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Progress and Development Trend of Drought Disaster Research Based on Bibliometric Analysis

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Abstract: With the intensification of climate change and the acceleration of urbanization, extreme climate events are occurring with increasing frequency. The associated drought disasters have caused significant economic losses, threatened human health, and destabilized ecosystems, making the study of drought disasters a focal point in academia. This paper employs bibliometric analysis methods such as Kleinberg's burst detection algorithm and cluster analysis to conduct a keyword co-occurrence analysis of 1,524 papers indexed in the Web of Science database from 1977 to 2021. By constructing a visualized knowledge graph, this study identifies the key research hotspots and future trends in drought studies. The main conclusions are as follows: (1) Fundamental research areas of drought disasters are rooted in scientific issues such as meteorological disasters, climate change, and drought. (2) The number of publications on drought disasters has shown an overall upward trend, progressing through three stages: initial exploration, fluctuating growth, and rapid growth. (3) The scope of drought disaster research has expanded beyond traditional precipitation and meteorological studies. Recent and future research hotspots include agricultural drought, its impacts on the sustainable livelihoods and adaptive capacities of smallholder farmers, the understanding of compound events, and responses to climate change and its impacts.

Keywords: Drought disasters; Visual analysis; Knowledge graph; Kleinberg algorithm; Cluster analysis.

1. Introduction

Drought is one of the most widespread, prolonged, and socioeconomically and environmentally impactful meteorological disasters globally [1]. Its onset is gradual and often imperceptible, but its effects are extensive and long-lasting, posing severe risks to populations and economies. The global extent of drought-affected areas has been expanding, with significant long-term trends observed in regions such as Africa, South and East Asia, Southern Europe, Eastern Australia, and Northern China [2]. According to statistics from the World Meteorological Organization (WMO), natural disasters caused approximately 1.94 million deaths worldwide between 1970 and 2012, with drought-related fatalities accounting for 35% of this total, and economic losses amounting to $191.3 billion [3]. For instance, the 2000 drought in Northern China affected 40 million hectares of crops, resulting in a 20-million-ton reduction in grain production and substantial economic losses. Similarly, extreme heat and drought in the United States and Canada in 2021 caused 1,319 deaths and affected 58 million people. In recent years, issues related to the prevention of large-scale natural disasters like drought and their connection to food security have garnered significant attention, with global disaster reduction strategies increasingly emphasizing "risk mitigation, sustainable development, and coexistence with disasters."

Research on drought disasters has become a prominent topic in the international disaster research domain, playing a critical role in informing disaster prevention and mitigation strategies as well as development policies. Studies at home and abroad have explored drought characteristics, mechanisms of occurrence, land-atmosphere interactions, and their impacts on societal development [4]. However, quantitative analyses based on bibliometric methods remain relatively limited. This paper constructs a knowledge graph to unveil the knowledge network of drought disaster research, analyzing research themes and development trends, aiming to systematically review progress in the field and provide fresh perspectives.

2. Method and Data

2.1. Data

This study is based on the Web of Science (WOS) Core Collection, where the keyword "drought disaster" was used to retrieve relevant literature up to 2022. An initial search yielded 4,447 papers. These were filtered based on the primary disciplinary fields of drought disaster research, such as Meteorology and Atmospheric Sciences, Geosciences Multidisciplinary, Environmental Studies, Geography, Remote Sensing, and Physical Geography. A total of 1,524 relevant papers were identified. Further refinement, including the removal of incomplete or weakly relevant data, resulted in a final dataset of 1,325 papers spanning the years 1991 to 2022. This dataset serves as a foundational resource for analyzing the overall trends and key hotspots in drought disaster research.

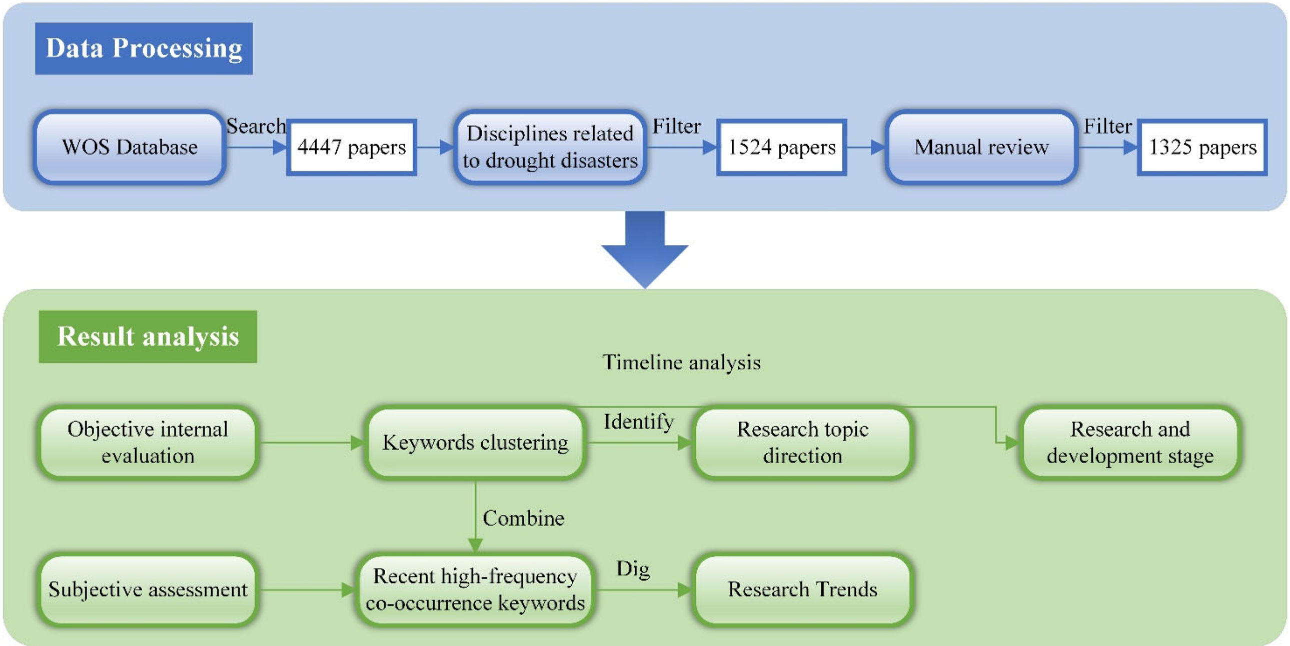

Figure 1. Research flow chart

2.2. Method

2.2.1. Betweenness Centrality.

To assess the importance of keywords within the drought disaster research network, betweenness centrality is used as an indicator. Betweenness centrality measures the bridging role of a node in connecting different research domains. Its calculation formula is as follows:

$$BC_i = \sum_{s \neq i \neq t} \frac{n_s^i}{g_{st}} \tag{1}$$

In this formula, g_{st} represents the number of shortest paths between two points in the network, and n_s^i represents the number of shortest paths between the same two points that pass through node i. From a network analysis perspective, nodes with high centrality play a more significant role in the dissemination of information within the network.

2.2.2. Kleinberg Burst Detection Algorithm.

The Kleinberg algorithm is used to detect emerging hotspots in drought disaster research. This algorithm identifies burst words, revealing research hotspots and their duration, while also capturing emerging directions. Burst intensity reflects the degree of attention a research area receives over a short period, serving as an important indicator for measuring the influence of emerging fields.

2.2.3. g-Index.

The g-index is used to rank and extract literature keywords as knowledge units [5]. The g-index examines the number of high-impact articles published by a researcher. Its calculation formula is as follows:

$$g^2 \leqslant k \sum_{i \leqslant g} c_i \,, \quad k \in Z^+ \tag{2}$$

In this formula, k is the scale factor, which is adjusted using values such as 10, 20, 30, and so on.

2.2.4. Cluster Analysis.

Cluster analysis is used to reflect the key themes and evolving trends in drought disaster research, and to demonstrate theme changes in relation to time parameters. The Log-Likelihood Ratio (LLR) algorithm is applied for clustering based on a keyword frequency matrix. Words that co-occur in only one paper or provide little informational value (such as prepositions) are filtered out, and clustering labels are generated based on word frequency groups. This analysis aims to objectively determine the research characteristics of the papers based on the frequency of their keywords [6].

Key parameters used to measure the clustering performance include Modularity and Silhouette values. Modularity is used to evaluate the degree of modularity in a network and is positively correlated with the strength of the network's clustering structure. Its value ranges from [0,1], with values greater than 0.3 indicating a significant clustering network structure. The closer the value is to 1, the better the quality of the network partition. The calculation formula for the Modularity value is as follows:

$$Q = \frac{1}{2m} \sum_{i,j} \left(a_{ij} - p_{ij}\right) \sigma\left(C_i, C_j\right) \tag{3}$$

In the formula, a_{ij} represents the adjacency matrix; p_{ij} denotes the expected value of the node connections; C_i and C_j represent the clusters to which nodes i and j belong. If they are assigned to the same cluster, then σ =1; otherwise σ =0.

The Silhouette value is used to evaluate the quality of clustering results. The closer the value is to 1, the better the clustering and separation of the network. When the value is greater than 0.7, the clustering results are considered highly reliable. The calculation formula for the Silhouette value is as follows:

$$S_i = \frac{b(i) - a(i)}{max\{\, a(i), b(i)\}} \tag{4}$$

In the above formula, the Silhouette value S satisfies the range $-1 \leq S_i \leq 1$. Here, a(i) represents the average distance between point i and other points within the same cluster, while b(i) represents the average distance between point i and all other points in the nearest cluster. The average Silhouette value refers to the mean value of the Silhouette scores for all sample points.

To comprehensively analyze the development trajectory and trends in drought disaster research, this study uses the results of cluster analysis and employs the WOS database to identify relevant literature under different clusters by filtering keywords. By extracting core information from the literature (such as topics, methods, and research outcomes), the clusters were objectively assessed. The analysis focuses on clusters covering a 30-year time span, identifying the research priorities and directions in different periods. Additionally, recent keywords from high-confidence clusters in the past 1-2 years are used to explore emerging hotspots and development trends. This analytical framework not only reveals the evolving patterns of drought disaster research but also provides important references and insights for the exploration of future research directions.

3. Result

3.1. Data

As shown in Figure 2, the computational network density of the drought disaster research knowledge network is 0.0198. High-frequency keywords are displayed with larger nodes and fonts, and the strength of their associations is reflected in the thickness of the connecting lines. Keywords with centrality greater than 0.1 are considered important nodes in the fundamental research areas. This study finds that "climate change," "climate," and "drought" are the most frequently cited keywords, all of which have a centrality exceeding 0.1 (see Table 1), highlighting their core role in drought disaster research.

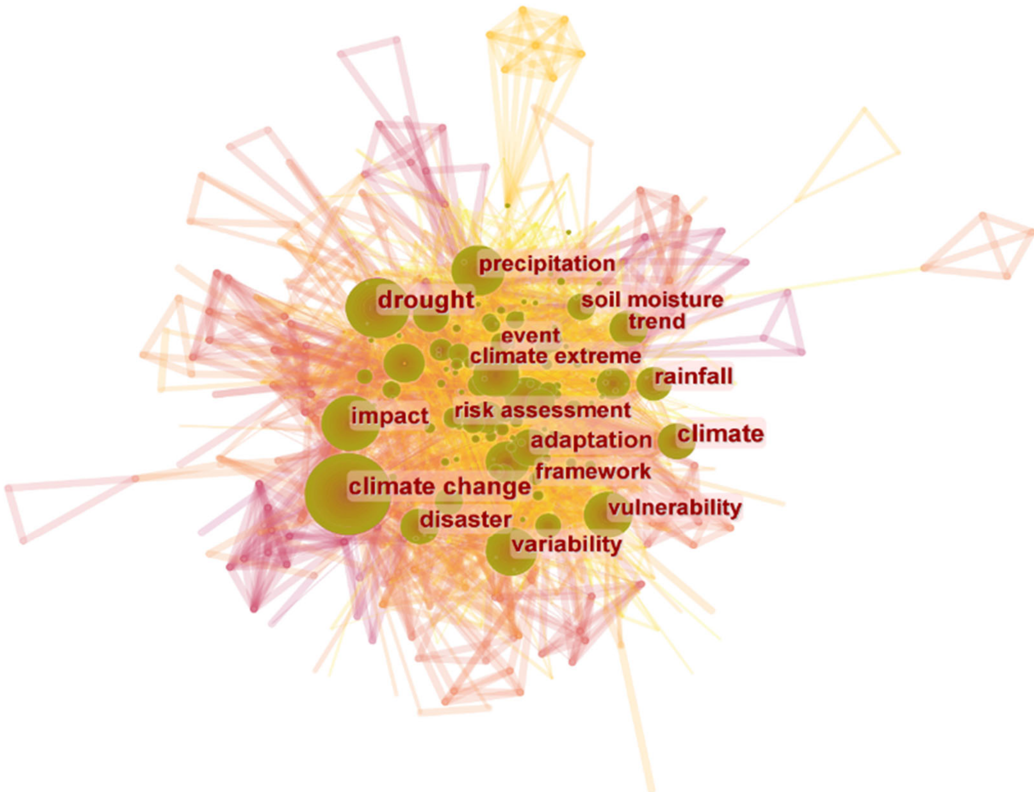

Figure 2. Keywords Co-occurrence knowledge graph

Analysis indicates that "climate change" and "climate" primarily focus on the fields of climate and meteorology, involving long-term climate change and short-term meteorological disasters, respectively. This underscores the critical importance of climate and drought in drought disaster research. Future studies should further explore the profound impacts of climate change on drought disasters and the underlying mechanisms.

Table 1. Keywords of drought disaster

Order number	Frequency	Centrality	Keywords	The earliest year
1	393	0.16	Climate change	1997
2	103	0.15	Climate	2001
3	196	0.12	Drought	2002
4	214	0.09	Impact	1998
5	154	0.09	Variability	1995
6	84	0.08	Rainfall	2000
7	34	0.08	El nino	2000

3.2. Analysis of Stage-specific Frontier Research Areas

Based on the literature analysis from 1991 to 2022, eight burst words were identified in drought disaster research (as shown in Figure 3): United States, adaptive capacity, Standardized Precipitation Index (SPI), social vulnerability, framework, streamflow, severity, and extreme events, reflecting the research hotspots and directions at different stages.

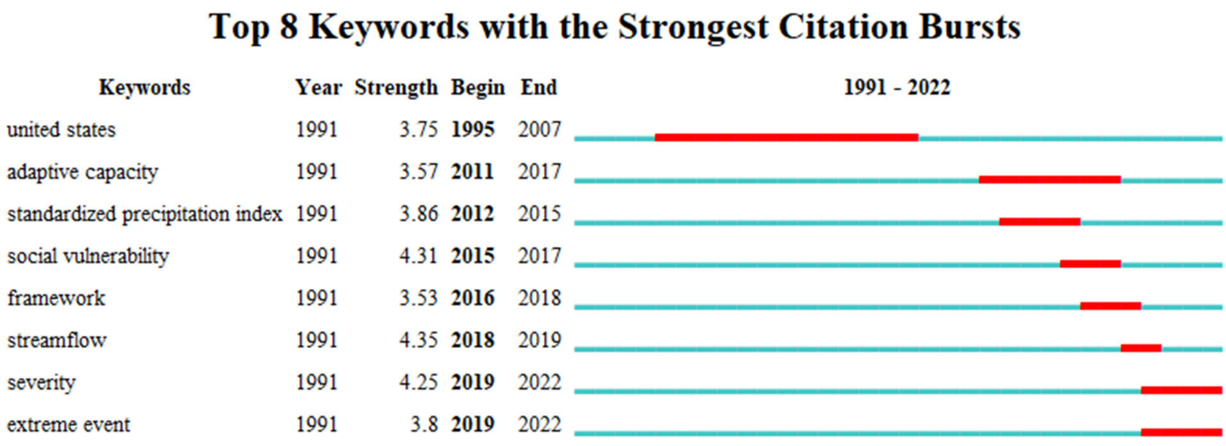

Figure 3. Burst terms of drought disaster keywords

From 1995 to 2007, "United States" was a key research focus. As a region prone to droughts, the United States established the Drought Monitoring System (USDM), which provides weekly drought status data and supports drought mitigation efforts with vital information [7].

From 2011 to 2017, "adaptive capacity" had the highest burst rate and was closely linked with "social vulnerability." Adaptive capacity is defined as the ability of a system to respond to climate change [8] and is a key component of social vulnerability. Research during this period gradually expanded to include social psychology and institutional dimensions, driving theoretical innovation [9].

From 2012 to 2015, "Standardized Precipitation Index (SPI)" became a research focus. Due to its multi-scale monitoring advantages, SPI has been widely used in hydrology, agriculture, and ecology [10], and its capacity for drought impact identification was further enhanced by the extended SPEI index [11].

From 2016 to 2018, "framework" emerged, encompassing both conceptual and technical frameworks. Research during this period included the application of Shared Socioeconomic Pathways (SSP) in climate change scenarios [12], as well as the role of deep learning frameworks in hyperspectral remote sensing [13-16].

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From 2018 to 2019, research on "streamflow" concentrated on the impact of climate change on water resource supply, including changes in low-flow hydrological systems in Europe [17] and the application of machine learning models in monthly streamflow prediction and historical grid data reconstruction [18].

From 2019 to 2022, "severity" and "extreme events" became the focus of research. Studies indicated that climate change significantly increased the probability and intensity of extreme drought events [19], and with global warming, the frequency and intensity of such events are expected to rise further, highlighting the urgent need for research on extreme droughts.

3.3. Research and development stages and thematic directions

3.3.1. Research Development Stages.

From 1991 to 2021, the annual publication volume in the field of drought disasters showed a significant upward trend (Figure 4), indicating substantial theoretical foundations and practical application potential in this field, which is still in the stage of accumulating results. Based on the burst word analysis, the research can be divided into three stages.

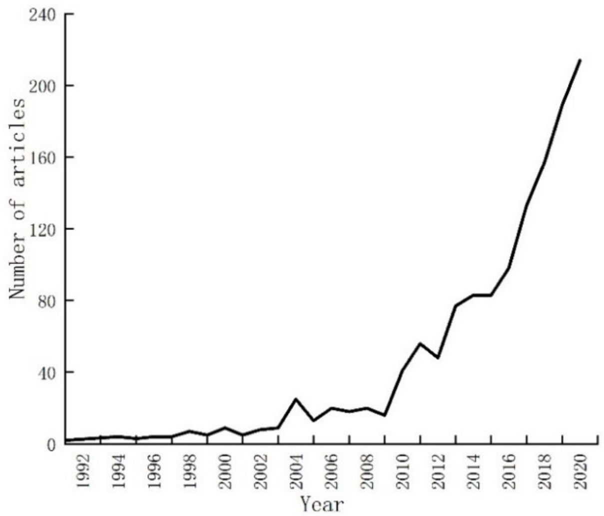

Figure 4. Number of drought disaster documents issued

The first stage (1991–2003) was the exploratory phase of drought disaster research, during which the annual publication volume remained relatively stable. The second stage (2004–2015) marked a period of fluctuating growth, driven by the development of remote sensing technology, especially the application of remote sensing data in real-time drought monitoring, which accelerated the growth of research output. The third stage (2016–2021) was a phase of rapid growth. Global climate change and the frequent occurrence of extreme climate events made droughts a research hotspot, leading to a sharp increase in the annual publication volume.

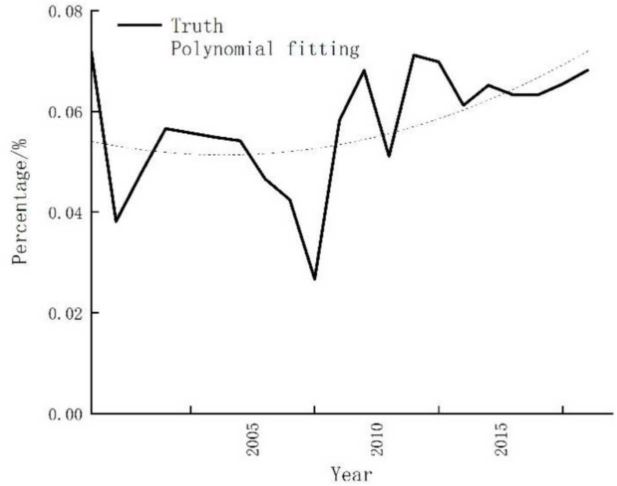

Figure 5. The proportion of drought disaster documents in all disaster disciplines

The importance of drought disasters within the disaster research field has also steadily increased (Figure 5). From 2001 to 2021, the proportion of drought disaster literature in the overall disaster field increased, particularly after 2005, reflecting a growing global interest in this area.

Through the timeline map of keyword clustering analysis (Figure 6), the evolution of research themes in drought disaster studies is clearly visible, and it aligns closely with the research development trends across the three stages. This process reveals the complete path of the field's progression from initial exploration to in-depth development.

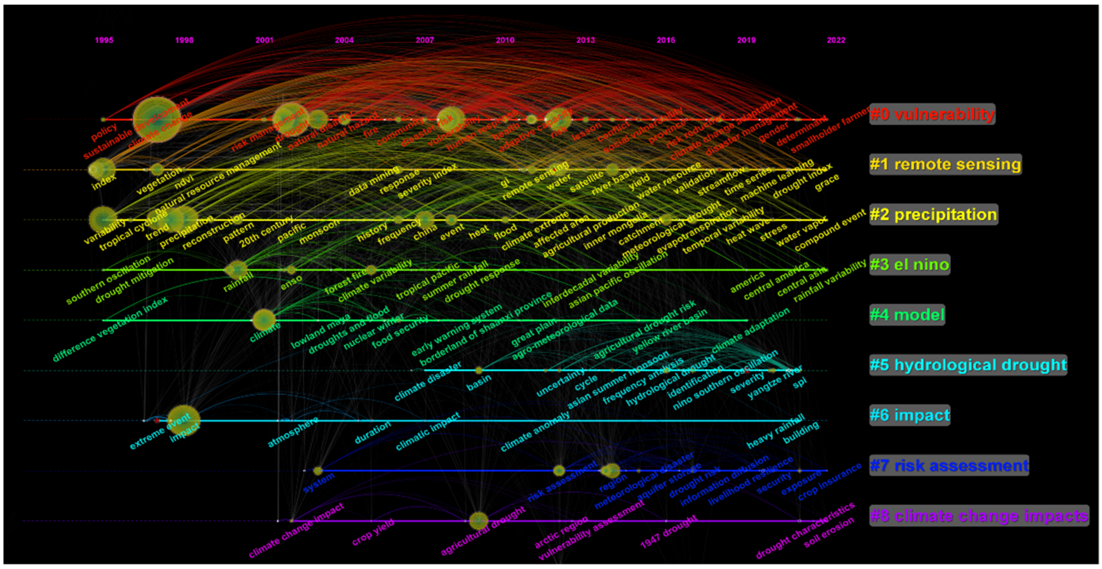

Figure 6. Keywords of drought disaster research timeline knowledge graph

First Stage: Exploratory Phase (1991–2003)

During this phase, 53 papers were published, accounting for 3.48% of the dataset. Research mainly focused on vulnerability, remote sensing, precipitation, the El Niño phenomenon, and drought impacts.In the field of vulnerability and sustainable development, Foody et al. [20] proposed a novel method for extracting sustainable resource utilization indicators from remote sensing imagery to support decision-making for sustainable development. Wilhite, DA et al. [21] emphasized that risk management is a superior strategy to emergency response in addressing drought.Regarding precipitation and climate change, Trenberth, KE et al. [22] improved precipitation prediction models, enhancing the understanding of precipitation characteristics. LANDSEA, CW et al. [23] revealed the connection between Atlantic tropical cyclones and West African monsoon rainfall.In remote sensing and NDVI applications, NDVI was widely used for drought monitoring due to its sensitivity to vegetation water conditions. Ji, L et al. [24] noted that NDVI effectively represents vegetation water status but highlighted the need to account for seasonal effects.In historical data reconstruction, drought reconstruction research emerged. Cook, ER et al. [25] reconstructed historical drought data for the continental United States from 1700 to 1978 using point-by-point regression.

Second Stage: Period of Fluctuating Growth (2004–2015)

During this phase, 426 papers were published, accounting for 27.95% of the dataset. Research directions expanded to include vulnerability, remote sensing, precipitation, the El Niño phenomenon, hydrological drought, model development, and climate change impact and risk assessment.In vulnerability studies, Shahid, S et al. [26] proposed a risk definition framework integrating hazard and vulnerability, while Antwi-Agyei, P et al. [27] developed a regional vulnerability assessment model based on multi-scale and multi-indicator approaches, providing a basis for drought policy formulation.In remote sensing, Feyisa, GL et al. [27] improved water classification accuracy by introducing the Automated Water Extraction Index (AWEI), enhancing image processing methods.In precipitation and drought monitoring, Vicente-Serrano, SM et al. [28] proposed the Standardized Precipitation Evapotranspiration Index (SPEI), a new tool for drought monitoring with improved adaptability to various timescales.In studies on the El Niño phenomenon, Yu, JY et al. [29] pointed out that Central Pacific El Niño events have exacerbated drought trends in the United States.In model development, Sheffield, J et al. [30] developed a drought monitoring and forecasting system for sub-Saharan Africa, enhancing agricultural resilience.In studies on climate change and agricultural drought, Zhang, Q et al. [31] found that increased extreme precipitation events, fewer consecutive wet days, and more dry days significantly impact agricultural drought.In risk assessment, Shahid, S et al. [26] assessed drought risk in Bangladesh by multiplying hazard and vulnerability factors, while Wu, H et al. [32] developed an agricultural drought risk assessment model, providing critical data for dryland crop risk evaluation.

Third Stage: Period of Rapid Growth (2016–2021)

During this phase, 874 papers were published, accounting for 57.35% of the dataset. Research directions further deepened, covering vulnerability, remote sensing, precipitation, hydrological drought, climate change impacts, and risk assessment.The strategies of smallholder farmers in coping with climate change became a focal point in vulnerability research [33]. The keyword "determinants" frequently appeared, contributing to conceptual model building, risk management framework development [34], and gravity model validation [35].In remote sensing research, drought indices, streamflow, and machine learning were major themes. Ji, T et al. [36] proposed a Composite Drought Index (CDI) and validated its accuracy. Pena-Gallardo, M et al. [37] used the Standardized Streamflow Index (SSI) to assess the severity of climate drought. Han, HZ et al. [38] developed a Combined Drought Monitoring Index (CDMI) using the random forest algorithm. Rhee, J et al. [39] optimized drought prediction models by integrating kriging interpolation and remote sensing data.In studies on precipitation and temperature, precipitation and evapotranspiration rates were central to meteorological drought research. SPI was effective for extreme drought events, while SPEI performed better for moderate to severe drought monitoring [40].In hydrological drought research, the Yangtze River basin attracted significant attention. Zhang, D et al. [41] found, using Copula functions, that drought in the Poyang Lake basin intensified without synchronously affecting the Yangtze River mainstream, possibly due to human activities. ENSO emerged as a high-frequency theme.In risk assessment studies, drought was identified as one of the most damaging natural disasters. Meza, I et al. [42] proposed a global framework for integrated drought risk assessment of irrigation and agricultural systems, analyzing drivers, spatial patterns, and mitigation measures.

International research on drought disasters demonstrates a trend toward diversification and interdisciplinary integration. Research priorities have gradually shifted from focusing solely on precipitation variables to comprehensive studies spanning ecological environments, agricultural production, and socioeconomic factors. Isolated drought studies are declining, with increasing emphasis on interdisciplinary collaboration for the integrated management and restoration of natural resources.

A series of international research programs, including the Global Energy and Water Cycle Experiment (GEWEX), the Climate Variability and Predictability Program (CLIVAR), the Global Observing Systems Research and Predictability Experiment (THORPEX), the International Satellite Cloud Climatology Project (ISCCP), and the Integrated Risk Governance Project (IHDP-IRG), have driven drought disaster research toward new models emphasizing interdisciplinary integration and application-oriented outcomes.

3.3.2. Research Themes and Directions.

The results of keyword clustering analysis show a well-structured clustering network, with a Q value of 0.4027 and an S value of 0.7012, indicating high clustering reliability. Clusters with smaller numbers exhibit higher homogeneity among their members, reflecting more focused research directions.

Cluster 1: Drought vulnerability; Cluster 2: Remote sensing studies; Cluster 3: Precipitation studies; Cluster 4: Research related to the El Niño–Southern Oscillation (ENSO); Cluster 5: Machine learning, risk assessment, and drought monitoring and prediction models; Cluster 6: Meteorological drought; Cluster 7: Analysis of drought impacts; Cluster 8: Risk assessment; Cluster 9: Impacts of climate change.

The keyword density map (Figure 8) highlights that research hotspots are concentrated around themes such as climate change, precipitation, drought, models, and temperature. This suggests that clusters with smaller numbers (e.g., Cluster 1 and Cluster 3) represent the primary research directions currently emphasized by scholars.

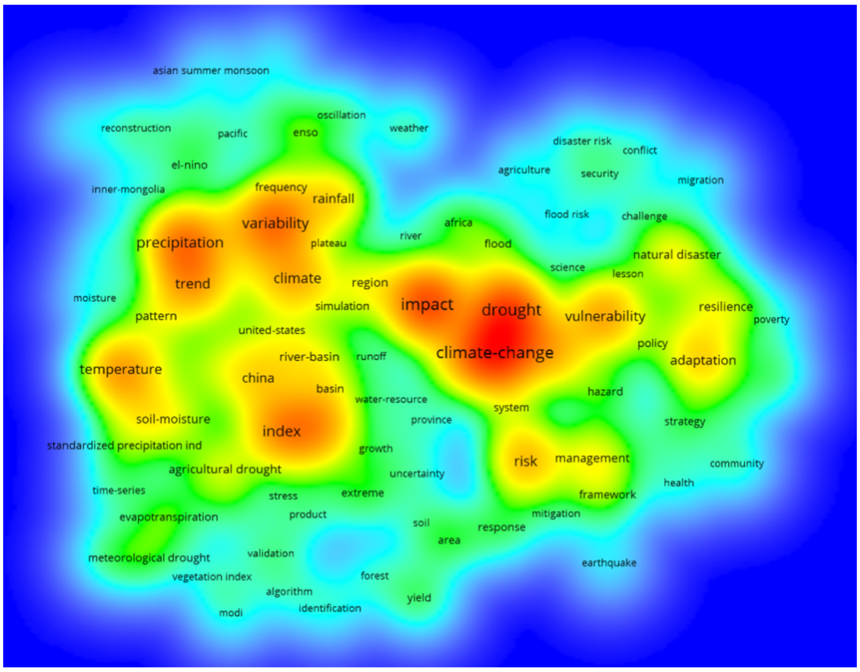

Figure 7. Density graph drought disaster keyword

4. Discussion

In reviewing the literature on drought disasters, an analysis of keyword frequency, centrality, and burst terms reveals recent research priorities and future development trends in this field.

4.1. Agricultural Drought and Its Impact on the Sustainable Livelihoods and Adaptive Capacity of Smallholder Farmers

With the intensification of global warming, the frequency of extreme climate events and droughts continues to rise, leading to severe agricultural droughts that trigger global food crises. Smallholder farmers, due to their livelihood vulnerability and limited adaptive capacity, are among the most affected groups [43, 44]. However, research focusing on the sustainable livelihoods and adaptive capacity of smallholder farmers remains scarce. Against the backdrop of the United Nations Sustainable Development Goals (SDGs), it is imperative to promote sustainable production models and conduct assessments of smallholder adaptive capacities, which have become pressing research topics [45].

4.2. Understanding Compound Events and Addressing Climate Change and Its Impacts

Climate change has increased the frequency and magnitude of extreme disaster events, such as droughts, floods, and wildfires, which often arise from the interaction of multi-scale physical processes to form "compound events." Traditional risk assessment methods often overlook the spatiotemporal interactions between such events, potentially underestimating the associated risks[46]. Terrestrial Water Storage (TWS), a crucial regulator of the hydrological cycle, is a key indicator in drought research [47]. Programs like GRACE and GRACE-FO have introduced new methods for measuring global TWS anomalies. Studies indicate that climate-change-induced declines in TWS have heightened the risk of future droughts [46]. Moving forward, it is essential to deepen the study of the mechanisms behind compound events, enhance quantitative analyses of extreme events driven by multiple factors, and explore new strategies to address the complex impacts of climate change.

5. Conclusion

Based on a keyword co-occurrence analysis of literature from the WOS database, this study examines the research progress and future trends in drought disaster studies. The findings are as follows:

The fundamental research areas of drought disasters are concentrated on scientific issues such as meteorological disasters, climate change, and drought.

From 1991 to 2022, the number of publications on drought disasters experienced four distinct phases: steady growth, stagnation, rapid growth, and steady decline.

The nine key research directions in drought disaster studies include: drought vulnerability research, remote sensing studies, precipitation studies, El Niño–Southern Oscillation (ENSO) research, machine learning (risk assessment, drought monitoring, and prediction) model development, meteorological drought studies, drought impact analysis, risk assessment studies, and research on climate change and its impacts.

The burst terms and their associated seven key phases are as follows:

1995–2007: Research on the United States

2011–2017: Frontier research on adaptive capacity

2012–2015: Research on the Standardized Precipitation Index (SPI)

2015–2017: Studies on social vulnerability

2016–2018: Research on conceptual frameworks and machine learning model frameworks

2018–2019: Studies on streamflow

2018–2019: Research on the severity of extreme events

A review of recent literature on drought disasters highlights two major research focuses and development trends:

Agricultural drought and its impacts on the sustainable livelihoods and adaptive capacities of smallholder farmers.

Understanding compound events and addressing climate change and its impacts.

6. Conflicts of Interest

The authors declare that they have no conflict of interest.

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