Review Article

A bibliometric analysis of deep learning applications in climate change research using CiteSpace

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Abstract: In recent years, artificial intelligence, particularly deep learning, has garnered significant attention among practitioners and scholars in meteorology and atmospheric sciences, leading to a substantial body of literature. This study aims to delineate the present research status and trends in climate innovation through CiteSpace visual analysis. To comprehend the current landscape, prevalent terms, and research frontiers of deep learning for climate change research (DLCCR) within meteorology and atmospheric applications, we gathered 256 published papers spanning from 2018 to 2022 from the Web of Science (WOS) core database. Employing these articles, we conducted co-authorship, co-citation, and keyword co-occurrence analyses. The findings unveiled a steady rise in DLCCR publications over the last five years. However, the correlation between high yield and high-citation authorship appears inconsistent and weak. Notably, prolific authors in this domain included Zhang Z.L. and Bonnet P. Furthermore, leading institutions such as the Chinese Academy of Sciences (China), le Centre National de la Recherche Scientifique (France), and Nanjing University of Information Science and Technology (China) have played pivotal roles in advancing DLCCR. The primary contributors among high-yield countries primarily cluster in a select group comprising China, the USA, South Korea, and Germany. Identifying significant information gaps in numerical weather, atmospheric physics and processes, algorithm parametrizations, and extreme events, our study underscores the necessity for future researchers to focus on these and related subjects. This study provides valuable insights into research hotspots, developmental trajectories, and emerging frontiers, thereby delineating the knowledge structure in this field and highlighting directions for further climate innovation research.

Keywords: deep learning; climate change; atmospheric sciences; visualization analysis; meteorology

1. Introduction

Climate change in the 21st century stands as the paramount threat to human survival and global sustainable development. As a result, there has been significant scholarly focus on devising innovative solutions to mitigate and adapt to this pressing issue[1,2]. Global warming, as a phenomenon, holds the potential to dramatically elevate global temperatures, leading to increased evaporation rates, heightened atmospheric water content, and subsequent alterations in rainfall patterns[3,4]. The acceleration of economic growth and industrialization intensifies human exploitation and intervention in the natural world, significantly impacting climate patterns and ecosystem development. Consequently, this has caused the depletion of natural resources across various ecosystems, the reduction of natural ecological areas, and the degradation of ecosystem services[5], consequently diminishing the capacity of climate systems to contribute to human well-being.

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Artificial Intelligence (AI) has emerged as a powerful tool in addressing climate change, drawing swift attention, and providing innovative solutions. By leveraging AI for prediction and analysis in climate and weather forecasting, we acquire valuable tools that enhance accuracy and efficiency in evaluating future outcomes. Through its capacity to process vast amounts of data, recognize patterns, and forecast potential scenarios, AI introduces novel pathways for studying climate change, devising effective policies, and implementing adaptive measures. This transformative technology holds the potential to significantly bolster our endeavors in both mitigating and adapting to the challenges posed by climate change[6,7].

Applications of machine and deep learning offer diverse possibilities in addressing climate modeling[8,9], predicting extreme weather and drought events[10,11], analyzing climate data[12], optimizing renewable energy sources[13], downscaling global climate[14], monitoring carbon emissions[15,16], and facilitating climate change adaptation[6,17].

Bibliometric analysis employs computational methods to sift through extensive literature, granting researchers a profound understanding of a specific research field's evolution and current status. By meticulously scrutinizing various publication items, this analysis not only reveals present conditions but also increase the capacity to predict future trends, offering invaluable insights for forthcoming scholarly inquiries[18,19]. CiteSpace software, a visualization tool developed by Chaomei Chen at Drexel University, USA, empowers researchers to visually explore and comprehensively comprehend research advancements across diverse scientific literature through knowledge mapping[20,21].

This paper presents a comprehensive overview of the climate change field, serving as a valuable resource for researchers seeking a foundational understanding of the subject. It conducts an in-depth analysis of current research in deep learning for climate change, delving into authorship, co-citation relationships, and keyword trends. Such analysis furnishes readers with an encompassing perspective of the research landscape, enabling a swift grasp of the field's present state and primary research trajectories. Moreover, the paper identifies future research focal points in climate innovation, underscoring the significance and efficacy of AI. By staying abreast of these trends, researchers can align their work more effectively with the evolving climate change research landscape, curbing wastage of time and resources while promoting human-centered research practices.

The authors aim to showcase a systematic review process employing visual analytic functions embedded in CiteSpace software[22] within this paper. This methodological approach facilitates a comprehensive literature analysis, enabling researchers to visualize connections and trends in research topics pertaining to climate change and AI. The systematic review aspires to offer a structured approach to synthesizing existing knowledge, pinpointing research gaps, and charting pathways for future studies in this dynamic and evolving field.

2. Current state of research

Tapping the value of AI in DLCCR

The utilization of AI to tackle climate change encompasses a wide array of applications[23]. These endeavors strive to address challenges stemming from environmental fluctuations exacerbated by economic growth and population expansion, leading to an amplified demand for energy. Deep learning emerges as a pivotal solution, holding promise in predicting energy demand, optimizing consumption, and fostering sustainability[24]. Despite its effectiveness in boosting energy efficiency, hurdles such as high implementation costs, data scarcity, and a shortage of experts persist[25–27].

Recent advancements in deep learning have facilitated successful predictions of weather and climate extremes. Researchers have made significant strides in forecasting events like hail[28], extreme heatwaves, droughts[29], and precipitation across various time scales[30]. For instance, applications such as convolutional neural networks (CNN), long and short-term memory (LSTM), and Extreme Gradient Boost (XGB) have been employed to predict extreme temperature events and drought within decadal time series[31–33].

DL-based weather and climate predictions have gained widespread attention across industries, demonstrated by innovative models like Pangu-Weather, ClimaX, GraphCast, and FourCastNet[34–37]. The integration of deep learning into models such as ModEx[38] is driven by the necessity to enhance Earth System Models (ESMs) with observational data[39]. In climate models with coarse horizontal grid spacing, statistical downscaling, and bias correction are vital for accurate representation[40,41].

Significant strides have been made in recent progress in bias correction methods, notably improving aspects like initial state quality control and sub-seasonal climate oscillation predictions[42,43]. DL algorithms contribute to early warning systems by processing real-time weather data, including satellite imagery and radar observations, to detect patterns and predict extreme climate events[44]. These algorithms can analyze large datasets of climate-related information, unveiling patterns, trends[45,46], and correlations that may not be evident through traditional analysis methods[47].

Moreover, DL plays a pivotal role in monitoring and managing carbon emissions[48], identifying sources, evaluating mitigation efforts, and contributing to the development of effective carbon reduction strategies[49]. Additionally, AI supports climate change adaptation by analyzing diverse datasets, identifying vulnerabilities[50], and assisting in planning and implementing adaptive strategies[51,52].

In recent years, increased attention has been devoted to applying deep learning techniques to predict oceanic conditions, particularly for seasonal to multi-year forecasts[53,54]. Initial efforts focused on directly predicting key indices such as the NINO 3.4 index[12]. For instance, Ham et al.[55] utilized a convolutional neural network (CNN) to generate skilled El Niño Southern Oscillation (ENSO) forecasts with a lead time of up to one and a half years[55].

3. Research methods and tools

3.1. Related theories and conceptual terms

The surge in academic publications has spurred interest in bibliometric research, leveraging the distinct characteristics of bibliometric data to construct a comprehensive overview for further analysis[56]. Scientific knowledge mapping, an interdisciplinary field amalgamating applied mathematics, information science, and computer science, has recently emerged within the realm of science metrology.

The primary goal of knowledge mapping and analysis is to extract and visually restructure knowledge from a vast collection of scientific research documents, facilitating knowledge discovery[20]. The visualization of scientific knowledge, employing social network analysis and graph theory, has emerged as a burgeoning field within bibliometric methods[1].

3.2. Research tools

This study utilizes CiteSpace 6.2.R4, a bibliometric analysis software deeply rooted in scientometrics and knowledge visualization, developed by Chaomei Chen. Additionally, the study specifically aims to unveil potential knowledge within scientific literature (see **Figure 1**). It assists researchers in comprehending fundamental aspects within a discipline, identifying foundational work, pinpointing research frontiers, and elucidating the contextual evolution of research[57,58]. Moreover, the software transforms research domain concepts into mapping functions, establishing connections between research boundaries and intellectual bases. Within this framework of mapping functions, three key concepts surface, each addressing distinct challenges:

(a) discerning the nature of the research frontier, (b) annotating the research domain, and (c) recognizing new trends and shifts over time[57].

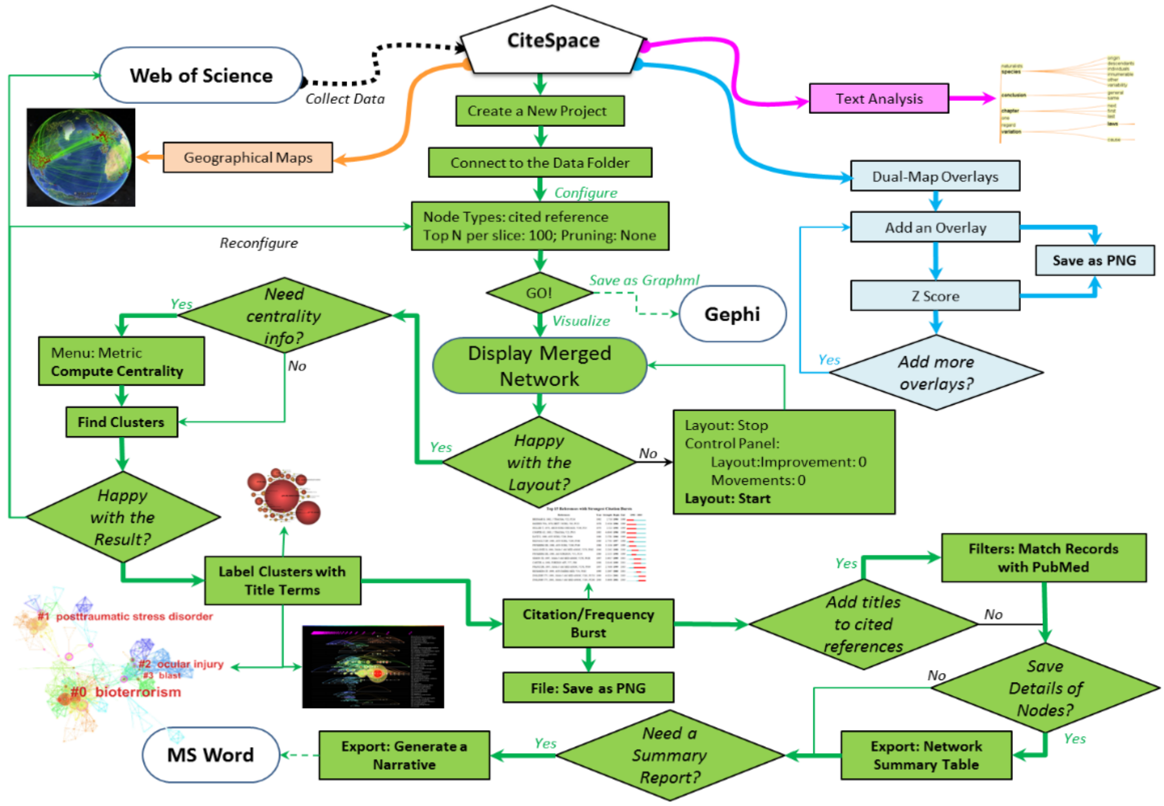

Figure 1. Major visual analytic paths supported by CiteSpace[57].

3.3. Data collection

The Web of Science (WoS) database serves as the primary data source for this study, meticulously curated to include essential literature. WoS stands as the gold standard for research discovery and analysis, interconnecting publications and researchers across various disciplines through its comprehensive citation and indexing databases. Utilizing reference searches, previous research within the fully indexed period of five years, from 2018 to 2022, can be meticulously tracked and monitored. The data processed by the CiteSpace software aligns with the WoS data download format, leveraging the extensive coverage of references, indexes, and researcher relationships.

3.3.1. Eligibility criteria

This study primarily utilized the SCIE database within the WoS Core Collection as the main data source. A specific search strategy was employed, and data were collected from the web version of the Nanjing University of Information Science and Technology (NUIST-China) Library. WoS offers multiple search strategy combinations, and CiteSpace focuses on tracking and analyzing the evolution of a topic, leading to improved outcomes for targeted topic retrieval. Subject words within WoS are derived from titles, abstracts, keywords, and full texts. Given the scholarly nature of articles, a longer publication span was preferred to compile a more comprehensive body of literature[58].

3.3.2. Including methods

In this study, the core set of the WoS database functions as the data source, utilizing the search strategy (Topic = “Deep learning” AND “climate change”, Document Types = “Article”, Research Areas=

"Meteorology Atmospheric Sciences", Languages = English). This strategy yielded a total of 256 articles as of 3 May 2023 (see **Figure 2**). To ensure data accuracy, the study meticulously reviewed the titles and abstracts of all articles, confirming that the collected data fully met the specified criteria. Subsequently, the article data were stored in "Plain text" format as "Full Record" and "Cite References" to facilitate further analysis. Although the dataset obtained for this study is relatively small, it fulfills the prerequisites for conducting CiteSpace analysis[59].

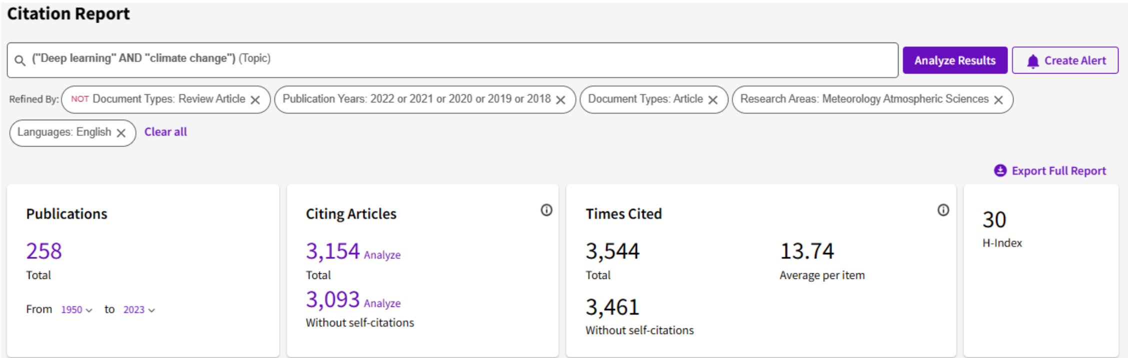

Figure 2. Research citations and different selections.

To analyze the field, we employed bibliometric techniques alongside CiteSpace 6.2.R3 software and Excel charts for visual representation. CiteSpace analyzes each bibliographic record, encompassing the title, abstract, authors, and their respective affiliations. These authors referred to as co-authors, denote collaborative bonds through their co-authorship[60].

3.3.3. Excluding methods

Review papers, meeting reports, and irrelevant, and duplicate documents were excluded from the dataset. Despite the relatively small size of the dataset obtained for this study, it meets the prerequisites for conducting CiteSpace analysis (refer to **Table 1**).

Table 1. Steps of data selection including and excluding methods criteria.

Filter	Selection	Excluding	n
First selection	"Deep learning" and "climate change"	/	n = 1128
Publication years	2018–2022 (5 years)	2023	n = 728
Document type	Article	Review article	n = 599
Author	All		n = 599
Database	Web of science	/	n = 599
Country	All	/	n = 599
Research area	Meteorology and atmospheric science		n = 284
Language	English	/	n = 284
CiteSpace integration	All paper	28 papers (duplication)	n = 256
Total	N = 256		

Through this approach, we scrutinized publication counts, authorship trends, and prominent research areas. Employing knowledge mapping and Excel charts, we delved into the current state and emerging patterns in ecosystem services research over the past five years. Additionally, we created visual charts illustrating country-wise distribution, institutional affiliations, author collaboration networks, keyword co-occurrence, and keyword clustering[61].

4. Visualization results and analysis

4.1. Analysis of the number of published papers

Figure 3 depicts the rapid advancement of DL research within the realm of climate change, notably from 2018 onwards. It illustrates a substantial surge in published papers, signifying the escalating interest and involvement in this domain. Further scrutiny reveals particular years, such as 2019, 2020, and 2021, as pivotal milestones in the trajectory of DLCCR (see **Figure 3**).

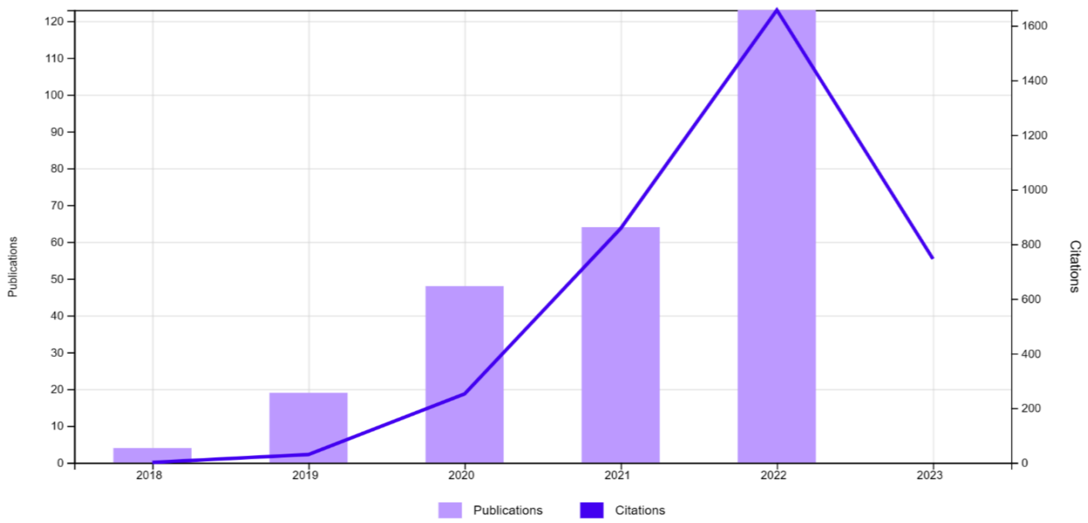

Figure 3. The number of published papers on DLCCR from 2018 to 2022.

4.2. Co-authorship analysis

Co-authorship manifests across three distinct levels: individual, institutional unit, and country. Analyzing co-authorship unveils collaboration dynamics among research institutions and their respective capabilities[62]. This technique aids in identifying key authors and collaborative networks among scholars in climate innovation, offering insights into research progression and international cooperation in climate-related studies[63].

4.2.1. Author co-authorship analysis

Authorship represents the smallest unit in a publication. By conducting author co-authorship analysis, we glean insights into publication statuses at a micro level. We constructed a graphical network depicting author co-authorship within the SCIE database. **Figure 4** summarizes information about the top 10 authors based on publication count. **Figures 5** illustrate academic collaborations among authors.

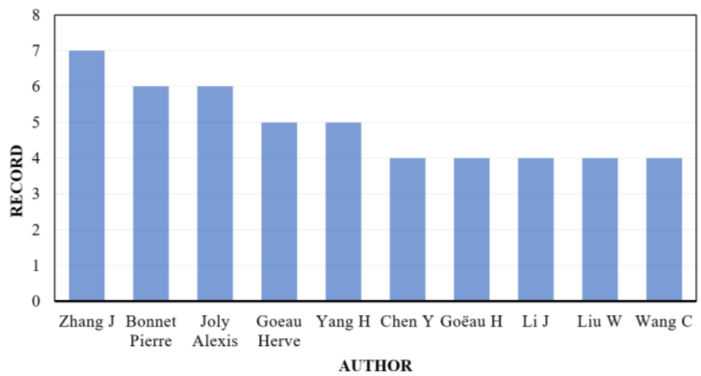

Figure 4. Top 10 authors with the highest research paper activity in DLCCR.

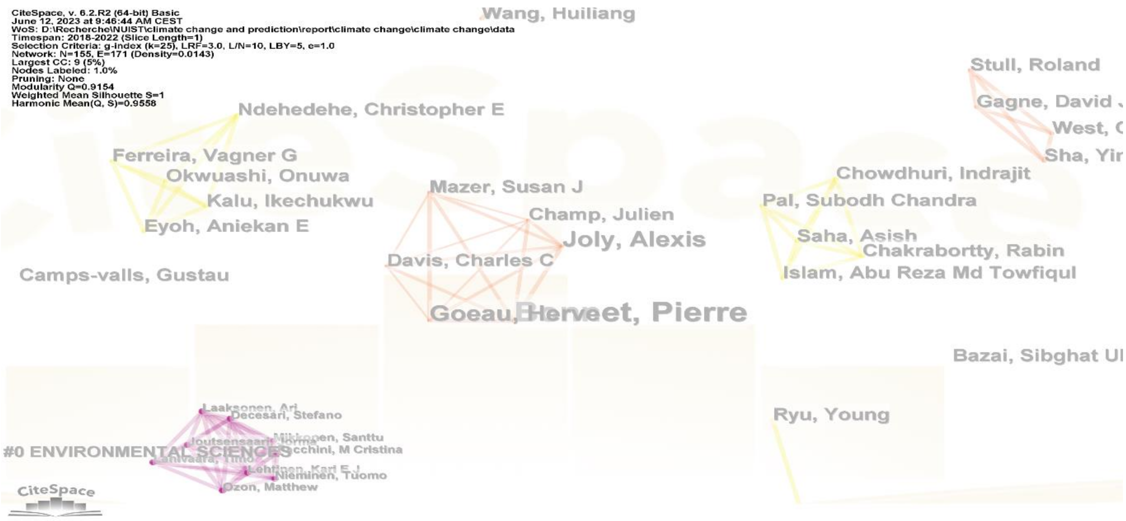

Figure 5. The academic collaboration among authors.

To craft cohesive network co-occurrence graphs, we set suitable thresholds and eliminated isolated nodes, preserving the most pertinent information within the graph. Each node is labeled with the respective author's name. Node size corresponds to the number of articles published by the author, while the lines connecting nodes signify collaborations between authors. The thickness of these lines indicates the strength of the connections among authors.

The network displays a low number of nodes, suggesting limited collaboration among authors and issuing institutions. Among the most prolific research teams in this network is a three-member team led by Shang J, Bonnet Pierre, and Joly Alexis, constituting the largest research team. Overall, there appears to be a lack of collaboration among researchers, with a tendency toward individual studies. Even in cases of collaboration, the teams tended to be relatively small. However, within the SCIE database, authors showed a greater inclination to collaborate, forming larger teams compared to other databases. While authors predominantly collaborated with peers from their own country, there were instances of inter-country authorships, indicating a degree of collaboration transcending geographical boundaries.

4.2.2. Institution co-authorship analysis

The identified authors were affiliated with various institutions, offering opportunities for these institutions to establish moderate-level collaborative networks through co-authorship. We visualized the co-authorship networks among institutions in SCIE (refer to **Figure 6**), providing a summary of the top 20 institutions based on publication count and relevant information. The findings remained consistent in both cases.

In terms of publication numbers, the top five institutions are the Chinese Academy of Sciences (China), Centre National de la Recherche Scientifique-CNRS (France), Nanjing University of Information Science and Technology (China), Helmholtz Association (Germany), and the University of Chinese Academy of Sciences (China), along with the University of California (USA) (refer to **Figure 6**).

Moreover, the CiteSpace analysis reveals the presence of 40 research institutes with limited collaboration links within the institute collaboration network. **Figure 7** illustrates that the majority of nodes are isolated points (1%), indicating that nearly all results have been accomplished by individual authors, suggesting minimal collaboration between institutions. The collaborative experiences among institutions are notably limited, and the intensity of collaboration appears very weak (see **Figure 7**).

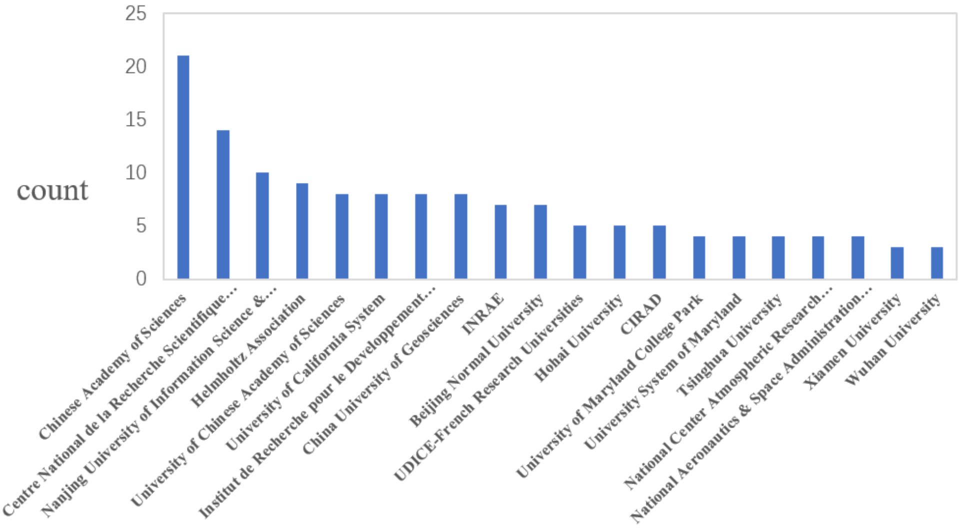

Figure 6. Co-authorship networks of institutions in SCIE.

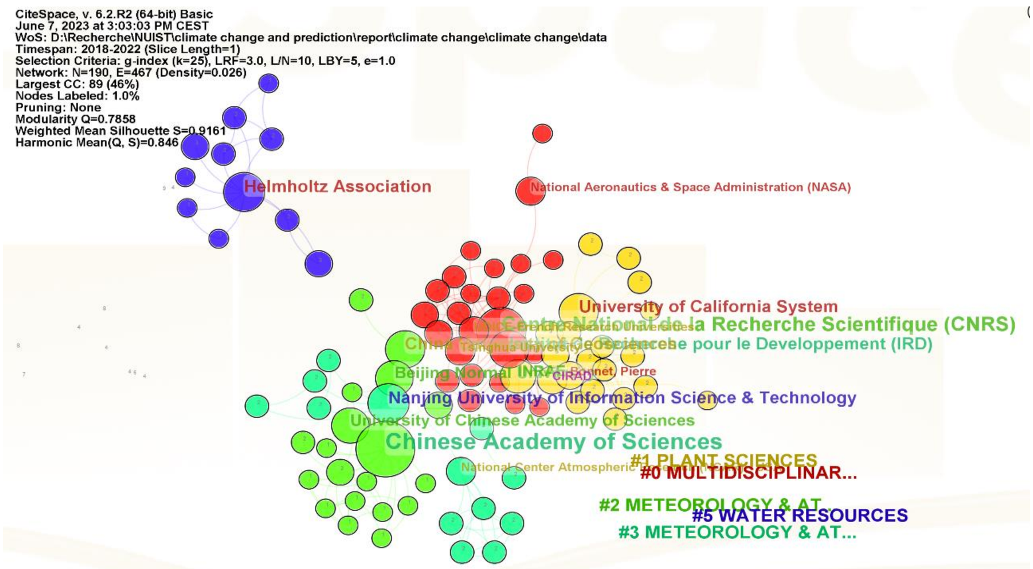

Figure 7. Map of the institution co-authorship network of DLCCR for SCI database.

4.2.3. Keywords co-authorship analysis

The selected keywords in this study represent the central themes and core content of the research. To trace developmental trends, this paper utilizes keyword co-occurrence analysis. Nodes characterized by high frequency and centrality in co-occurrence analysis are typically considered key nodes, signifying their significant influence across the entire network. Delving into these key nodes enables the extraction of valuable information embedded within them[58]. The keywords can be categorized into two primary groups: "Deep learning" and "Climate change", encompassing Atmospheric science and meteorology. The primary focus of the research revolves around predicting climate change and conducting model analysis using AI technology. Through mapping the keywords, we've identified the following clusters[64].

Artificial neural networks possess the capability to manage enormous volumes of data. These networks operate by processing data through multiple layers within the program. There are various types of artificial neural networks (refer to **Figure 8** and **Figure 9**).

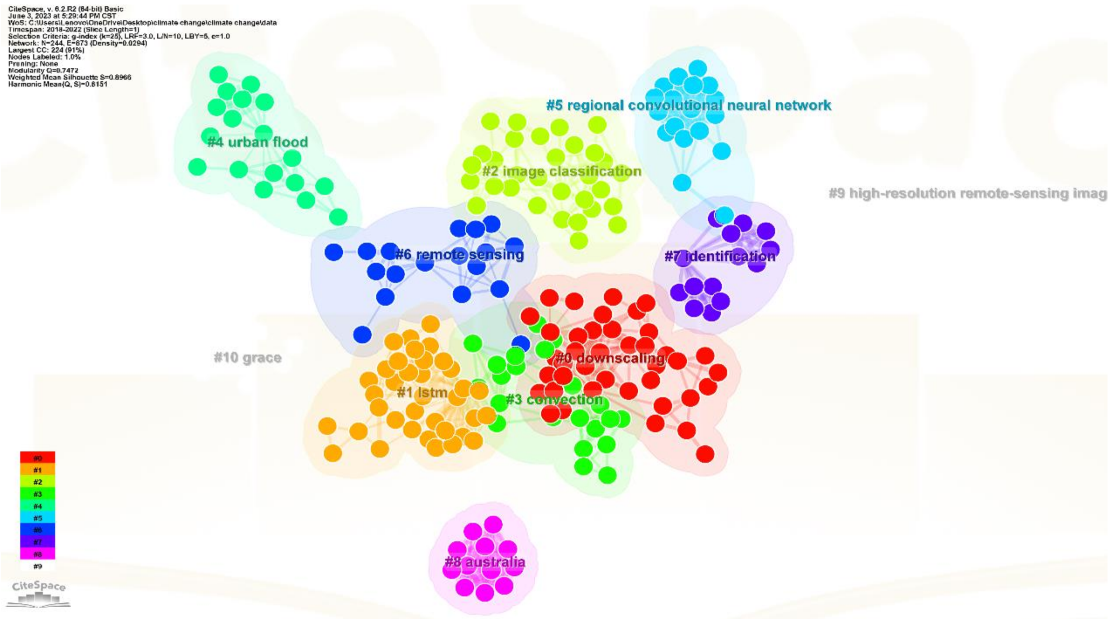

Figure 8. keywords co-authorship networks.

Keywords	Year	Strength	Begin	End	2018 - 2022
convolutional neural networks	2018	1.68	**2018**	2020	
classification	2018	1.3	**2018**	2020	
algorithms	2018	0.84	**2018**	2020	
lstm	2019	1.07	**2019**	2020	
abundance	2019	0.9	**2019**	2020	
forest	2020	1.48	**2020**	2022	
index	2020	1.18	**2020**	2022	
performance	2020	0.68	**2020**	2022	

Figure 9. Top 8 keywords with the strongest citation bursts.

In **Figure 9**, the top 8 keywords exhibiting notable citation bursts are highlighted. The keyword with the highest citation strength across all papers is “convolutional neural network” (1.68), followed by “Forest” (1.48) and “classification” (1.3). Subsequently, “index” holds a citation strength of 1.18, followed by “LSTM” (1.07), “Abundance” (0.9), “algorithms” (0.84), and “performance” (0.68). These findings underscore the significant keywords driving attention and interest within the research landscape. Moreover, AI techniques are increasingly employed for predicting certain climate change parameters, particularly in the area of convolutional neural networks, which stands as an area of significant interest.

4.2.4. Country co-authorship analysis

Figure 10 illustrates the trend in annual publication numbers from the top 10 productive countries between 2018 and 2022. A total of 64 regions/countries contributed to the field of DLCCR research, with the top 10 countries making significant contributions to the total outputs (refer to **Figure 10**). The network of collaborating countries comprised 152 nodes and 58 links (see **Figure 11**).

The People’s Republic of China emerges as the foremost contributor, boasting a total of 93 published papers. Following closely is the United States with 71 papers, trailed by South Korea with 28 contributions. Within the European region, noteworthy contributions come from Germany with 22 papers and France with 19, establishing a diverse global distribution of research output in the field (refer to **Figure 10**).

The CiteSpace analysis revealed a total of 64 countries and regions, encompassing 54 collaboration links (refer to **Figure 11**). This suggests prevalent cross-country and cross-region connections within the research landscape. Generally, the volume of outputs correlates with the presence of research institutions, the availability of research funding, and the involvement of leading institutions in AI research. While the network demonstrates frequent links between countries and regions, the strengths of these connections tend to be relatively weak, indicating that collaborative efforts across borders are present but not yet firmly established. Remarkably, China, the United States, South Korea, Germany, and France emerge as the top countries in terms of publication volume. Notably, China leads in both publication citations and collaborative efforts.

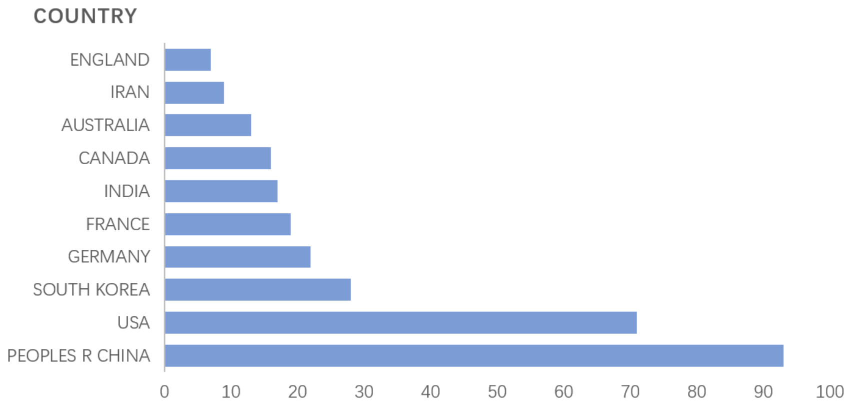

Figure 10. scientific BDFCCR production for each country.

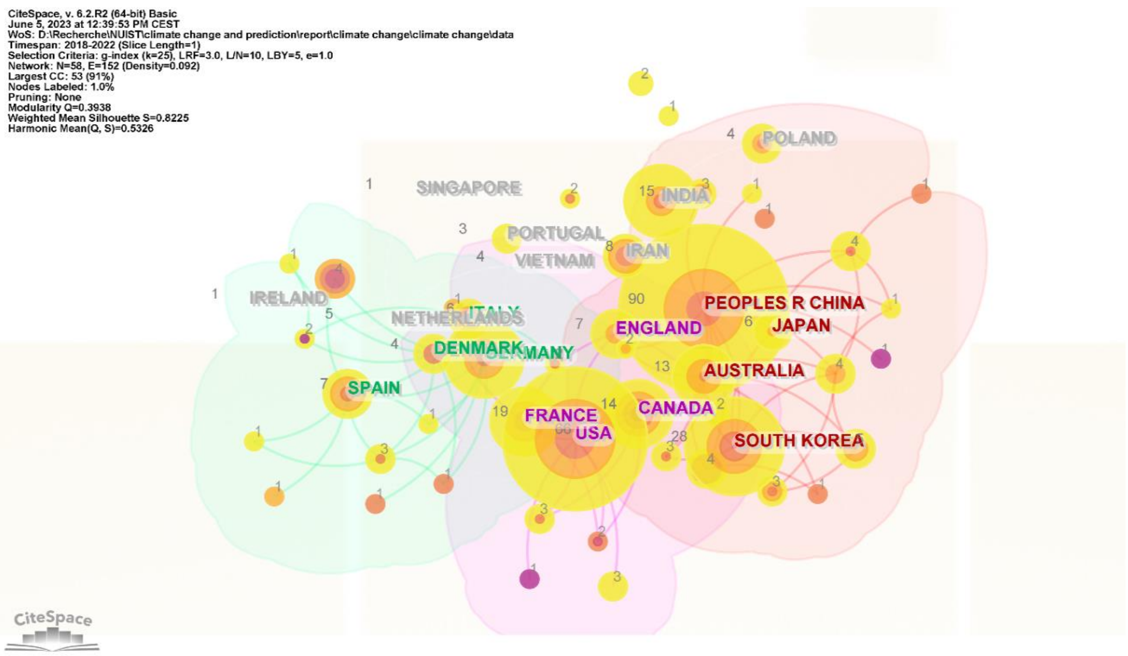

Figure 11. Visualization of the co-country network.

5. Discussion

The existence of pivot nodes allows us to swiftly narrow our visual search to a handful of excellent candidate nodes, a promising outcome. Easily pinpointing these pivotal points is crucial for effectively detecting paradigm shifts in a knowledge domain. The smaller network, incorporating these turning points, is notably clearer, while the larger, unpruned network appears cluttered. Nonetheless, it’s still plausible to identify multiple pivot points within it.

However, our bibliometric analysis in this study encountered limitations. Primarily, we solely utilized the WOS database due to restricted access provided by our research institution. It's important to note the existence of other publicly available and commercial bibliometric databases like Scopus and PubMed. Although WOS enjoys global recognition for its longstanding history and being the primary bibliographic database before Scopus, it has coverage limitations compared to Scopus.

Additionally, our search strategy employed specific keywords related to climate change variables, such as deep learning, meteorology, climate change, and atmospheric sciences. This approach might have restricted the identification of studies covering all aspects of climate change. Therefore, future studies could benefit from broader search strategies to comprehensively explore the literature on this topic.

Future trends of DLCCR

Ensuring responsible AI use is vital in addressing climate issues, steering clear of unnecessary reliance on technological solutions, and establishing realistic expectations[65]. The study highlights the importance of frameworks to address gaps and adaptability in deep learning for climate modeling[7]. Seamlessly integrating climate and digital transitions is crucial while upholding scientific values[6]. The future path of AI in climate change necessitates increased international cooperation aligned with broader climate initiatives. For instance, it's critical to identify and tackle risks, particularly in countries less capable of strategizing adaptations[24].

Moreover, collaborative events and projects, such as forums and conferences, should facilitate discussions among governments, scientists, and experts on AI development, as demonstrated by the Global Partnership Conference in December 2020[23,66]. Future efforts in deep learning should streamline access to data and digital infrastructure[67]. Challenges persist in validating climate model simulations, especially for longer timescales and rare events[68]. Overcoming these challenges involves diverse strategies, including undersampling, hyperparameter optimization, and custom loss functions.

Recent research must address limitations in data quality and quantity, foster interdisciplinary collaboration, enhance model interpretability, and resolve issues related to fidelity prediction, such as overparameterization[69]. Addressing data coverage issues and bridging communication gaps is crucial. The challenge extends to potential biases and uncertainties in representing climate models within deep learning frameworks. Inconsistencies in AI results underscore the complexity of climate applications. Integrating deep learning with traditional models and staying attentive to emerging gaps contributes to a comprehensive understanding of climate change dynamics[70].

Ensuring model transferability across diverse regions, effective management of computational resources, and quantifying uncertainties are crucial. Urgent development of causal methods considering the physical characteristics of studied climate phenomena is necessary. Mitigating limitations in observational records, addressing class imbalances, and characterizing extreme event precursors can be achieved through advanced deep-learning algorithms. In the near future, deep learning can enhance open-source micro-scale comparative analysis data limitations, providing a reasonable basis for uncertainty quantification and combining data-based and physics-based approaches for improved spatiotemporal downscaling.

6. Conclusion

Once adaptation and mitigation strategies for climate change are developed, sustainable development for human societies will become attainable. The field of Deep Learning and climate change research has seen rapid expansion in recent years. The annual volume of published articles has steadily increased from 2012 to 2021. While the majority of scholars come from China and the United States, significant contributions to cooperative network development come from the United States and South Korea. The Chinese Academy of

Sciences stands out as the dominant research institution. However, there's room for improvement in collaboration among research institutions, which could significantly benefit this research field.

Expanding the number of predicted parameters, especially through the combined use of AI and environmental science methods like long short-term memory (LSTM) and neural network algorithms, is currently a research hotspot. Future research should prioritize the prediction of climate variable concentrations. Additionally, direct government support for research, innovation, and the implementation of AI technologies in climate change domains is crucial. This review paper can assist scientists across various domains in promoting the responsible integration of AI for climate action. Ultimately, it contributes to advancing climate change research and facilitates the process of climate change adaptation.

Author contributions

The achievement of this manuscript is attributed to the synergistic collaboration between the authors. BG played a key role in conceptualization, methodology, and software analysis. BRL provided expertise in validation, formal analysis, and writing. KA led the meticulous revision, editing, and supervision. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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