 308 out of 3284 papers (which is 9.4% of all papers) were published in these sources. Over the entire period from 2000 to 2022, the most significant growth is observed for the Journal of Hydrology source (with a total of 119 documents), followed by other journals, such as: Hydrology and Earth System Sciences (with a total of 98 documents), Journal of Hydrometeorology (with a total of 91 documents). These sources would be identified as the most dynamic

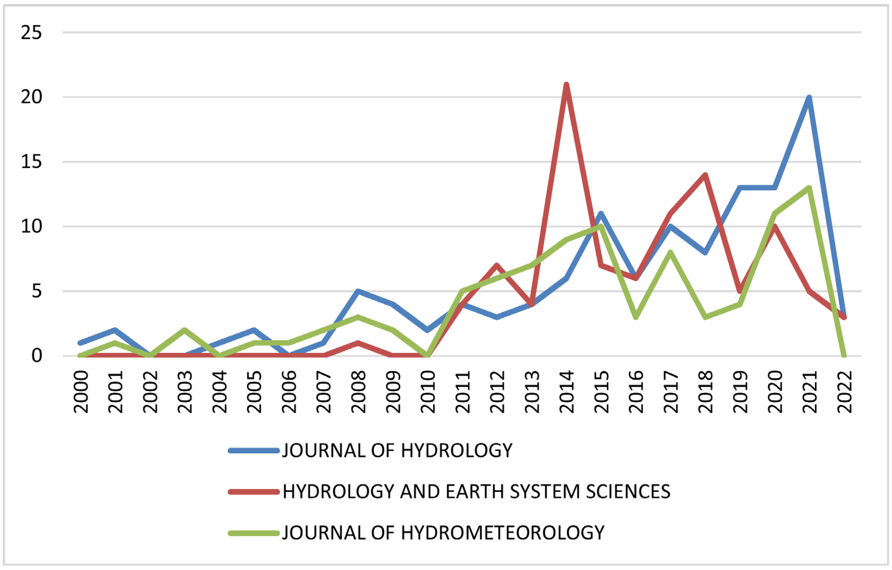

Figure 3. Source dynamics.

sources because they would be sources exclusively related to the climate field.

3.4. Ranking of the Most Relevant Authors and Affiliations

Table 2 shows the ranking of the 20 most relevant authors who have published on drought forecasting. Looking at the most relevant authors, we can see that WANG Y. leads the race with 36 published papers, followed by LI J; WOOD EF; LI Y. with 31, 31, 30 published papers respectively. Then PENG C and WANG J follow them with 29 papers each. To the previous duo, follows another group of authors consisting of ZHOU X.; YUAN X.; SINGH VP; ZHANG X.; ZHANG Y. with respectively 26, 25, 24, 22, 22 papers each. LI X., is in the 12th place with 21 published papers. Finally, the authors WANG H; WANG S.; HE X.; JULIO CAMARERO J.; FUNK C.; KUMAR A.; PAPPENBERGER F. and ZHU Q. close this list of the 20 most relevant authors having published on drought forecasting.

The ranking of the top 10 most relevant affiliations published in Web of Science (WoS) on drought forecasting is shown in Table 3. COLUMBIA UNIV sets the scene for the top affiliations with the most papers (141 papers). This is followed by NANJING UNIV INFORMAT SCI AND TECHNOL, COLORADO STATE UNIV, HOHAI UNIV, TEXAS AANDM UNIV holding 125, 113, 107, 107 papers respectively. UNIV ARIZONA takes 6th place in the ranking with a total of 103 documents. The last four places in this ranking go to INST ATMOSPHER PHYS, UNIV COLORADO, BEIJING NORMAL UNIV and PRINVETON UNIV holding respectively 93, 91, 89, 88 documents.

This top 10 most relevant affiliations reveals that American and Chinese universities have paid much attention to the concern of drought forecasting while underdeveloped countries, especially those in Africa which suffer the full brunt of the consequences brought about by droughts have little affiliation. According to [15], Africa has the least developed observation network of all the continents and only 22% of existing stations meet all the data communication requirements

Table 2. Top 20 most relevant authors.

Rank	Authors	Articles
1	WANG Y	36
2	LI J	31
3	WOOD EF	31
4	LI Y	30
5	PENG C	29
6	WANG J	29
7	ZHOU X	26
8	YUAN X	25
9	SINGH VP	24
10	ZHANG X	22
11	ZHANG Y	22
12	LI X	21
13	WANG H	21
14	WANG S	20
15	HE X	19
16	JULIO CAMARERO J	19
17	FUNK C	18
18	KUMAR A	18
19	PAPPENBERGER F	18
20	ZHU Q	18

Table 3. The 10 most relevant affiliations.

Rank	Affiliations	Articles
1	COLUMBIA UNIV	141
2	NANJING UNIV INFORMAT SCI AND TECHNOL	125
3	COLORADO STATE UNIV	113
4	HOHAI UNIV	107
5	TEXAS AANDM UNIV	107
6	UNIV ARIZONA	103
7	INST ATMOSPHER PHYS	93
8	UNIV COLORADO	91
9	BEIJING NORMAL UNIV	89
10	PRINVETON UNIV	88

set by the Global Observing System (compared to 57% in 2011). These constraints are undoubtedly an obstacle to research in Africa and may explain the absence of African countries in the affiliations. It is therefore urgent to put in place strategies and action plans to stimulate research in drought forecasting, which will not only mitigate the consequences of droughts but also enable universities in underdeveloped countries to join the ranks of the best affiliations.

3.5. Top 10 Most Cited Documents

The distribution of the most cited papers in the world is presented in Table 4. It shows that the study by HOU AY (2014) has the highest total number of citations (1342), followed by KNAPP AK (2008) with 768 citations. The third position is occupied by HUXMAN TE (2004) with 757 total citations. XIA Y's (2012) article is in fourth position based on the total number of citations (684) while PIANI C (2010) is ranked fifth with 669 citations. WOOD AW (2002), ROBOCK A (2000), MISHRA AK (2011), DETTINGER MD (2011), and KUMAR KK (2006) close the circle with respectively 637, 604, 543, 543, and 510 citations each. However, it is surprising that no author in the top 10 most relevant authors has their paper(s) in this top 10 most cited papers. This may be due to several factors. Indeed, it was noticed on the one hand, that the most cited papers had titles with a word count of ten words, plus or minus three words [16]. On the other hand, the more an article has several co-authors, the more it is read and the more it is cited [16]. In addition, the more freely accessible an article is, the more it is cited [16]. Referring to these remarks, we made a connection with our study and we noticed that most of the papers of the most relevant authors were either paid, single-authored or less than four authors. This would certainly explain their absence in the top 10 most cited papers. On the other hand, when we analyze the most cited papers, we notice that these papers usually have more than five authors and are free, which favors access to mass reading and consequently increases the number of citations of the said papers.

Table 4. Top 10 most cited documents.

Rank	Paper	Total number of citations
1	HOU AY, 2014, BULLAMER METEOROL SOC	1342
2	KNAPP AK, 2008, BIOSCIENCE	768
3	HUXMAN TE, 2004, NATURE	757
4	XIA Y, 2012, J GEOPHYS RES—ATMOS	684
5	PIANI C, 2010, THEOR APPL CLIMATOL	669
6	WOOD AW, 2002, J GEOPHYS RES—ATMOS	637
7	ROBOCK A, 2000, BULLAMER METEOROL SOC	604
8	MISHRA AK, 2011, J HYDROL	543
9	DETTINGER MD, 2011, WATER	543
10	KUMAR KK, 2006, SCIENCE	510

3.6. Top 10 Scientific Production and Most Cited Countries

Table 5 presents the scientific production by country on drought forecasting. From this table, we can see that the USA occupies the first place with a production frequency amounting to 4387, followed by China which holds a production frequency of 2281 and the United Kingdom in third position with a frequency of 743. Then we have Australia which is ranked fourth with a document production frequency equal to 692, while Spain and India occupy the fifth and sixth places with respectively a production frequency amounting to 577 and 478. The other four countries in this short list have less than 450 relevant publications. These are: Iran (431), Germany (392), France (367) and Italy (365).

Regarding the top 10 most cited countries, Table 6 shows that the USA leads with the highest number of citations (38,049), followed by China with 6795. Next

Table 5. Top 10 country-related scientific productions.

Rank	Region	Frequency
1	USA	4387
2	CHINE	2281
3	Royaume-Uni	743
4	AUSTRALIE	692
5	Espagne	577
6	INDE	478
7	IRAN	431
8	GERMANIE	392
9	FRANCE	367
10	ITALIE	365

Table 6. Top 10 most cited countries.

Rank	Country	Total number of citations	Average article citations
1	USA	38,049	40.26
2	CHINE	6795	14.10
3	AUSTRALIE	5129	31.06
4	ROYAUME-UNI	5027	34.20
5	CANADA	3422	38.89
6	ESPAGNE	3125	22.81
7	ITALIE	2952	29.52
8	INDE	2555	17.74
9	IRAN	2278	17.66
10	NETHERLAND	1686	34.41

is Australia with a total of 5129 citations, the UK with 5027 citations, Canada with 3422 citations and Spain with a total of 3125. All other countries in this top 10 have a total number of citations below 3000 (between 2952 and 1686). This tendency could be justified by the fact that scientists from these countries would have carried out a lot of research in this field, which would have resulted in an increase in their scientific production in terms of documents.

3.7. Word Cloud Related to Drought Forecasting

Figure 4 and Figure 5 show the word cloud related to drought forecasting and the most used words, based on results from the WoS database.

These figures highlight the keywords most frequently used by authors in their

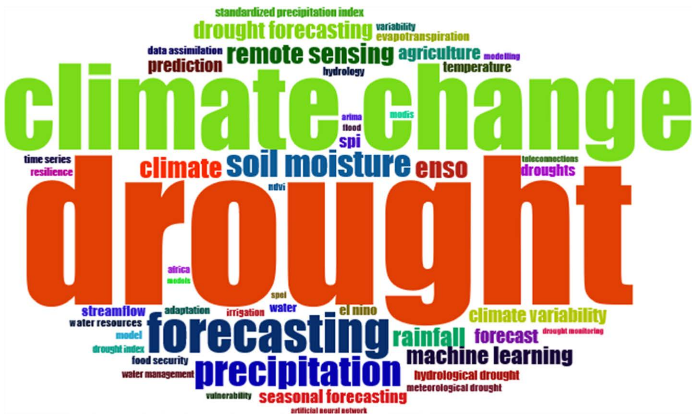

Figure 4. Word cloud related to drought forecasting in WoS.

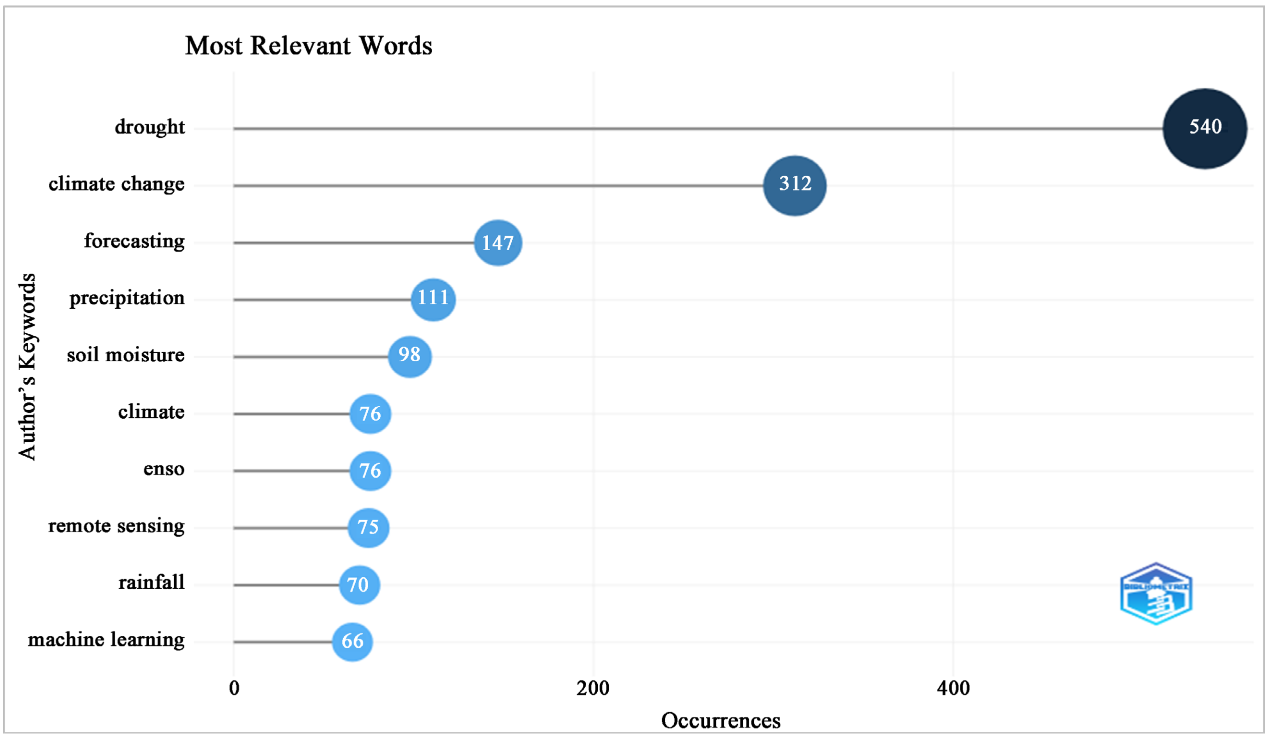

Figure 5. Most frequent words.

various publications. According to Figure 4 and Figure 5, the three words with the highest number of occurrences are drought (540 occurrences), climate change (312 occurrences) and forecasting (147 occurrences). Indeed, the word cloud reveals that drought and climate change are two highly correlated phenomena. The word forecasting is also highlighted because drought forecasting occupies an important place in measures against droughts. We also note the presence of keywords such as SPI and machine learning in the word cloud because they are respectively an index and a technique to predict droughts. The word cloud also contains the word ENSO which is one of the most important climatic phenomena on earth because of its ability to the global atmospheric circulation which in turn influences the temperature as well as the precipitation in the world.

3.8. Co-Occurrence Network

The co-occurrence network is shown in Figure 6. Indeed, co-occurrence is the fact that two or more words appear together. It would be considered as a method of text analysis including a graphical visualization of existing relationships between concepts, organizations or people. Our co-occurrence analysis revealed four (04) clusters (see Figure 6). In each cluster, there is one element that predominates the other elements. Through this figure, we notice that "drought" and "climate change" are the most cited elements when considering all four clusters. This reveals that these two topics were the most discussed in all publications.

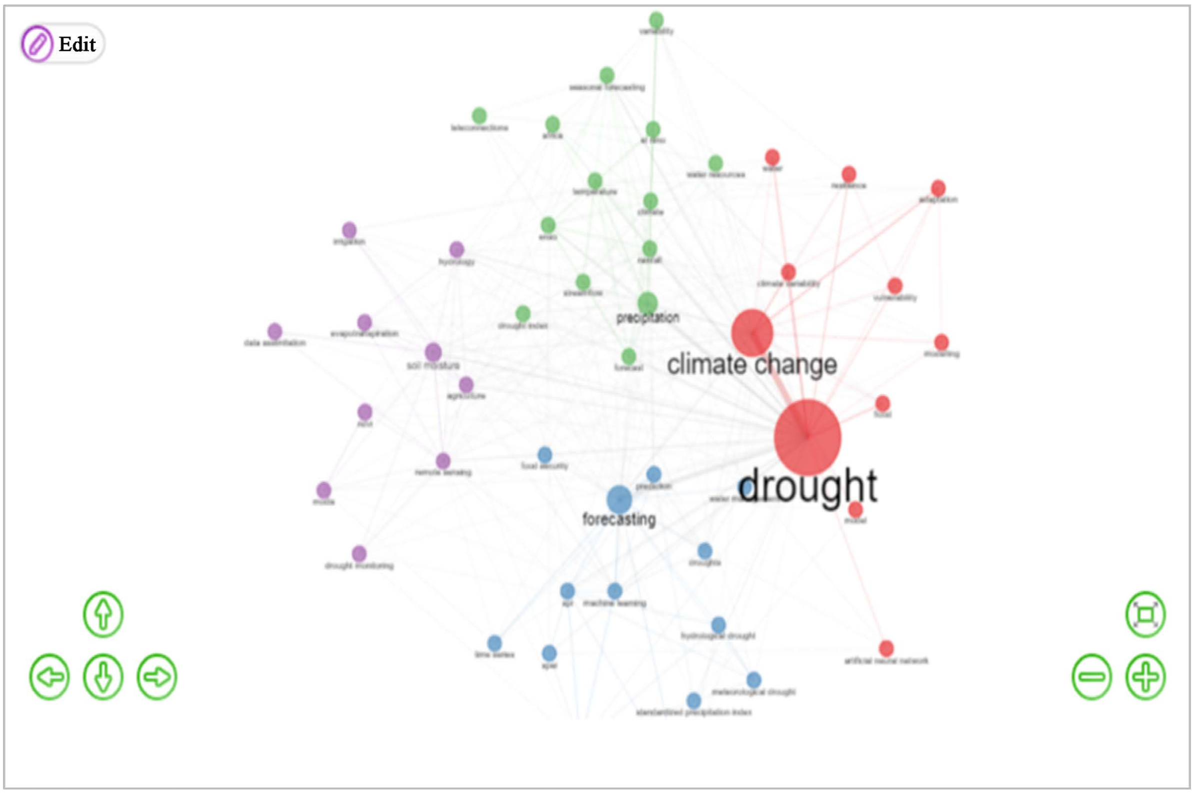

Figure 6. Co-occurrence network.

3.9. Conceptual Structure Map

Figure 7 shows the result of the conceptual structure. It represents the word analysis that was performed on the word co-occurrences of the bibliographic data on drought forecasting extracted from the articles in the WoS database. Using multiple correspondence analysis (MCA), we were able to identify two (02) groups (clusters) of documents communicating similar concepts. Thus, it can be observed that both clusters deal with drought related topics but the first cluster containing more concepts (e.g. droughts, machine learning, spi, evapotranspiration...) generally deals with drought forecasting while the second cluster made of two elements NDVI (Normalized Difference Vegetation Index) and MODIS (Moderate-Resolution Imaging Spectroradiometer) is related to vegetation. The fact that they come in second position, reveals that there is a convincing link in vegetation and drought. MODIS represents the technology used to collect the satellite data and NDVI represents the graphical indicator used to analyze the remote sensing measurements. These two elements of the second cluster are found together because it is the spatial data (remote sensing measurements) collected through MODIS satellite that are analyzed using the NDVI indicator.

3.10. Collaboration Mapping between Countries

Figure 8 shows some key collaborations between countries. As shown in the figure, the strongest collaborations are nurtured by American and Asian researchers, who link with their counterparts in various countries around the world. Furthermore, we recognize that European and African countries have few international collaborations compared to America and Asia.

3.11. Word Cloud of Drought Indices

Figure 9 shows the different indices used to monitor and predict droughts early

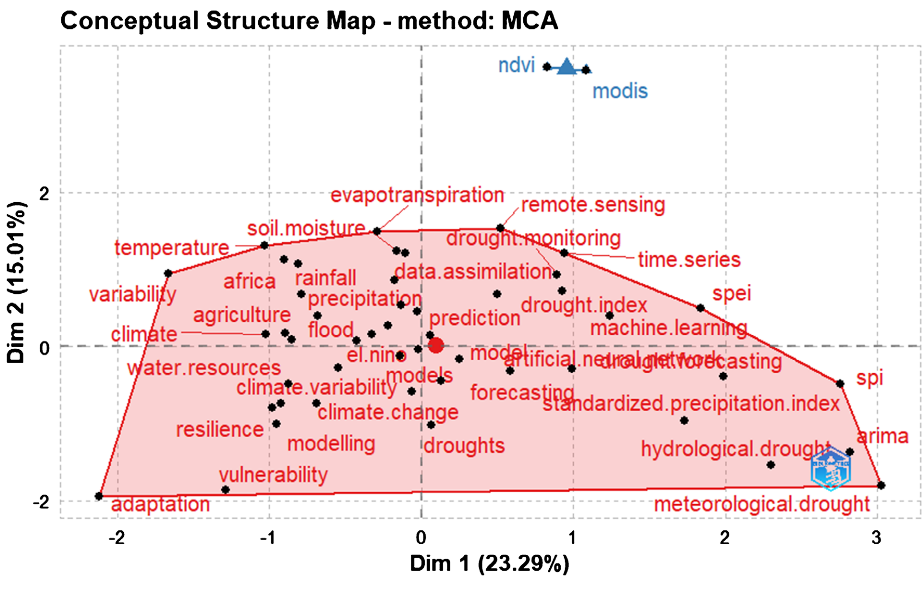

Figure 7. Conceptual structure map.

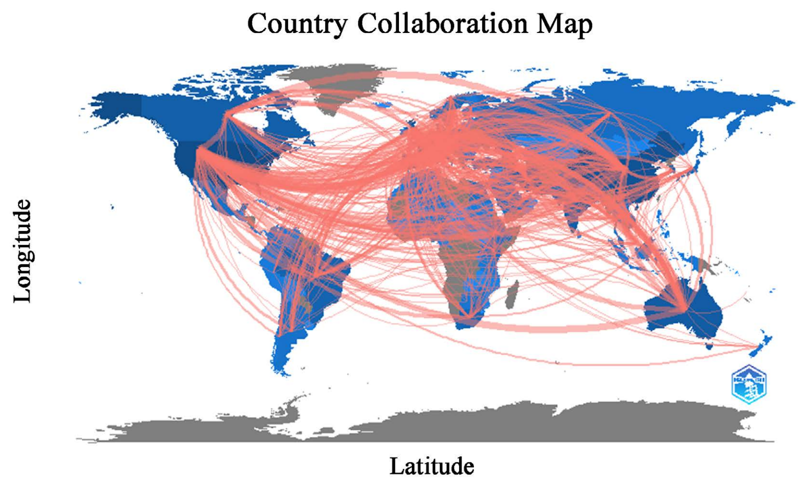

Figure 8. WorldMap collaboration.

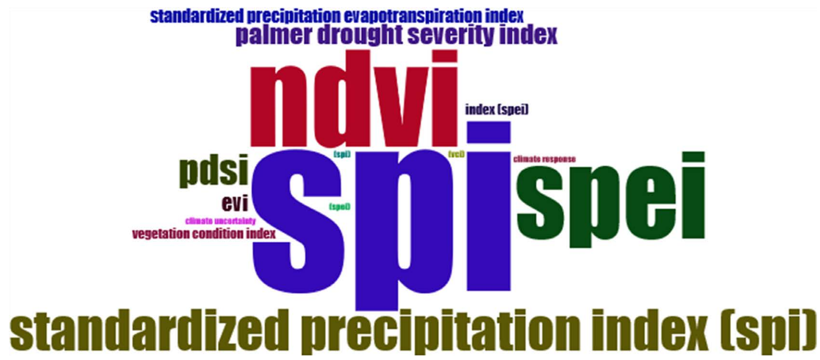

Figure 9. Word cloud of drought indices.

in order to facilitate the implementation of mitigation plans and measures in the regions most affected by these droughts in the world. These indices have been approved by the World Meteorological [17]. This word cloud puts more emphasis on the index: SPI, NDVI, SPEI, whose occurrence of appearance are respectively: 49, 28 and 25. The Standardized Precipitation Index (SPI) was developed in 1992 by McKee and co-workers at Colorado State University (USA). It makes it possible to follow droughts through their intensity, their occurrence and their amplitude. It is simple to use as it only requires one set of rainfall data to be calculated. It has been exploited in [10] [18] to monitor droughts in the state of Karnataka in India and the Awash River Basin in Ethiopia, respectively. Another index commonly used in drought prediction is the standardized precipitation and evapotranspiration index (SPEI). It was implemented by Vicente-Serrano and his collaborators at the Pyrenean Institute of Ecology in Zaragoza (Spain). Its calculation is based on the same indicators as the SPI except that the temperature is added to it in order to take it into account on the evolution of the drought. It has been adopted by the works [3] [19]. The Normalized Difference Vegetation Index (NDVI) is a simple graphical index that is used to monitor vegetation by analyzing measurements obtained using remote sensing. The only parameters necessary for its implementation are information from satellite platforms. [20] used this index to map the occurrence, extent as well as intensity of drought in Kenya based on data from the Moderate Resolution Imaging Spectrometer (MODIS) at 250 meter resolution. Through this word cloud, we notice that SPEI is written in several different ways namely: spei, index (spei), (spei), and standardized precipitation evapotranspiration index. Also, we see that SPI is written in several different ways: (spi), spi, standardized precipitation index (spi). This multiple appearance of these terms means that several works have exploited the SPI and the SPEI using different ways of writing these indexes.

3.12. Word Cloud of Drought Prediction Algorithms

Figure 10 outlines the different algorithms or approaches used to predict droughts. All of these approaches have one thing in common. They use historical climate data to create models that can be used to predict drought conditions or events. These algorithms thus presented can be categorized into two groups, namely: Statistical methods and Machine Learning (Artificial Intelligence) methods. Statistical methods include: ARIMA model, linear regression, logistic regression. Machine learning methods include the rest of the algorithms. As can be seen in the word cloud, the algorithms: ANN (artificial neural networks), support vector machine, ARIMA model, extreme machine learning, ANFIS (Adaptive Neuro Fuzzy Inference System) and LSTM (Long Short Term Memory) are those that are most highlighted with respectively the following occurrences: 16, 10, 10, 9, 9 and 7. This means that these algorithms have been used more in the works whose references we have collected from WoS. These different approaches have been used in several research projects on drought prediction. LSTM was used by [1] to implement a model to help examine different characteristics of drought; Artificial neural networks and support vector regression were used by [3] to create a model to understand the effect of drought in the New Wales region of South in Australia; The extreme learning machine (ELM) was used to identify drought situations by predicting SPI and SPEI in the Cai River Basin in Vietnam [19]; to name just those

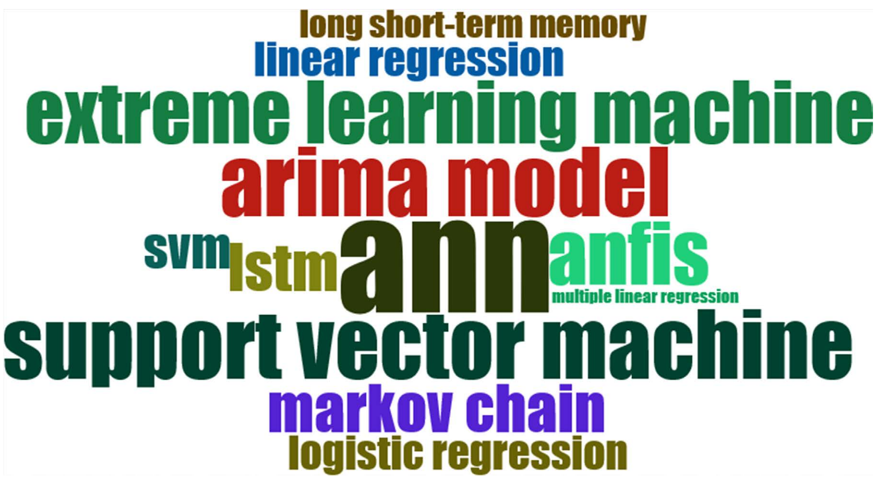

Figure 10. Word cloud drought prediction algorithms.

4. Contributions

This work provides essential information on the authors who have worked the most on drought forecasting, the most cited affiliations, and the most relevant existing sources on this topic. In addition, this study reveals the dynamics of the evolution of drought forecasting research over the years. One of the important points raised by this study is that despite Africa being one of the most drought-prone continents, no African country appears in the top 20 most cited countries. Kenya and Zimbabwe are only ranked 28th and 30th respectively. Among the top 100 most relevant affiliations, no affiliation from Africa is present. This reveals the delay of Africa in terms of studies relating to drought forecasting compared to other continents which invest enormously in this area. This study also demonstrates that Africa's lag behind other continents in drought forecasting research is not only due to the fact that Africa has little data communication infrastructure that meets the standards set by the Global Observing System but also her lack of national funding for research projects carried out by African scientists. All this constitutes a major constraint to research in Africa.

5. Limits

Despite the important aspects covered by this study, it is not without limitations. The fact that we used keywords to carry out the search does not guarantee that all the articles that have been published and that deal with the analyzed subject have been fully taken into account. Similarly, restricting our choice to a single database, in this case Web of Science (WoS), could represent a limitation in the search. Moreover, this study was conducted using a traditional bibliometric approach as the primary method of literature analysis. Future studies could combine several literature analysis approaches for more enriching results.

6. Conclusion and Future Research Directions

The main objective of this paper was to provide a holistic view of the evolution of the field of drought forecasting. In order to achieve this objective, a bibliometric analysis of drought forecasting data extracted from the Web of Science (WoS) database was conducted. Key ideas presented included:

- The most relevant authors, affiliations and sources in the field of drought forecasting.
- The most relevant countries as well as those most cited in the field of drought forecasting.
- Most cited papers in the field of drought forecasting.
- Most used index and algorithms for drought forecasting.

For example, this study found that the majority of documents dealing with drought forecasting extracted from WoS were articles (3042 articles, compared to 37 early access articles), thus representing 93.63% of all documents identified. Therefore, for future research, it would be desirable to either balance the amount of document production by type a bit. Compared to other fields of study and based on the data extracted from the Web of Science (WoS), it is quickly realized that the topic of drought forecasting is a new subject because the first article having been published only dates from 2000. However, looking at the publication trend on drought forecasting since then (417 in 2021 and 147 in the second quarter of 2022), we can say that drought forecasting is a really worrying subject for the scientific world and it is attracting more and more research. Today, climate change is the greatest challenge facing humanity. Studies have shown that climate change is a factor that increases the duration and intensity of droughts. It is therefore quite normal that there is enough research on this subject.

According to [2] by 2050, more than three-quarters of the world's population could be affected by droughts, and an estimated 4.8 to 5.7 billion people will live in water-scarce regions for at least a month each year, compared to 3.6 billion today. And up to 216 million people could be forced to migrate by 2050, mostly due to drought, water scarcity, declining crop productivity, rising sea levels and overpopulation. These data prove once again the importance of taking seriously the issue of the drought which is slowly plunging humanity into chaos. According to the same COP15 report, Africa has suffered more frequent droughts than any other continent with a total of 134 droughts, including 70 in East Africa. But despite this, there is not enough research focused on drought forecasting in Africa. This remains a worrying situation and there is an urgent need for African countries to invest much more in research related to the development of drought forecasting tools.

In addition, this study has identified a multitude of research directions for further study. These are as follows:

1) Optimizing irrigation techniques for more profitable agriculture using Machine Learning approaches;

2) Applying Machine Learning and the Standardized Precipitation Index (SPI) to predict droughts in Africa;

3) Monitoring hydrological droughts using Machine Learning techniques;

4) Modeling climate variability in Africa using Machine Learning approaches;

5) Predicting the Evapotranspiration Index (SPEI) for estimating the intensity of meteorological droughts in Africa;

6) Combining the normalized difference vegetation index (NDVI) and Machine Learning techniques to assess drought dynamics in Africa;

7) Study the environmental vulnerability of African countries to the scale of climate change;

8) Applying Machine Learning to predict climate change in Africa.

We also believe that future studies should expand the scope of this study and improve its results by collecting more data from other sources, including other reference databases such as: Science Direct, Scopus, Dimensions, to name a few. [2].

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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