The global pattern and development trends & directions on the drought monitoring research from 1983 to 2020 by using bibliometric analysis

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ABSTRACT

As impacted by climate change and further global warming, drought turns out to be the most frequent meteorological extreme event worldwide, which severely affects agriculture, ecosystem, water management and even human survival. In this study, the global pattern and development trends & directions on drought monitoring were presented based on Web of Science database by conducting a bibliometric analysis from 1983 to 2020. The following conclusions were drawn. (1) The USA and China were found as the most productive and influential nations, accounting for 24.63% and 14.30% in publication outputs and taking up 5023 and 2040 in local citations, respectively. (2) Chinese Academy of Science was reported as the core institution with 5.73% publication outputs and 829 local citations. (3) *Remote Sensing of Environment* and *Remote Sensing* were found as the most influential journals and the most productive journals with 1045 local citations and 210 publication outputs, respectively. (4) Agricultural drought profoundly affecting food security was found as the most concerned drought type in the world. The drought monitoring research mainly focus on the research and development of drought index, the response of terrestrial ecosystems to drought, and the trends and dynamics of drought in context of climate change. This study explored key findings, contradictions, and limitations of drought monitoring studies were summarized and explored. In addition, the development trend and research direction of drought monitoring researches in the future were also explored.

**Keywords:** drought monitoring, bibliometric analysis, climate change, drought indices
CAPSULE

Academic landscape, research trend and direction on drought monitoring at a global prospective was achieved by using bibliometric analysis that based on published outputs and citations during 1983-2020.

1. Introduction

It is now considered that climate change is one of the primary threats for the planet earth in the 21st century (Mishra; Singh 2010). In the context of climate change, drought has become one of the most frequent meteorological extreme events and has various impacts on agriculture, ecosystem functions, and human social economy. According to the Intergovernmental Panel on Climate Change Assessment Report 5 (IPCC AR5), some parts of the world had experienced a trend of increasing drought intensity and longer duration since the 1950s, especially in Southern Europe and West Africa (Field et al. 2012). The USA had experienced a severe drought that devastated the Southern Plains region throughout the 1930s which affected almost two-thirds of the country and parts of Mexico and Canada (Schubert et al. 2004). From 1962 to 1963 and 2010 to 2011, two severe drought events affected more than half of the non-arid regions in China (Xu et al. 2015). From April to June 1988, many districts in Illinois, Wisconsin, Ohio, and Indiana of the USA experienced the driest April-May-June since 1895 (Trenberth et al. 1988), which caused many crops failure affecting the economy of this region and the country as a whole. Since September 2009, precipitation in Yunnan Province, China, was 60% less than normal years, and the estimated economic losses to reach 2.5 billion U.S. dollars due to crop failure (Qiu 2010). Severe droughts could also cause agricultural losses, food crises and even famines (Devereux; Sussex Univ. 2000; Zhang et al. 2018b; Zhang et al. 2020a). In recent years, drought was still raging most parts of the world and caused a certain economic loss (WMO 2019a, 2019b, 2021). Drought risk continued to increase in southwestern and southern China in context of climate change (Han et al. 2021; Zhang et al. 2015; Zhang et al. 2019b). Therefore, accurate drought monitoring is essential for reducing economic losses and ensuring food security. Drought monitoring provides an important basis for understanding and clarifying the mechanism of droughts occurrence and for deeper drought prediction. How to monitor and reduce the impacts of droughts scientifically and effectively has important social significance. Furthermore, revealing the problems in drought monitoring is also crucial to reducing the impact of drought.
Drought is usually considered as the following four primary types which are meteorological drought, agricultural drought, hydrological drought, socioeconomic drought by the American Meteorological Society (Orville 1990). Meteorological drought, agricultural drought, and hydrological drought were also called the three main physical drought types (Zargar et al. 2011). Recently, a new type of drought, ecological drought, had been proposed separately. Ecological drought referred to the deficit of effective ecological water that caused the ecosystems to exceed the vulnerability thresholds and thereby affecting the ecosystem service functions and services (Ramirez et al. 2017; Zhang et al. 2015). Droughts could be effectively monitored by drought indices that quantitatively assessed the intensity, duration, severity, and spatial extent for different across time scales, and especially for a longer periods (Mishra; Singh 2010).

There had been hundreds of indices for drought monitoring that could be classified into site-based and remote sensing-based (Heim 2002; Liu et al. 2016). WMO and GWP (Global Water Partnership) (Svoboda; Fuchs 2016) classified the drought indices by five classifications, that were meteorology (n = 27), soil moisture (n = 4), hydrology (n = 8), remote sensing (n = 10), and composite or modeled (n = 5). Among these indices, the most commonly used were Palmer drought severity index (PDSI) (Palmer 1965), Deciles (Gibbs; Maher 1967), crop moisture index (CMI) (Palmer 1968), Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), surface water supply index (SWSI) (Shafer; Dezman 1982), standardized precipitation index (SPI) (McKee et al. 1993), vegetation condition index (VCI) (Kogan 1995), and standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano et al. 2010) (Beguería et al. 2014; Mishra; Singh 2010; Zargar et al. 2011). The early drought indices are developed by site-based commonly, but they cannot effectively detect large-scale drought, especially in the areas of sparse ground sites. The combination of site-based and remote sensing-based is the tendency for recent relevant drought monitoring studies. Remote sensing-based drought indices had been widely developed to monitoring drought (Du et al. 2013; Hao et al. 2015; Keshavanzet al. 2014; Park et al. 2017a; Zhang; Jia 2013a).

Academic studies in the field of drought monitoring can promote people to control and reduce drought disasters indirectly and have high research value and application prospects. Recently, related studies on drought monitoring had rapidly increased (Jiao et al. 2021; West et al. 2019). Yet, we cannot know a huge amount of the related studies on drought monitoring...
one by one. More importantly, the traditional literature review is not easy to fully understand
the main context of the development of drought monitoring, as well as the main concerns of
various types of drought, and grasp the development direction of the discipline.
Consequently, a quantitative analysis of development trends on drought monitoring is helpful
to clarify the research results in the field and help researchers to keep up with the research
frontiers in this field. Furthermore, with the development of computer technology and big
data technology, it is possible to collect a certain amount of metadata to analyze the
development trend and research frontier of one research field. To obtain a systematic
understanding of the research field on drought monitoring, the bibliometric analysis was
employed to show research trends/topics and revealed the objective connections of each
research direction.

The bibliometric analysis, as a subdomain of scientometric, used a quantitative method
that took advantage of computer technology and statistics to identify the current research
status and trends of a specific research area (Chen et al. 2016a; Li et al. 2021; Zhang; Chen
2020). In addition, the bibliometric analysis could quantitatively study the information
process of a research field and effectively depicted the rules of discipline development which
had been used in many studies, including environmental footprint family (Xie et al. 2020),
remote sensing (Zhuang et al. 2012), spatial analysis (de Queiroz 2020), climate change
vulnerability (Wang et al. 2014), carbon emissions and environmental management (Su et al.
2020), world aerosol (Xie et al. 2008), ecological network (Borrett et al. 2018). However,
there is little research that focuses on the bibliometric analysis of drought monitoring at a
global level. Therefore, we revolved around the drought monitoring studies to present the
research trends to fill the gap in the bibliometric study on the field of drought monitoring.

To demonstrate the landscape of academic research in the field of drought monitoring, the
primary objective of the present paper used the bibliometric method to analyze the
development of studies of drought monitoring from 1983 to 2020. According to the
bibliometric analysis on drought monitoring field, we can (1) know global pattern on the
research field of drought monitoring, (2) present the developing trends and future research
directions, and (3) hold out key findings, contradictions and limitations of drought monitoring
studies.

2. Data and Method
a. Data Collection

The Science Citation Index Expanded (SCI-E) database is one of the main bibliographic databases produced by Clarivate Analytics, providing comprehensive coverage of the most important and influential research results from all over the world (Zhang; Chen 2020). This database has been used as data sources of the bibliometric analysis in many studies (Jiang et al. 2020; Liu et al. 2021; Verrall; Pickering 2020; Xie et al. 2020; Zhang; Chen 2020). Therefore, a bibliometric collection based on the SCI-E database was built in the “Web of Science Core Collection” as of Dec. 29, 2020. The retrieval formula “TS = (‘drought*’ AND ‘monitor*’) AND PY = (1980-2020)” was used, and 6322 items mainly in English, with Article (N = 5852; 81.96%), Proceedings papers (N = 1092; 15.29%), and Review (N = 196; 2.75%), were obtained from Web of Science (WoS) (http://apps.webofknowledge.com/) which less included Early access, Data paper, Book chapter, and Retracted publication.

b. Bibliometric Analysis

The bibliometric analysis mainly included co-citation analysis (Marshakova 1973; Small 1973), co-occurrence analysis (Callon et al. 1983), and co-authorship analysis (Li et al. 2021) in scientometric mapping, and they were used to detect and identify the research topics and trend that using keywords, collaboration network, and key references. The co-citation analysis, which was defined as two publications that were cited together in one article, could analyze the research front in a scientific domain (Boyack; Klavans 2010). The co-occurrence analysis also called co-words analysis which measures the frequency that two words appear in the same publication and reveals the relationships between research topics. After the construction of a co-occurrence network on keywords, the research trends and hot topics would be obtained (Leung et al. 2017). The co-authorship analysis means the collaboration relationship studies between countries, institutions, and authors, in other words, the authors from institutions of countries collaborate with other authors on a publication means they have collaboration relationships. In this study, co-citation analysis, co-occurrence analysis, and co-authorship analysis were conducted to use VOSviewer and bibliometrix (Aria; Cuccurullo 2017) of R. The bibliometrix was used to analyze the trends in research output regarding drought monitoring. The WOS metadata converted the bibliometrix package in R and author statistics are not affected by their countries and institutions. And it will not count the institution repeatedly, for example, if several authors of the same institution appear in one publication output, the institution will not be counted several times, as well as country. The
local citation score (LCS) and global citation score (GCS) of countries/territories, institutions, journals, and authors were calculated by HistCite. The LCS was the cited frequency of one publication output by an author in the “drought monitoring” were cited by other research field. The LCS and GCS of one publication output was assigned to corresponding authors, institutions, and countries that participated in the publication outputs.

Co-word analysis was employed to identify and visualize knowledge networks and their evolution of one research topic. The main principle was counting the similarity (or association strength) by the number of co-occurrences between subject words and keywords. Researchers could extract the concepts behind the words based on the frequency of the words appearing in the document, and directly capture the co-occurrence relationship and construct an analysis structure. A network relationship among different keywords could also generate by co-word analysis among different keywords. This was similar to identifying the co-citation of references and some visualization tools are adopted to depict their intricate relations. Keywords could provide important information about research trends, hot topics, and frontiers (Chiu; Ho 2007; Ji et al. 2014; Liu et al. 2012). In this study, the co-occurrence analysis on keywords was used to explore the topics and subjects on drought monitoring by VOSviewer (https://www.vosviewer.com). Similarity is a key parameter for co-word analysis, and it can be described as $s_{ij}$ between two items $i$ and $j$, which calculate as follows:

$$s_{ij} = \frac{c_{ij}}{w_i w_j}$$

where $c_{ij}$ denotes the number of co-occurrences of items $i$ and $j$ and where $w_i$ and $w_j$ denote either the total number of occurrences of items $i$ and $j$ or the total number of co-occurrences of these items (van Eck; Waltman 2010).

3. Results and discussion

a. Overall publication outputs trends

The annual publication outputs are figure out in Fig. 1a. There are only 11 publication outputs related to drought monitoring before 1991 and break through 100 publication outputs in 2006. The annual publication outputs increase from 1 in 1983 to 740 in 2020, with an average annual growth rate of 19.55% and 6322 accumulated publication outputs. The publication outputs per year have increased nearly 7 times from 2006 to 2020. While entering the 21st century, the number of annual publication outputs shows a steady growth trend. The
LCSs increase slowly from 1983 to 2012 and decrease rapidly after 2017. After new papers were published, it took time for the growth of LCS to appear, and there was a time lag between the increase of publication output and local citations. In addition, it can be observed from Fig. 1a that the highest LCS is found in the year 2013 with a publication output more than 700, and instead, the lowest LCS is observed before 1991. The average publication citations per year is shown in Fig. 1b. The average publication citations per year have continued to increase slowly from 2003 to 2020.

Fig. 1 Overall trends of topic publication from 1983 to 2020, a is accumulated publication and annual publication, where LCS represents local citation score.

b. Publication outputs and citation analysis of regions, institutions, journals, and authors
1) Territories and Countries Analysis

It is shown the top 30 most productive countries from the six continents with single country publication outputs and multiple country publication outputs in Table 1 and Fig. 2. The authors from 164 countries and territories participate in drought monitoring studies. North America represented by the USA has the highest continental publication outputs with 1790, followed by Europe with 1746 and Asia with 1564. Especially, Europe has the most authors over the top 30 most productive countries that participate in drought monitoring studies. The continental publication outputs of North America, Europe and Asia account for majority of all publication outputs which indicate that these three territories are the core area in drought monitoring studies, and the representative countries of these three core areas are the USA, Spain and China. The first most productive country is the USA with more than 1500 publication outputs, followed by China with more than 900 publication outputs. China has the highest multiple country publication outputs with 337, followed by the USA with 289 publication outputs. This shows that China is more interested in cooperating with other countries.

<table>
<thead>
<tr>
<th>Continent</th>
<th>Publication Output</th>
<th>LCS</th>
<th>GCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>North America</td>
<td>1790</td>
<td>5326</td>
<td>84269</td>
</tr>
<tr>
<td>Europe</td>
<td>1746</td>
<td>4247</td>
<td>108544</td>
</tr>
<tr>
<td>Asia</td>
<td>1564</td>
<td>3366</td>
<td>36099</td>
</tr>
<tr>
<td>Oceania</td>
<td>364</td>
<td>436</td>
<td>13914</td>
</tr>
<tr>
<td>South America</td>
<td>183</td>
<td>267</td>
<td>15070</td>
</tr>
<tr>
<td>Africa</td>
<td>84</td>
<td>85</td>
<td>4354</td>
</tr>
</tbody>
</table>

Table 1. The publication output, LCS and GCS of every continent.
According to Table 1, the top 30 highest LCS countries from North America have the highest continental LCS of 5326; Europe and Asia are behind North America with continental LCS of 4247 and 3366, respectively. North America, Europe and Asia are the top three most influential continents. It is clear to find that North America, Europe and Asia are the core areas for drought monitoring studies from 1983 to 2020. In Fig. 2, the USA has the highest LCS with 5023, followed by China with 2040, and LCS of the USA is more than twice that of China. Besides, the researchers from Spain also contribute higher LCS with 1241. The USA has the highest GCS at 74690, which has the highest LCS and publication output.

The top 30 most productive countries are analyzed by co-authorship analysis in the field of drought monitoring during 1983-2020. As shown in Fig. 3, the collaborative network between the USA and China is the closest over the top 30 most productive countries, and the
USA, China, Australia, and Canada belong to the representative countries of red collaboration network. The blue collaboration network mainly represents by Germany, U.K., Spain, Netherland, and Switzerland. The USA and China cooperate with other countries most frequent in the field of drought monitoring.

Fig. 3. The cooperation network of the top 30 countries which have the closest collaboration relationship. The thickness of connected line between every node of countries shows the level of partnership between countries, the thicker the line, the closer the partnership is. The size of node of countries represents the frequency of international collaboration, the larger the node size, the more frequent it is. The fill color of the circle only represents the belongingness of the cooperative network.

The top 10 most relevant keywords of every continent analyzed by bibliometrix package are shown in Table 2. North America represented by the USA focus on the utilization of remote sensing for meteorological drought and agricultural drought monitoring, and using datasets derived from remote sensing to drive climate models to study the impact mechanism of climate change on droughts. Europe countries represented by Spain, Germany, Italy, the U.K. and France focus on monitoring agricultural drought with remote sensing as the main methods and studying the response of terrestrial ecosystems to drought in context of climate change. Asian countries represented by China tend to use remote sensing to monitor agricultural droughts and use climate models to study the impact of climate change on terrestrial ecosystems and agriculture. Oceania countries represented by Australia tend to study the use of remote sensing to monitor hydrological droughts, forest fires that are closely
related to droughts, and water resource management. South America represented by Brazil focus on studying the response of terrestrial ecosystems to droughts and monitoring and assessing the impact of seasonal drought on forest ecosystems. African countries represented by South Africa focus on remote sensing monitoring of agricultural droughts and monitoring of terrestrial ecosystem responses to droughts with a focus on forest mortality and forest fires.

<table>
<thead>
<tr>
<th>Continents</th>
<th>Author’s Keywords</th>
<th>Keywords Plus</th>
</tr>
</thead>
<tbody>
<tr>
<td>North America</td>
<td>drought, climate change, remote sensing, soil moisture, MODIS, evapotranspiration, NDVI, monitoring, drought monitoring, precipitation</td>
<td>drought, climate change, growth, model, vegetation, dynamics, climate, temperature, variability, precipitation</td>
</tr>
<tr>
<td>Europe</td>
<td>drought, climate change, remote sensing, drought stress, NDVI, water stress, soil moisture, MODIS, drought monitoring, monitoring</td>
<td>drought, climate change, growth, variability, responses, climate, vegetation, dynamics, model, water</td>
</tr>
<tr>
<td>Asia</td>
<td>drought, remote sensing, soil moisture, drought monitoring, climate change, MODIS, SPI, drought stress, NDVI, agricultural drought</td>
<td>drought, temperature, vegetation, variability, model, precipitation, index, climate change, soil moisture, growth</td>
</tr>
<tr>
<td>Oceania</td>
<td>drought, climate change, Australia, monitoring, remote sensing, climate variability, groundwater, rainfall, stomatal conductance, fire</td>
<td>drought, climate change, variability, rainfall, growth, management, vegetation, Australia, dynamics, responses</td>
</tr>
<tr>
<td>South America</td>
<td>drought, climate change, Brazil, drought monitoring, remote sensing, Amazonia, water deficit, photosynthesis, seasonality, SPI</td>
<td>drought, climate change, growth, variability, dynamics, climate, vegetation, patterns, precipitation, temperature</td>
</tr>
<tr>
<td>Africa</td>
<td>drought, climate change, South Africa, remote sensing, mortality, southern Africa, agriculture, drought stress, fire, food security</td>
<td>rainfall, drought, vegetation, climate-change, dynamics, patterns, variability, biodiversity, fire, growth</td>
</tr>
</tbody>
</table>

Table 2. The top 10 most relevant keywords of territories/countries.
2) INSTITUTION, JOURNAL, AND AUTHOR ANALYSIS

According to this study, 5811 institutions worldwide have joined in research on drought monitoring (Fig. 4). Chinese Academy of Science (CAS), which accounts for 15.74% of publication outputs in the top 10 most productive institutions, is far ahead of other institutions with 362 publication outputs from 1983 to 2020, followed by USGS (United States Geological Survey) with 140 publication outputs. The University of Nebraska has the highest LCS with 1529, followed by the CAS with 829 (Fig. 4). However, the CAS has the highest contribution for drought monitoring study, its LCS is only 829 which does not exceed 1000. The institutions from the USA and China are the dominant organizations of the top 10 highest LCS institutions that engaged in this study topic, such as the University of Nebraska and the CAS. Only the CAS and Beijing Normal University belong to China’s organizations, dominated by institutions from the USA over the top 10 highest LCS institutions. Beijing Normal University from China has 50 publication output as the first institution. The highest GCS is NASA with 8272, followed by the CAS with 6908. Therefore, the CAS is the core institution in the field of drought monitoring research which has higher publication outputs, LCS and GCS.

Fig. 4. The top 10 authors with publication outputs, LCS, and GCS.

A total of 1123 journals publish 6322 publication outputs related to drought monitoring, with 4 publication outputs per journal on average (Fig. 5). The top three journals, Remote Sensing (N = 210; IF2020 = 4.848), Remote Sensing of Environment (N = 118; IF2020 = 10.164), and International Journal of Remote Sensing (N = 116; IF2020 = 3.151), have
exceeded 100 publication outputs per journal which almost focus on remote sensing technology and show that studies from this field usually using remote sensing as tools to monitor drought. Remote Sensing of Environment which with LCS of 1045, GCS of 8609, and higher publication outputs, followed by Bulletin of The American Meteorological Society (BAMS) with LCS of 969 and GCS of 4417.

The analyzed publication outputs record 22416 authors, of whom 17976 (80.19%) had published only one paper from 1983 to 2020. It should be noted that when calculating publication outputs, we do not distinguish the order of the authors in the name list. Owing to the abbreviation of the name of Chinese scholars are easy to confuse, the publication outputs of Chinese scholars are identified and distinguished one by one to avoid duplicate statistics. The top 10 most productive authors mainly come from the USA (Singh V. P., Anderson M. C., Svoboda M., and Tadesse T.), Spain (Penuelas J., Camarero J. J., and Vicente-Serrano S. M.), and China (Qin QM) whose publication outputs are more than 10. The top 10 highest LCS authors are shown in Fig. 3. The top 3 authors have both high publication outputs and LCSs, who are Svoboda M. with LCS of 611, Anderson M. C. with LCS of 542, and Kogan F. N. with LCS of 537. Singh V. P. is the most productive author with 32 publication outputs; however, he is not the top 10 LCS authors. Hao ZC, as an influential author with higher LCS and GCS, has 13 publication output as the first author. The highest GCS on authors is Anderson M. C. with 2038.
Fig. 6. The top 10 authors with publication outputs, LCS, and GCS.

c. Research topics and themes

The most frequent keywords during 1983-2020, including the top 30 most frequent author’s keywords and keywords plus, are shown in Table 3, except for “drought”, “monitoring”, and “drought monitoring”. The top 3 most frequent author’s keywords are “climate change” (385 occurrences, 12.84%), “remote sensing” (259 occurrences, 2.59%), and “soil moisture” (178 occurrences, 5.94%) (Table 3). The ranked first keyword plus is also “climate change” with occurrences of 609, and “growth” rank second with 525 occurrences. Within the author’s keywords, “remote sensing”, “soil moisture”, “SPI” (145 occurrences, 4.84 %), and “NDVI” (129 occurrences, 4.30 %) are the commonly utilized methods or metrics to monitor drought during 1983-2020, and “MODIS” (148 occurrences, 4.94 %) is the primary satellite remote sensing datasets to monitor drought. Furthermore, several studies focus on monitoring water and vegetation changes to assess drought, such as “soil moisture”, “NDVI”, “precipitation” (117 occurrences, 3.90 %), “water stress” (93 occurrences, 3.10 %), and “photosynthesis” (88 occurrences, 2.94 %). The “soil moisture” is usually related to the study of agricultural droughts because it is an important input parameter of agricultural drought index. The “SPI” (145 occurrences, 4.84 %) is the only drought index within the top 30 most frequent author’s keyword since it was proposed. It can obviously understand that the observation and simulation on some parameters, including “soil moisture”, “precipitation”, “evapotranspiration” (103 occurrences, 3.44 %), “temperature” (63 occurrences, 2.10 %), and “groundwater” (60 occurrences, 2.00 %), can indirect to monitor
drought. Some author’s keywords, including “management” (60 occurrences, 2.00 %) and “irrigation” (54 occurrences, 1.80 %), show the importance of human regulation activities to resist and reduce the effects of drought. In addition, some keywords, such as “photosynthesis”, “transpiration”, “phenology”, “stomatal conductance”, and “growth”, have been utilized to the research field of drought monitoring from the perspective of vegetation physiology and ecology.

<table>
<thead>
<tr>
<th>Author's keywords</th>
<th>Freq.</th>
<th>Keywords plus</th>
<th>Freq.</th>
</tr>
</thead>
<tbody>
<tr>
<td>climate change</td>
<td>385</td>
<td>climate change</td>
<td>609</td>
</tr>
<tr>
<td>remote sensing</td>
<td>259</td>
<td>growth</td>
<td>525</td>
</tr>
<tr>
<td>soil moisture</td>
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<td>vegetation</td>
<td>479</td>
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<tr>
<td>MODIS</td>
<td>148</td>
<td>variability</td>
<td>441</td>
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<tr>
<td>SPI</td>
<td>145</td>
<td>temperature</td>
<td>402</td>
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<tr>
<td>NDVI</td>
<td>129</td>
<td>model</td>
<td>392</td>
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<td>drought stress</td>
<td>126</td>
<td>dynamics</td>
<td>368</td>
</tr>
<tr>
<td>precipitation</td>
<td>117</td>
<td>responses</td>
<td>368</td>
</tr>
<tr>
<td>water</td>
<td>113</td>
<td>precipitation</td>
<td>366</td>
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<td>evapotranspiration</td>
<td>103</td>
<td>climate</td>
<td>364</td>
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<tr>
<td>water stress</td>
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<td>water</td>
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<tr>
<td>photosynthesis</td>
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<td>index</td>
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<td>forest</td>
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<td>management</td>
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<td>temperature</td>
<td>63</td>
<td>impacts</td>
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</table>
Table 3. The top 30 most frequent keywords from 1983 to 2020. The “Percentage %” represents the percentage of the top 30 author’s keywords or keywords plus.

<table>
<thead>
<tr>
<th>keyword</th>
<th>frequency</th>
<th>keyword</th>
<th>frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>groundwater</td>
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<td>plants</td>
<td>209</td>
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<tr>
<td>management</td>
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<td>trends</td>
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<td>transpiration</td>
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<td>MODIS</td>
<td>183</td>
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<td>phenology</td>
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<td>NDVI</td>
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<td>stomatal conductance</td>
<td>59</td>
<td>impact</td>
<td>180</td>
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<td>resilience</td>
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<td>soil</td>
<td>177</td>
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<td>United-States</td>
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<tr>
<td>soil</td>
<td>55</td>
<td>photosynthesis</td>
<td>174</td>
</tr>
<tr>
<td>irrigation</td>
<td>54</td>
<td>tolerance</td>
<td>160</td>
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<tr>
<td>growth</td>
<td>52</td>
<td>evapotranspiration</td>
<td>151</td>
</tr>
<tr>
<td>index</td>
<td>50</td>
<td>yield</td>
<td>144</td>
</tr>
</tbody>
</table>

The frequencies of keywords for every year were counted, and the trend topic was achieved by the bibliometrix package in R (Aria; Cuccurullo 2017). As shown in Table 4, owing to the study topic is drought monitoring, the highest author’s keywords “monitoring” cannot represent the trend topic in 2016 to a certain extent, while the followed author’s keyword is “evapotranspiration” with 103 frequencies which should be the trend topic in 2016. Thus, the most frequent trend topic is “water” with 113 frequencies from 1983 to 2020, followed by “evapotranspiration” in 2016. During 2016-2020, “evapotranspiration” is the most frequent trend topic, followed by “agriculture” with 68 frequency. Especially, the trend topic of 2020 is “machine learning”, and this results in line with the development trend on drought monitoring forecasts in recent years. Some drought monitoring methods that combine mathematical and physical methods may be the mainstream direction of drought monitoring in the future. SPEI is a popular drought index in recent studies proposed by Vicente-Serrano et. al in 2010, and it becomes the trend topic in 2019. The trend topics relate to plant or crop closely from 2011 to 2015, like “photosynthesis”, “growth”, “yield”, and “stomatal conductance”. The stomatal conductance of plants characterized the level of soil moisture and vegetation photosynthesis capacity to a certain extent. Further, soil moisture and agriculture drought are relevant, and soil moisture drought is also termed agricultural drought. During
2006-2010, “nitrogen” is the most frequent trend topic. The nitrogen content of plant leaves can show soil moisture condition, therefore, according to the nitrogen content of plant leaves can reflect drought stress indirectly. It is specially mentioned that “Australia” is the trend topic of 2010 and the only country that appears in trend topics, due to severe drought from 2000 to early 2010 in Australia which is also known as the Millennium drought. The “water relations” is the most trend topic from 2001-2005. Before 2000, most trend topics are related to plants that deeply responding to drought stress, like “sap-flow”, “leaf water”, “bud break”, “crassulacean acid metabolism”, and “leaf growth”. Furthermore, there were few studies on drought monitoring that retrieved, so some keywords were not very closely related to drought monitoring studies before 2000.

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Freq.</th>
<th>Year</th>
<th>Keywords</th>
<th>Freq.</th>
<th>Year</th>
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<tr>
<td>machine learning</td>
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<td>sap-flow</td>
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<td>seasonal drought</td>
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<td>2000</td>
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<tr>
<td>agriculture</td>
<td>68</td>
<td>2017</td>
<td>drought policy</td>
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<td>2000</td>
</tr>
<tr>
<td>monitoring</td>
<td>170</td>
<td>2016</td>
<td>leaf water</td>
<td>5</td>
<td>2000</td>
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<td>water</td>
<td>113</td>
<td>2015</td>
<td>Mojave Desert</td>
<td>5</td>
<td>1999</td>
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<tr>
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<td>88</td>
<td>2014</td>
<td>osmotic potential</td>
<td>9</td>
<td>1998</td>
</tr>
<tr>
<td>growth</td>
<td>52</td>
<td>2013</td>
<td>patch dynamics</td>
<td>3</td>
<td>1997</td>
</tr>
<tr>
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<td>59</td>
<td>2012</td>
<td>desert tortoise</td>
<td>3</td>
<td>1997</td>
</tr>
<tr>
<td>yield</td>
<td>28</td>
<td>2011</td>
<td>arbuscular mycorrhiza</td>
<td>4</td>
<td>1996</td>
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<tr>
<td>Australia</td>
<td>32</td>
<td>2010</td>
<td>bud break</td>
<td>4</td>
<td>1995</td>
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<td>2009</td>
<td>crassulacean acid metabolism</td>
<td>5</td>
<td>1994</td>
</tr>
<tr>
<td>population dynamics</td>
<td>20</td>
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<td>cam</td>
<td>3</td>
<td>1993</td>
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<tr>
<td>nutrients</td>
<td>23</td>
<td>2007</td>
<td>nicotiana-tabacum l</td>
<td>3</td>
<td>1993</td>
</tr>
<tr>
<td>potential</td>
<td>19</td>
<td>2006</td>
<td>leaf growth</td>
<td>5</td>
<td>1992</td>
</tr>
<tr>
<td><em>picea abies</em></td>
<td>19</td>
<td>2005</td>
<td>sorghum-bicolor</td>
<td>2</td>
<td>1991</td>
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</tbody>
</table>
Table 4. Trend topics of author’s keywords produce by the bibliometrix package in R, and word minimum frequency and the number of words per year are both set as 1.

<table>
<thead>
<tr>
<th>Water Relations</th>
<th>Year</th>
<th>Tuber Growth</th>
<th>Year</th>
<th>Water Movement</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>quercus ilex</td>
<td>17</td>
<td>2003</td>
<td>1</td>
<td>1989</td>
<td></td>
</tr>
</tbody>
</table>
impacts of internal climate variability and anthropogenic climate change on future meteorological drought trends over China. The green cluster, including “precipitation”, “soil moisture”, “model”, “climate”, “evapotranspiration”, “water”, “severity index”, “United-States”, tend to study the response of soil moisture and ET to drought using model simulation. The 2012 meteorological drought in the Great Plains of the United States depleted soil moisture by 72% to 80% what was land surface model simulations revealed (Livneh; Hoerling 2016). By using hydrological model simulation, meteorological droughts caused by decreased precipitation had greater effects on evapotranspiration and soil moisture than increased temperature and disturbed land cover over the North America High Plains (Hein et al. 2019).

Fig. 8. Co-occurrence network of agricultural drought.

The red cluster includes “drought”, “climate change”, “variability”, “agriculture”, “impacts”, “trends”, “dynamics”, “management”, “yield”, and “irrigation”. This cluster focuses on the impacts of climate change and climate variability on agricultural drought dynamics and trends, and water management in agricultural drought. The climate models and hydrological models were used to assess the impacts of climate change on agricultural drought (Wang et al. 2011). Based on future climate scenarios of General Circulation Models (GCMs), the evolution of future global drought would bring a threat on utilization and management of global water for agricultural production, and the trend of severe drought in Africa, North America, South America and Oceania in the future was detected (Lu et al. 2019). The green cluster, tending to the utilization of remote sensing vegetation index for
agricultural drought monitoring, includes “agricultural drought”, “MODIS”, “NDVI”, “vegetation”, “temperature”, “remote sensing”, “vegetation index”, “drought monitoring”, “meteorological drought”, “satellite”, “stress”. Applying of MODIS NDVI and LST data, the temperature vegetation dryness index (TVDI) was calculated for agricultural drought monitoring and important for water planning and management to mitigate impacts on agriculture in the region (Son et al. 2012). To solve the problem that characterizing drought conditions in humid regions was limited, the Scaled Drought Condition Index (SDCI) was developed by combining the LST and NDVI from MODIS for agricultural drought monitoring in both arid and humid regions (Rhee et al. 2010). The blue cluster is consisted by “soil moisture”, “model”, “precipitation”, “climate”, “evapotranspiration”, “SPI”, “water”, “indexes”, “China”, “validation”, and “United-States”, focused on using soil moisture, precipitation, and evapotranspiration to develop drought index to characterize and analyze the agricultural drought. A hybrid drought index that based on a simple water balance model, the Precipitation Evapotranspiration Difference Condition Index (PEDCI), was introduced to monitor agricultural drought and meteorological drought over Oklahoma, USA (Tian et al. 2020). Using concept of copulas, a multivariate, multi-index drought-modeling approach is proposed to develop Multivariate Standardized Drought Index (MSDI) combined the SPI and the Standardized Soil Moisture Index (SSI) for drought characterization (Hao; AghaKouchak 2013).

Fig. 9. Co-occurrence network of hydrological drought.
The green cluster includes “SPI”, “hydrological drought”, “meteorological drought”, “index”, “drought monitoring”, “streamflow”, “prediction”, and “river-basin”. This cluster tends to study the response of hydrological drought to meteorological drought and agricultural drought, and the prediction of hydrological drought using the meteorological drought index. To predict hydrological drought, the copula function was adopted to model the dependence structure between meteorological and hydrological drought indices (Dehghani et al. 2019). Using observed precipitation and agricultural reservoir and dam storage levels with SPI, the relationship between droughts was analyzed (Bae et al. 2019). The red cluster includes “drought”, “climate change”, “hydrology”, “climate”, “impacts”, “dynamics”, “patterns”, and “groundwater”, which focuses on the impacts of climate change on hydrological drought from the perspective on groundwater and river of surface water. To quantify the impacts of climate change on hydrology, the climate projections of climate models were used to assess it, and the runoff can be an indicator for droughts (Hattermann et al. 2015). Using the global climate model (GCM) and hydrological model, the frequency of hydrological droughts, drought durations and intensities would have obvious increasing trends in the future under dry GCM conditions over the Weihe River basin, China (Zhao et al. 2019). The blue cluster includes “soil moisture”, “model”, “GRACE”, “MODIS”, “water”, “remote sensing”, and “evapotranspiration”, which tended to use soil moisture or terrestrial water component from model simulations or remote sensing to monitor hydrological drought. Combined soil moisture from the land surface model and remote sensing and total water storage from GRACE was employed to map droughts and floods (Abelen et al. 2015). Data assimilation of GRACE terrestrial water storage to estimate root-zone soil moisture could have a substantial impact on drought monitoring (Li et al. 2012b). The yellow cluster includes “precipitation”, “variability”, “temperature”, “management”, “trends”, and “United-States”, focuses on the impacts of variability in precipitation on hydrological drought, tended to study the influence of precipitation variability and trend on hydrological drought (Chu et al. 2010; Niu et al. 2017).

According to the co-occurrence analysis on keywords, the drought monitoring researches mainly concentrate on the research and development of drought index, the monitoring of drought dynamics and changes, and the monitoring the impacts of drought on terrestrial ecosystems.

4. Key findings, Contradictions, and Limitations
Satellite remote sensing, as the main approaches of earth observation, had been widely used in drought monitoring and analysis. Various land parameter products generated from satellite remote sensing observations were important inputs for drought monitoring. Key findings were explored around new sensors and instruments, data sets diversity, and data fusion/data assimilation. The contradictions and limitations in drought monitoring from the perspectives of satellite observational approaches, observational environment affecting the quality of datasets and products and data continuity were also explored.

a. Key findings

New satellite sensors and instruments facilitated the generation of new data sources, which improved the ability of drought monitoring and analysis. These new sensors and instrument included Global Navigation Satellite Systems (GNSS), Global Position System (GPS), and Sentinel-2 (Fig. 10). The surface displacements from GNSS observation could be used to infer temporal and spatial terrestrial water storage and further drought detection (Bonafoni et al. 2019). Joining Global Navigation Satellite System (GNSS) and GRACE, TWS with a higher spatial resolution was provided (Carlson et al. 2022) which could give a reference to groundwater monitoring with high spatial resolution. GNSS signal-to-noise data was used to estimate soil moisture and captured wet and dry events (Vey et al. 2016). GPS instruments were used to estimate drought-induced TWS variations in near real time what proved that GPS had potential to monitor drought (Chew; Small 2014). GPS-observed vertical crustal deformations (VCDs), strongly correlated to GRACE TWS, were employed to develop the GPS-based drought index (DIVCD) to monitor hydrological drought in Brazil which was useful to predict drought events (Ferreira et al. 2018). Sentinel-2 had higher spatial and temporal resolution than Landsat and MODIS, making it had potential on characterizing vegetation, soil moisture, ET, and surface water (Varghese et al. 2021). Some vegetation indices derived from sentinel-2, such as Carotenoid Reflectance Index, Anthocyanin Reflectance Index, Red-Green Ratio, Normalized Difference Infrared Index, Short Wave Infrared Ratio, Plant Senescence Reflectance Index, and Soil Adjusted Total Vegetation Index, might be give potential to assess droughts (Varghese et al. 2021). Yet, satellite remote sensing indices, such as NDVI, had a lag of roughly one to two months in response to changes in precipitation (Di et al. 1994; Yang et al. 1997). While solar-induced fluorescence (SIF) was closely related to plant photosynthesis and could be used for plant physiology and water stress assessment (Mohammed et al. 2019). SIFs, such as OCO-2 (Sun
et al. 2017) and TanSat (Du et al. 2018) provided, was well spatial resolution data; but their spatial and temporal continuity was poor, which still has limitations for long-term drought monitoring. The launch of some new satellite sensors, such as NASA OCO-3 and ESA Sentinel-4, would make up for this shortcoming (Chen et al. 2019).

Abundant products and datasets of droughts related metrics facilitated the generation of integrated drought monitoring indices and the monitoring of various types of droughts (Table 5). It was important to adopt an integrated index approach to drought monitoring (Jiao et al. 2021; Zhang et al. 2017b). Recently, serval new drought indices based on various datasets or products had been developed for meteorological, agricultural, and hydrological drought monitoring. These integrated index included Soil Moisture Evapotranspiration Index (SMEI) (Ajaz et al. 2019), Energy-based Water Deficit Index (EWDI) and Water Budget-based Drought Index (WBDI) (Sur et al. 2020), Standardized Evapotranspiration Deficit Index (SEDI) (Kim; Rhee 2016; Vicente-Serrano et al. 2018), Daily Evapotranspiration Deficit Index (DEDI) (Zhang et al. 2022), and Precipitation Evapotranspiration Difference Condition Index (PEDCI) (Tian et al. 2020). The satellite remote sensing-based integrated indexes included Synthesized drought index (SDI) (Du et al. 2013), Geographically Independent Integrated Drought Index (GIIDI) (Jiao et al. 2019), Scaled Drought Condition Index (SDCI) (Rhee et al. 2010), Multivariate Standardized Drought Index (MSDI) (Hao; AghaKouchak 2013), and Microwave Integrated Drought Index (MIDI) (Zhang; Jia 2013b). Most of these integrated drought indices could monitor and analyze meteorological droughts as well as agricultural droughts, but there were few integrated drought indices that could monitor and analyze hydrological droughts.

Data assimilation of land surface hydrological models and Multi-source data fusion improved the accuracy and resolution of drought related products and datasets. Combining or merging data derived from fused information to provide more accurate estimations than single-source data alone was called data fusion (Alizadeh; Nikoo 2018). The fusion of multi-source satellite precipitation data for drought monitoring improved the accuracy of capturing drought events (Alizadeh; Nikoo 2018; Chen et al. 2022). Merged satellite precipitation datasets had significant promotion in precipitation estimation hydrological applications, which had consistent drought trends compared with rain gauges (Rahman et al. 2021). Though multi-sensor data fusion, seven MODIS and TRMM surface factors were used to downscale AMSR-E soil moisture using random forest for meteorological, agricultural and
hydrological drought monitoring (Park et al. 2017a). The Sentinel-2 was fused with MODIS to obtain vegetation temperature condition index with higher spatial and temporal resolution for drought monitoring at field scales that improved the accuracy of drought monitoring (Zhou et al. 2020). With data continuity, the fusion of Sentinel-2 and Landsat-8 offered greater possibilities in drought analysis (Varghese et al. 2021). Data fusion methods improved drought monitoring accuracy by increasing the spatial and temporal resolution of drought-related parameters or factors. Data assimilation of land surface model had been widely used to monitor drought (Li et al. 2019). Soil Moisture Active Passive (SMAP) soil moisture data was assimilated into Variable Infiltration Capacity (VIC) hydrologic model to provide more reliable surface layer soil moisture, and this approach could identify some severe to extreme drought events and captured flash drought (Xu et al. 2020). The soil moisture assimilated from land surface models was used for near-real time drought monitoring in China (Zhang et al. 2017a). By fusing the space-borne SMAP soil moisture data with the North American Land Data Assimilation System (NLDAS) Noah land surface model (LSM) outputs, standardized soil moisture index (SSI) was developed to drought monitoring which was effective and sensitive for short-term drought monitoring across large areas (Xu et al. 2018a). Data assimilation of soil moisture based on a land surface model can well capture the conditions of root-zone soil moisture (Baldwin et al. 2017; Mladenova et al. 2019; Seo et al. 2021), as well as a more realistic spatial representation of drought conditions. In conclusion, data fusion and data assimilation approaches provided great potential for accurate monitoring of drought and could offer reference for drought assessment and analysis. Further, improving the remote sensing retrieval products before assimilating it into the land surface model or hydrological model was necessary (Kumar et al. 2018).
Fig. 10 The flow chart for drought monitoring to reveal key findings, contradictions, and limitations, where Prec, GW, ET, SM, DPrec, and DSM represent precipitation, groundwater, evapotranspiration, downscaled precipitation, and downscaled soil moisture, respectively.

b. Contradictions and Limitations

Low temporal and spatial resolution still limited real-time and regional monitoring of drought. Drought monitoring related products and datasets did not have both high spatial and temporal resolution. As indicated in Fig. 11, for the time being, remote sensing cannot provide relevant drought monitoring products or datasets with both high temporal resolution and high spatial resolution. The ground information obtained by optical remote sensing was easily affected by clouds and fog, but it had the characteristics of high spatial resolution. Microwave remote sensing was not disturbed by clouds and fog and could achieve all-weather observation with high temporal resolution but low spatial resolution. As a result, microwave remote sensing-based drought metrics had coarse spatial resolution to monitor and detect regional drought events inappropriately. Thus, some studies aimed to downscale drought-related products and datasets to improve the precision of drought observations.

Moreover, the heterogeneity of precipitation affected the spatial and temporal distribution of droughts (Wang et al. 2021). The downscaled precipitation was used to improve the drought monitoring capabilities of satellite precipitation data due to coarse spatial resolutions for most precipitation products could not characterize the changes on droughts (Yu et al. 2020b). Satellite-based soil moisture products were downscaled to provide more refined information.
on the spatial distribution and pattern for in-situ soil moisture to improve drought monitoring (Abbaszadeh et al. 2019; Dandridge et al. 2020; Im et al. 2016; Wang et al. 2016). In addition, downscaling methods for remote sensing soil moisture products that were not limited to climatic conditions had also been proposed (Abbaszadeh et al. 2019). The soil moisture datasets based on land surface model were also downscaled with daily high resolution to local and regional soil moisture monitoring (Park et al. 2017b). Due to the coarse spatial resolution of GRACE (at 200 to 500 km), regional TWS or groundwater estimations and further drought monitoring were still challenging (Carlson et al. 2022; Chen et al. 2016b; Van Loon et al. 2017). Several studies tended to GRACE data downscaling for drought monitoring, such as the data assimilation method (Li et al. 2012b), machine learning method (Seyoum; Milewski 2017), and so on. SIF with coarse spatial resolution was not suitable for local and regional agricultural drought monitoring, therefore, SIF was downscaled using CNN-based (Convolutional Neural Network) method for regional agricultural drought monitoring (Zhang et al. 2021). Flash drought was a critical sub-seasonal phenomenon and characterized by a period of rapid drought intensification (Christian et al. 2021). Thus, improving the accuracy on precipitation estimation with the high temporal resolution was vital for flash drought monitoring, as well as sub-month, near-real-time, early warning of drought monitoring. However, neither satellite precipitation products nor reanalysis datasets had weak performances in daily precipitation estimation (Pedreira et al. 2021; Wei et al. 2020b), which caused they could not capture the dynamic of flash drought.

![Image of soil moisture datasets and GRACE TWS](image)
Fig. 11 The resolution comparison between major drought related metrics, where GPM IMERG is precipitation product; AMSR2 SM is soil moisture from AMSR2; GRACE TWS is terrestrial water storage from GRACE.

Sparse field measurements affected satellite data calibration and data assimilation of land-surface models and hydrological models. As shown in Fig. 12, in-situ stations for FLUXNET and ISMN are still sparse over most areas, and rain gauge sites were dense in North America, Europe, India, and Australia, but sparse elsewhere. Drought monitoring in the regions distributed sparse ground-site was subject to error as station density directly affects satellite data calibration (Wei et al. 2021). Some satellite precipitation products tended to overestimate the magnitude, duration, and severity of droughts in dry months over the arid and semi-arid regions (Guo et al. 2022), as well as the region distributed sparsely ground sites and complex terrain (Cheng et al. 2021; Xiao et al. 2020). Gauge-based precipitation products also had a poor capability in capturing precipitation patterns in such regions (e.g. Tibetan Plateau) which caused errors in drought monitoring (Wei et al. 2020a). Based on a multiple timescale SPI accuracy assessment, the performance of the satellite-derived precipitation products was poor in the areas with high elevations in the western Yellow River Basin (Wei et al. 2019). Limited ground observation data still constrained the assimilation of GRACE TWS data into land surface models and hydrological models (Houborg et al. 2012; Soltani et al. 2021). Satellite precipitation products had a significant difference with the reanalysis dataset (ERA5) in drought detection, while the difference in regions where existed rain gauge was much less (Chua et al. 2020). The best performing satellite precipitation and evapotranspiration products, GPM IMERG and GLEAM (Global Land Evaporation Amsterdam Model) PET, respectively, were used for drought monitoring with SPEI; however, both of them had weak performance in Tibetan Plateau and Xinjiang of mainland China where had sparse meteorological stations and complex terrain (Jiang et al. 2021). ET estimated by data-driven methods was very dependent on observational data, so it was difficult to guarantee the accuracy of ET in areas with sparse observation sites, resulting in uncertainty in drought monitoring in such areas.
Fig 12. In-situ station density of rain gauge, international soil moisture net, and FLUXNET that used the eddy covariance technique to measure the cycling of carbon, water, and energy between the biosphere and atmosphere.

Topography, terrain, land surface cover, and climate limited the accuracy of a product or dataset. Variations of satellite precipitation products were based on the complex geomorphology of different climatic zones (Ayugi et al. 2019). GPM IMERG, the commonly used satellite precipitation products in drought monitoring, had poor accuracy in dry (December, January and February) and wet (July, August and September) months over China (Ma et al. 2021). Owing to larger uncertainties in precipitation inversions in western China which characterized by arid and semiarid climate conditions and complex landscapes, satellite-based SPI was more precise in eastern China (Lu et al. 2018). The large inconsistencies in areas with vegetation, water bodies, urban, and high slope terrains were not friendly for satellite observations (Xu et al. 2018b). The current satellite soil moisture products were still strongly influenced by vegetation cover, and there were great uncertainties in areas of high vegetation (Wang et al. 2016).

The time series of products and datasets were short, which made it difficult to study the occurrence and propagation mechanism of drought events from a climatological perspective, thus causing difficulties in drought monitoring and prediction. The time series of most current satellite products or dataset were still short, and the time series of satellite products or datasets of the same parameters were not continuous, resulting in their poor temporal and spatial continuity (Table 5); and they could not provide climatological information on drought monitoring related parameters which formed a hurdle for long-term drought monitoring. The lack of reliable products or datasets for evapotranspiration with long time series made drought monitoring and water management difficult (Zhang et al. 2018a). Record length and spatial resolution of the different precipitation products was various which led to the significantly distinctions of precipitation-based drought metrics. The time series of observational data provided by GRACE was still short, with time scales no more than 30 years, adding a lot of uncertainty to drought monitoring and drought index development (Jiao et al. 2021; Li et al. 2012b; Nie et al. 2018).

<table>
<thead>
<tr>
<th>Data</th>
<th>Temporal Res.</th>
<th>Spatial Res.</th>
<th>Time Period</th>
</tr>
</thead>
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<td>Precipitation</td>
<td>CPC-Global</td>
<td>D</td>
<td>0.5°</td>
</tr>
<tr>
<td>Data Source</td>
<td>Resolution</td>
<td>Frequency</td>
<td>Time Period</td>
</tr>
<tr>
<td>------------</td>
<td>------------</td>
<td>-----------</td>
<td>---------------</td>
</tr>
<tr>
<td>GPCP</td>
<td>D/M</td>
<td>1°/2.5°</td>
<td>1979-present</td>
</tr>
<tr>
<td>GPM</td>
<td>30 min/3 h/D</td>
<td>0.1°</td>
<td>2015-present</td>
</tr>
<tr>
<td>GSMaP</td>
<td>1 h/D/M</td>
<td>0.1°</td>
<td>2002-2012</td>
</tr>
<tr>
<td>CMAP</td>
<td>M</td>
<td>2.5°</td>
<td>1979-present</td>
</tr>
<tr>
<td>TRMM</td>
<td>3 h/D/M</td>
<td>0.25°/0.5°</td>
<td>1998-2015</td>
</tr>
<tr>
<td>PERSIANN-CCS</td>
<td>30 min/3 h/6 h</td>
<td>0.04°</td>
<td>2003-present</td>
</tr>
<tr>
<td>PERSIANN-CDR</td>
<td>3 h/6 h/D</td>
<td>0.25°</td>
<td>1983-present</td>
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</table>

**Soil Moisture**

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<th>Frequency</th>
<th>Time Period</th>
</tr>
</thead>
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<td>D</td>
<td>25 km</td>
<td>2002-2011</td>
</tr>
<tr>
<td>AMSR2</td>
<td>D</td>
<td>25 km</td>
<td>2012-present</td>
</tr>
<tr>
<td>SSM/I</td>
<td>D</td>
<td>25 km</td>
<td>1987-present</td>
</tr>
<tr>
<td>ASCAT</td>
<td>3 Days</td>
<td>12.5/25 km</td>
<td>2007-present</td>
</tr>
<tr>
<td>SMAP</td>
<td>2-3 Days</td>
<td>3/9/36 km</td>
<td>2015-present</td>
</tr>
<tr>
<td>SMOS</td>
<td>&lt; 3 Days</td>
<td>&lt; 50 km</td>
<td>2010-present</td>
</tr>
</tbody>
</table>

**Groundwater/Surface water**

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<th>Data Source</th>
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<th>Frequency</th>
<th>Time Period</th>
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</thead>
<tbody>
<tr>
<td>GRACE TWS</td>
<td>M</td>
<td>0.25°</td>
<td>2002-present</td>
</tr>
<tr>
<td>GRACE-FO TWS</td>
<td>M</td>
<td>0.25°</td>
<td>2017-present</td>
</tr>
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**ET**

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>MODIS</td>
<td>8-day</td>
<td>500 m</td>
<td>2000-present</td>
</tr>
<tr>
<td>GLEAM</td>
<td>D</td>
<td>0.25°</td>
<td>1980-2018</td>
</tr>
<tr>
<td>GLDAS</td>
<td>3 h/month</td>
<td>1°</td>
<td>1979-2016</td>
</tr>
<tr>
<td>METRIC</td>
<td>16 days</td>
<td>30 m</td>
<td>2012-present</td>
</tr>
</tbody>
</table>

**Vegetation**

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Frequency</th>
<th>Resolution</th>
<th>Time Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVHRR NDVI/EVI</td>
<td>bi-week</td>
<td>0.083°</td>
<td>1982-present</td>
</tr>
<tr>
<td>MODIS NDVI/EVI</td>
<td>8 days/M</td>
<td>500 m/1 km</td>
<td>2000-present</td>
</tr>
<tr>
<td>Landsat NDVI</td>
<td>16 days</td>
<td>30 m</td>
<td>1972-present</td>
</tr>
<tr>
<td>MODIS LAI</td>
<td>8 days</td>
<td>500 m</td>
<td>2000-present</td>
</tr>
<tr>
<td>SMOS VOD</td>
<td>D</td>
<td>~40 km</td>
<td>2009-present</td>
</tr>
<tr>
<td>GOME-2 SIF</td>
<td>D</td>
<td>0.5°</td>
<td>2007-present</td>
</tr>
</tbody>
</table>
5. Development trend and research direction

a. Development trend on method and index of drought monitoring

The main method of drought monitoring has gradually developed from ground site-based to combining of large-scale satellite remote sensing and data fusion/data assimilation. Satellite remote sensing turned the conventional “point” monitoring to novel “planes” monitoring and made up for the lack of spatial representativeness of the site observation, and it can achieve more information from land surface and atmosphere. Early drought monitoring used the key input parameters, such as precipitation and temperature observed by ground stations, and the resulting drought indices (SPI, SPEI, CMI and PDSI) to drought monitoring. After the advent of satellite remote sensing technology, a large amount information of land surface and atmosphere that applied in drought monitoring could be estimated or retrieved (AghaKouchak et al. 2015), such as precipitation (Du et al. 2013; Yu et al. 2020a), land surface temperature (Hu et al. 2020; Kogan 1995), evapotranspiration (Kustas et al. 2011; Wang; Dickinson 2012), soil moisture (Martínez-Fernández et al. 2016; Sánchez et al. 2016), groundwater (Li et al. 2012a; Long et al. 2014), and vegetation information (Goldberg et al. 2010; Liu et al. 2018). These key input parameters of satellite remote sensing products that used in drought monitoring most retrieved or estimated from passive microwave remote sensing which lead to these products has coarse spatial resolution. Thus, some key input parameter for drought monitoring, including precipitation, SIF (Solar-Induced Chlorophyll Fluorescence) and soil moisture, were downscaled and used to regional drought monitoring (Abbaszadeh et al. 2019; Park et al. 2017a; Zhang et al. 2021).

The drought monitoring index have gradually developed from single-parameter index to comprehensive index. In the early development stage of drought monitoring based on ground observations, some drought indices were developed based on a single parameter. With the

<table>
<thead>
<tr>
<th>Product</th>
<th>Resolution</th>
<th>Time Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>TROPOMI SIF</td>
<td>D</td>
<td>7*3.5 km</td>
</tr>
<tr>
<td>OCO-2 SIF</td>
<td>D</td>
<td>2.25*1.29 km</td>
</tr>
<tr>
<td>SCIAMACHY SIF</td>
<td>D/M</td>
<td>1.5°/1°</td>
</tr>
<tr>
<td>MODIS GPP/NPP</td>
<td>8 Days</td>
<td>500 m</td>
</tr>
</tbody>
</table>

Table 5. Summary of major drought related satellite products (Jiao et al. 2021). D and M represent Daily and Monthly, respectively.
increase of the parameters obtained by satellite remote sensing, multi-variable and comprehensive drought indices had been developed to monitor various types of droughts. Relying on hydrological models or satellite remote sensing, drought indices with a single input parameter had also been developed, such as SRI (Standardized Runoff Index) (Shukla; Wood 2008), SSI (Standardized Soil Moisture Index) (Hao; AghaKouchak 2013), TCI (temperature condition index), VCI (vegetation condition index) (Kogan 1995), and GRI (Groundwater Resource Index) (Mendicino et al. 2008). Due to the complex mechanism of occurrence of drought, the drought index developed by using a single parameter could not reflect some situations of droughts. Recently, some integrated drought indices that combined multiple parameters and based principle of water balance and statistical methods were developed to drought monitoring, such as microwave integrated drought index (MIDI) (Zhang; Jia 2013a), scaled drought condition index (SDCI) (Rhee et al. 2010), vegetation supply water index (VSWI) (Cunha et al. 2015), optimized meteorological drought index (OMDI), optimized vegetation drought index (OVDI) (Hao; Singh 2015), and geographically independent integrated drought index (GIIDI) (Jiao et al. 2019).

b. Research directions in the future

Improving the application level of ground observation data, satellite remote sensing data and reanalysis data, and promoting the fusion and assimilation of multi-source data, will have an important impact on improving drought monitoring capabilities. The occurrence of drought lied in the obstruction of the water cycle (Zhang et al. 2019a). The elements of terrestrial water cycle mainly include precipitation, evapotranspiration, soil moisture, ice & snow, surface runoff, and groundwater. However, there were still large uncertainties in inversion, estimation and simulation on these elements by land surface hydrological models and remote sensing. Joining satellite remote sensing and data fusion methods could provide more accurate land surface parameters with multiple temporal and spatial scales, such as the above elements. Yet, the time series of satellite remote sensing data was still relatively short compared to ground observation data and reanalysis data. Nowadays, satellite remote sensing technologies could observe information of land surface, atmosphere, and ocean in various perspectives. How to use remotely sensed multi-source information to develop various land surface parameter products would play an important role in clarifying the occurrence mechanism of drought and improving the ability of drought monitoring and early warning. Furthermore, driving the land surface parameters estimated or inverted by satellite remote
sensing into the land surface hydrological model to generate corresponding parameter products with high temporal-spatial resolution, and long time series would make up for the shortcomings of satellite remote sensing and land surface hydrological models.

The evolution and propagation of droughts can be comprehensive monitoring. In general, the propagation and evolution of droughts presented the sequence of meteorological drought, agricultural drought, hydrological drought, ecological drought, and socioeconomic drought (Zhang et al. 2020b). During the evolution of drought, it is not clear what conditions could promote propagation and type conversion of drought. Currently, the threshold of environmental factors that lead to irreversible damage on vegetation or corps is not clear during the propagation of drought. Multiple drought events may occur at the same time during the entire drought processes. Therefore, it is necessary to develop an ideal drought index for monitoring the entire drought processes.

The earth system science data in the future will show an explosive trend. Relying on big data technology and cloud-based computing to achieve comprehensive earth observation and further drought monitoring would be a new direction for future development (Jiao et al. 2021). The advent of the information age has greatly promoted the development of earth sciences. The improvement in computing power of computer has made it possible to mine massive amounts of data. The mining platforms of earth system science data represented by Google Earth Engine (GEE) had been globally used in land change and utilization monitoring (Ge et al. 2019), forest monitoring (Bastin et al. 2017), drought monitoring and assessment (Sazib et al. 2018). The shared dataset of GEE has reached the Petabytes level which contain almost dataset used in drought monitoring. Furthermore, GEE also provides numerous machine learning algorithms for mining and analysis of earth system science data which involves supervised learning functions and unsupervised learning functions (Wang et al. 2020). Thus, with the support of GEE, the mining and analysis of earth system science data will be a new stage, and researchers will have more energy for scientific data analysis in addition to various data preprocessing. Consequently, making full utilizations of big data and cloud-based computing technology will be more beneficial to achieve large-scale monitoring and forecasts on droughts.

Observations and researches on ecological drought and groundwater drought should be carried out comprehensively. The agricultural drought and socio-economic drought defined in the past were all human-centered (Ramirez et al. 2017), which quantitatively measured the
indirect impacts of droughts on human production and livelihood. However, ecological drought researches need to assess the impacts of droughts on the ecological environments through the perspective of the ecological environments. There are relatively few studies on the response of the ecological environment to drought through the development of the ecological drought index, and there is no widely accepted ecological drought index. SPEI had been widely used in drought monitoring, and whether SPEI could accurately monitor the ecosystem's response to drought was controversy (Vicente-Serrano et al. 2012; Zang et al. 2020). Consequently, it is urgent to develop an effective drought index for ecological drought monitoring. Groundwater drought refers to the drop of groundwater level or reduction of underground runoff. It is difficult to recover to normal status in a short period of time once groundwater drought occurs. At present, the main means of monitoring groundwater is gravity satellite monitoring (Thomas et al. 2017), but the spatial resolution of gravity satellites is low, and there are still limitations to regional groundwater drought monitoring. Therefore, the deep integration of land surface hydrological models and satellite remote sensing will be the key to solving gravity satellite drought monitoring.

6. Conclusions

In this study, to understand the drought monitoring research trends and topics in a global perspective during 1983-2020, the database of SCI-E from Web of Science was retrieved, and 6322 publication outputs were obtained which were mainly including articles from 1983 to 2020. Then, the bibliometric analysis was used to identify the landscape of academics on drought monitoring according to countries, institutions, journals, authors, and keywords. Finally, we proposed a comprehensive overview of drought monitoring researches based on the analysis of publication outputs, local citation scores, and co-words, and some valuable and meaningful findings were obtained.

According to the analysis on publication outputs of the contribution of countries, the USA and China are the dominant countries who focus on drought monitoring. And, authors who focus on drought monitoring studies mainly come from Europe, North America, Asia, Oceania, and sparsely from South America and Africa. China and the USA have greater attractiveness for cooperation with drought monitoring researchers from other countries. According to citation analysis using LCS and GCS, the USA and China were the most competitive countries in the studies of drought monitoring, and the University of Nebraska and CAS were the most competitive institutions of the USA and China, respectively. Singh
V. P. (USA), Penuelas J. (Spain), and Hao ZC (China) were the three most competitive authors in the drought monitoring research field.

Remote sensing of environment, BAMS, and Agricultural and Forest Meteorology are the most influential journals in the field of drought monitoring, but except for Remote Sensing which is the most productive journals. It is specially mentioned that the most productive journals and the most influential journals were all focused on remote sensing technology to monitor drought. In other words, drought monitoring of a combination of site-based and remote sensing-based has become a popular and effective monitoring technology.

Keywords could provide important information about the research trends and topics. According to co-occurrence analysis on keywords, climate change has a profound impact on drought monitoring. Agricultural drought is the most concerning type of drought due to the top 3 most frequent keywords included soil moisture. The utilization of multi-source satellite remote sensing data for drought monitoring will be the main trend in future research. In recent drought monitoring studies, data-driven approaches as machine learning had become a popular method to improve the parameters related to drought monitoring. The combination of mathematical and physical methods will be a popular drought monitoring method in the future. Recently, combination of satellite remote sensing and data fusion/data assimilation has replaced conventional sited-based methods to monitor drought in a large-scale measurement.

Acknowledgments

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Data Availability Statement

Datasets analyzed during the current study are available in the Science Citation Index Expend of Web of science. These datasets were derived from the following public domain resources: https://www.webofscience.com/wos/woscc/basic-search.
REFERENCES


