



Mapping the Landscape of Artificial Intelligence for Climate Resilience in Rural Areas: A Bibliometric Study

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Abstract

Rural areas are particularly vulnerable to climate-related risks, yet limited access to locally available environmental data can constrain effective mitigation and adaptation strategies. This study maps the global research landscape on the application of Artificial Intelligence (AI) to climate resilience in rural areas through a bibliometric analysis of 254 documents indexed in the Scopus database. Biblioshiny and VOSviewer were used to examine publication trends, geographic contributions, keyword co-occurrence patterns, and thematic evolution. The findings show a sharp increase in publications after 2021, with China, the United States, and Saudi Arabia among the leading contributors. The intellectual structure of the field is primarily organized around three interconnected themes: Machine Learning, climate change, and Remote Sensing. Thematic analysis further indicates a transition from relatively conventional land-use and environmental monitoring approaches toward more advanced applications involving Deep Learning, carbon-emission analysis, decarbonization strategies, and site-level environmental monitoring. These developments suggest that AI-based climate resilience research is becoming increasingly interdisciplinary and application-oriented. By specifically isolating rural areas as the unit of analysis, this study complements broader bibliometric studies that commonly examine agriculture, climate change, or AI at a more general level. The findings provide an evidence-based overview of the current knowledge structure, emerging themes, and research directions that may support future interdisciplinary research and the responsible development of AI-based climate adaptation strategies for rural communities.

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INTRODUCTION

Climate change poses substantial challenges to rural communities, particularly those whose livelihoods depend heavily on climate-sensitive agricultural systems. Increasing weather variability and extreme climatic events can disrupt food production and intensify socioeconomic vulnerability, especially in areas with limited infrastructure and adaptive capacity (Wheeler & Braun, 2013; Lesk et al., 2016). Rural communities may be particularly exposed because access to financial resources, environmental information, and technological infrastructure is often more limited than in urban settings (Adger et al., 2003). Moreover, the economic consequences of climate change may disproportionately affect already vulnerable populations, potentially reinforcing existing inequalities (Differbaugh & Burke, 2019). This step is also crucial for supporting the United Nations' Sustainable Development Goals (SDGs), particularly SDG 13 and SDG 11. Strengthening climate resilience in rural areas is therefore closely related to broader sustainable-development priorities, particularly those associated with climate action and resilient communities.

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As a solution for the future, Artificial Intelligence (AI) offers a new way to address the problem of environmental data scarcity in remote villages, which has long hindered the effectiveness of disaster mitigation policies (Lobell et al., 2008). AI-based approaches, including Machine Learning (ML) and Deep Learning (DL), are capable of identifying complex patterns in large and heterogeneous environmental datasets and can support the analysis of climate-related processes that may be difficult to capture using conventional approaches (Reichstein et al., 2019). Machine-learning techniques have also been explored for climate-change mitigation, environmental prediction, and decision support across different sectors (Rolnick et al., 2023). In agricultural and environmental applications, the integration of data-driven methods with process-based approaches may provide additional opportunities for improving the analysis of ecological processes, although their performance remains dependent on the availability and quality of empirical data (Ellis & Paustian, 2024).

Despite this growing technological potential, the application of AI to climate resilience is not evenly represented across geographical and socioeconomic contexts. Much of the broader discourse surrounding digital environmental governance and smart technologies has developed around data-rich and highly connected environments, whereas rural regions frequently face more limited data availability, infrastructure, and technological access (Galaz, 2024). These constraints may affect how AI-based solutions are designed, validated, and ultimately applied in rural communities. At the same time, developments in smart agriculture and data analytics demonstrate increasing opportunities for integrating digital technologies into agricultural systems, while also revealing persistent challenges related to accessibility, infrastructure, and implementation (Acharya et al., 2021). Consequently, understanding how the scientific literature has addressed the intersection of AI, climate resilience, and rural contexts is increasingly important.

Existing research has increasingly explored the application of AI in climate change, environmental monitoring, precision agriculture, and related sustainability domains. In rural contexts, however, the effectiveness of AI-based applications remains highly dependent on the availability and quality of local data (Ellis & Paustian, 2024). Recent developments also indicate a transition from predominantly descriptive environmental monitoring toward more predictive and context-specific analytical approaches, including machine-learning-based evapotranspiration prediction in water-constrained agricultural regions (Monavvar Sabegh et al., 2026). At the same time, technological advancement alone does not necessarily ensure equitable outcomes for rural communities, underscoring the importance of responsible and context-sensitive implementation (Upadhyay & Kamble, 2024).

Recent knowledge-mapping studies have further clarified the expanding intersections among artificial intelligence, climate change, and digitally enabled agriculture. Lewis et al. (2024) mapped the global AI-climate change research landscape and identified applications across climate modeling, climate impacts, emissions, energy, and land-use research, although their analysis remained global and cross-sectoral. Xu et al. (2024) examined 344 publications on sustainable agriculture in the digital era and identified major themes related to smart agriculture, digitalization, geospatial technologies, and technology adoption. Rejeb et al. (2024) similarly mapped precision agriculture and highlighted machine learning, remote sensing, the Internet of Things, and climate-smart agriculture as prominent research components. More recently, Pervez et al. (2026) analyzed 645 Scopus-indexed publications on AI for sustainable agriculture and emphasized machine learning, deep learning, precision agriculture, the Internet of Things, and regional disparities in research productivity. Collectively, these studies provide important insights into AI-climate and AI-agriculture research, yet rural climate resilience has generally remained embedded within broader agricultural, environmental, or sustainability frameworks rather than being examined as a distinct knowledge domain. This gap warrants a focused investigation of how research on AI-supported climate resilience in rural areas has developed, including its leading contributors, conceptual structure, thematic evolution, and emerging research directions.

Bibliometric analysis provides a systematic approach for examining these developments by revealing patterns of publication growth, scientific contribution, collaboration, conceptual structure, and thematic evolution. Rather than assessing the performance of individual AI models, such an approach can identify how the scientific field itself has developed and where emerging research directions are concentrated. In this context, the present study focuses specifically on rural areas as

the analytical context, allowing the literature on AI and climate resilience to be examined separately from broader studies of agriculture, climate change, or artificial intelligence. The study therefore maps the development of this research domain and identifies its principal contributors, conceptual clusters, and evolving thematic directions.

To fill this gap, this study employs an in-depth bibliometric analysis to examine research productivity, the impact of publications, and global collaboration networks surrounding AI applications for climate resilience in rural areas. The novelty of this study lies in its specific focus on isolating rural areas as the primary unit of analysis, distinguishing it from existing general bibliometric studies. The scientific contribution of this paper is to provide a structured roadmap that charts conceptual shifts, ranging from conventional land mapping to decarbonization strategies and advanced Deep Learning applications. Through this quantitative mapping, this study is designed to answer four main research questions:

- RQ1: What are the trends in the annual growth of publications related to the use of AI for climate change in rural areas over the past decade?
- RQ2: Who are the main contributors dominating the scientific discourse in this field, and what patterns of international collaboration have emerged?
- RQ3: What are the main research themes emerging in the current literature, and how is this intellectual structure divided into thematic clusters?
- RQ4: How have research topics evolved over time, and which topics are predicted to become future research trends?

METHOD

This study uses bibliometric analysis to map the application of Artificial Intelligence (AI) in climate change mitigation and adaptation in rural areas, conducted in three main stages. The first stage involved literature collection through a document search strategy in the Scopus database. Scopus was selected as the sole data source due to its reputation as one of the largest global abstract and citation databases that applies very strict peer-review standards and provides comprehensive publication metadata compatible with quantitative bibliometric analysis (Mongeon & Paul-Hus, 2016). The document search was conducted on January 1, 2026, using the TITLE-ABS-KEY search parameters, which include title, abstract, and keywords. The search terms were organized into three conceptual groups corresponding to the central focus of the study: artificial intelligence, climate change, and rural contexts. The first group represented the technological dimension and included "Artificial Intelligence," "Machine Learning," "Deep Learning," "Neural Network," "Algorithm," and "Expert System." The second group represented the climate dimension through the terms "Climate Change," "Global Warming," "Greenhouse Gas," "Climate Variability," "Carbon Emissions," "Climate Mitigation," and "Climate Adaptation." The third group captured the rural context through "Rural," "Countryside," "Village," "Remote Areas," "Agricultural Region," "Non-urban," "Rural Community," and "Peasantry." Terms within each conceptual group were connected using the OR operator to accommodate variations in terminology, whereas the three groups were combined using AND to ensure that the retrieved documents simultaneously addressed the technological, climate-related, and rural dimensions of the study. The search formula used combined Boolean operators as follows: TITLE-ABS-KEY (("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Network" OR "Algorithm" OR "Expert System") AND ("Climate Change" OR "Global Warming" OR "Greenhouse Gas" OR "Climate Variability" OR "Carbon Emissions" OR "Climate Mitigation" OR "Climate Adaptation") AND ("Rural" OR "Countryside" OR "Village" OR "Remote Areas" OR "Agricultural Region" OR "Non-urban" OR "Rural Community" OR "Peasantry")). An initial search using this comprehensive formula successfully identified 674 documents.

The second stage focused on data screening and cleaning in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol to ensure transparency in sample selection; the second stage involved data screening and cleaning (Page et al., 2021). The inclusion criteria in this study strictly limited the sample to journal articles and conference papers written in English that had been published as final articles. The restriction to scientific articles and conference papers aims to ensure that the analyzed literature possesses high scientific validity because it has undergone a peer-review process, while the selection of English was

made to ensure global linguistic standardization in text network analysis (Tennant et al., 2016). However, this limitation has methodological consequences in the form of potential publication bias, whereby relevant local studies from specific rural areas written in the national language or published in subscription-based journals risk being overlooked in this analysis. Based on an eligibility assessment of 674 initial documents, 419 documents were excluded, with the following breakdown: 372 documents were excluded because they were not articles or conference papers, 40 documents were excluded because they were not in English, and 7 documents were excluded because they had not yet reached final article status. This eligibility evaluation process yielded 255 documents. Terminological inconsistencies in the keyword data were subsequently addressed using Microsoft Excel and OpenRefine. This procedure focused on reducing duplicated expressions and consolidating synonymous terms that could otherwise fragment conceptually identical topics across different nodes in the bibliometric networks. Finally, after undergoing a final data cleaning stage to verify the completeness of the publication's metadata components, a final sample of 254 relevant documents was obtained for analysis in the next stage.

The third stage involved determining the analysis parameters using two integrated software packages namely, Biblioshiny and VOSviewer to answer the four research questions. Biblioshiny, which serves as an interactive web interface for the bibliometrix package in the R programming language, is used to conduct an in-depth analysis of bibliographic performance metrics. The Biblioshiny software is used to evaluate descriptive performance metrics, including parameters such as trends in annual publication growth, the productivity of key contributors, and the visualization of thematic evolution maps to predict future research trends (Aria & Cuccurullo, 2017). Meanwhile, VOSviewer was used to map bibliometric network parameters, including an analysis of cross-country collaboration to examine patterns of international cooperation, as well as an analysis of keyword co-occurrence to identify dominant research theme clusters and analyze the novelty of topics based on temporal visualization. This visualization helps reveal dominant topic clusters and detect emerging research themes within the global literature (van Eck & Waltman, 2010). The analysis workflow using these two tools is schematically illustrated in Figure 1.

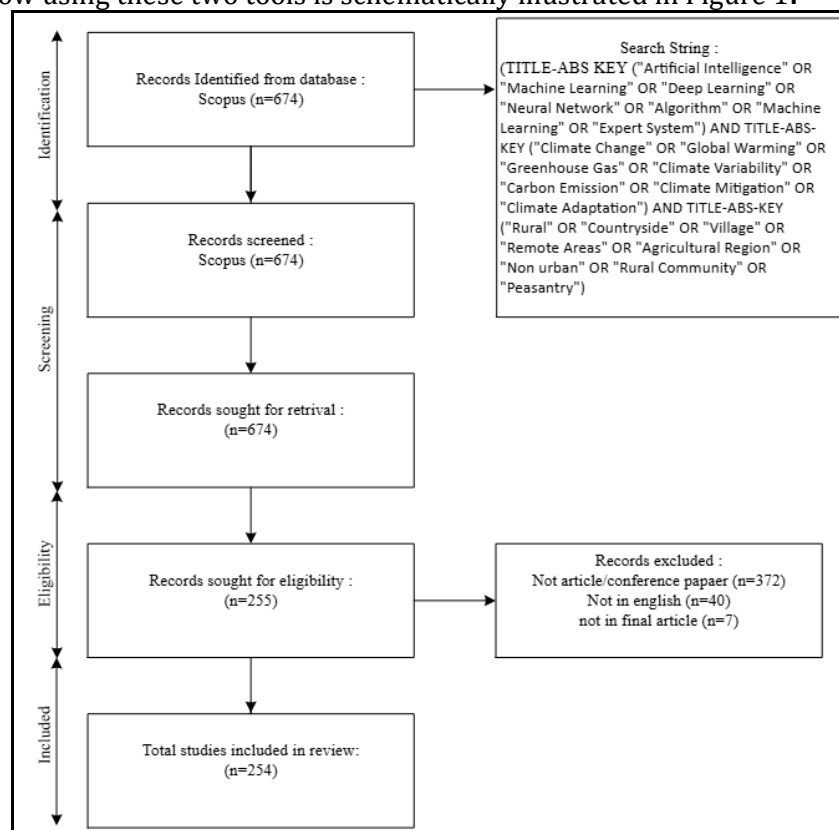


Figure 1. Search strategy adapted from the PRISMA flow diagram. (Page et al., 2021)

RESULTS AND DISCUSSION

Results

Publication Trends and Research Performance

The analysis of publication trends and research performance in this study began by examining the macro characteristics of the entire dataset that had been successfully extracted. Based on a summary of key data from the Biblioshiny software, this study covers the publication period from 2015 to 2025, with a total sample of 254 unique scientific journal articles. An evaluation of the initial characteristics of the dataset indicates that this field has a very young average document age of 2.62 years. This pattern suggests confirms that the application of artificial intelligence in rural climate resilience is a cutting-edge research area that is developing very rapidly.

Furthermore, the level of collaboration among researchers within this research ecosystem is very high, as evidenced by an average of 5.07 authors per document and an international collaboration rate of 37.4 percent. These descriptive statistics provide an initial analytical foundation indicating that this scientific discourse is driven by a strong and extensive network of researchers spanning various countries. This high level of cross-border collaboration reflects the interdisciplinary nature of rural climate challenges, which require synergy between global computational expertise and local ecological understanding to formulate adaptive policies (Adger et al., 2003; Sharma et al., 2021).

Conceptually, this analysis of annual publication trends aims to provide an overview of the evolution of academic interest and research intensity related to the application of Artificial Intelligence in building climate resilience in rural areas. Through these metrics, patterns of knowledge growth can be identified to determine whether this topic is in the early stages of development or has reached research maturity. As emphasized in the global literature, the integration of smart technologies into environmental mitigation strategies is a crucial response to increasingly unpredictable weather anomalies (Rolnick et al., 2023). Mapping these trends also serves as a vital tool for policymakers to evaluate the effectiveness of technology adoption in minimizing socioeconomic risks for agrarian communities (Fawzy et al., 2020). The following is a graph of annual scientific output.

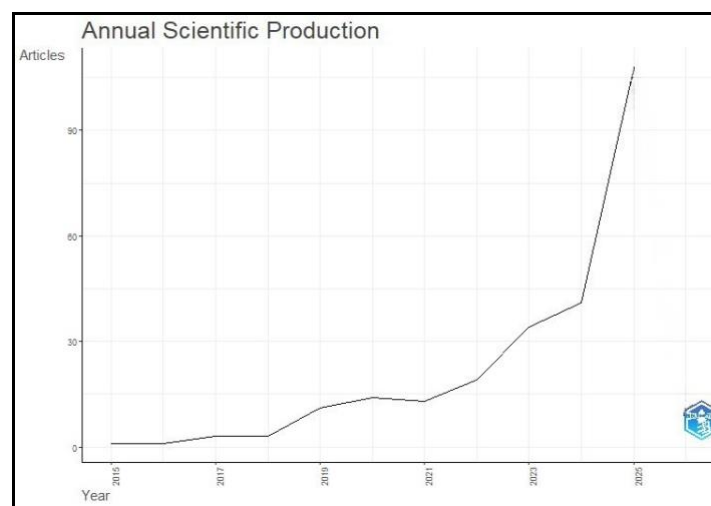


Figure 2. Annual Scientific Production

As illustrated in Figure 2, it is clear that the scientific discourse on the application of artificial intelligence to rural climate resilience has experienced exponential growth, with a significant turning point occurring in 2021, when the overall annual growth rate of the dataset reached 17.69 percent. This data pattern indicates that while publications in this field during the 2015–2020 period tended to be sporadic and limited with a total of only 33 documents, signaling that the field was still in a conceptual initiation phase the period after 2021 witnessed a very sharp surge, contributing a total of 221 documents. This acceleration peaked significantly between 2024 (41 documents) and 2025 (108 documents), marking a major leap in the intensity of global research. This sharp increase in publication output indicates growing scholarly attention to the topic. When considered together with the thematic and keyword analyses presented in the following sections, it may also reflect a broader

shift toward more predictive and data-driven approaches in the field. The bibliometric evidence indicates a gradual shift in research focus toward more predictive and data-driven approaches. The thematic evolution analysis shows that earlier studies were more strongly associated with terms such as “expert systems,” “decision support systems,” and “environmental protection,” whereas post-2020 publications increasingly featured “deep learning” and “artificial neural networks.” This pattern suggests growing scholarly emphasis on advanced computational approaches for addressing climate-related challenges in rural and agricultural contexts, consistent with the broader expansion of data-driven technologies in smart agriculture reported by [Acharya et al. \(2021\)](#). This massive shift in the post-2021 phase is also driven by the increasing availability of high-resolution satellite data, combined with the urgency of meeting the UN Sustainable Development Goals (SDGs) related to climate action and food security in rural areas ([LeCun et al., 2015](#); [Sitokonstantinou et al., 2021](#)).

Alongside the growth in publication output, the dataset recorded an average of 13.77 citations per document, indicating substantial scholarly attention to this research field. Citation impact, however, primarily reflects academic influence and visibility and should not be interpreted as direct evidence of practical adoption. Nevertheless, the broader literature demonstrates the potential of advanced computational and deep-learning approaches for environmental monitoring, climate prediction, and decision-support applications ([Reichstein et al., 2019](#)).

Contribution of Sources and Countries

The analysis of key contributors aims to map the distribution of scientific authority and centers of excellence in the AI literature on climate change in rural areas. By identifying the most productive journals, institutions, and countries, researchers can understand how knowledge is disseminated and how global collaboration patterns emerge to address environmental challenges at the local level. The following figure shows the most relevant sources.

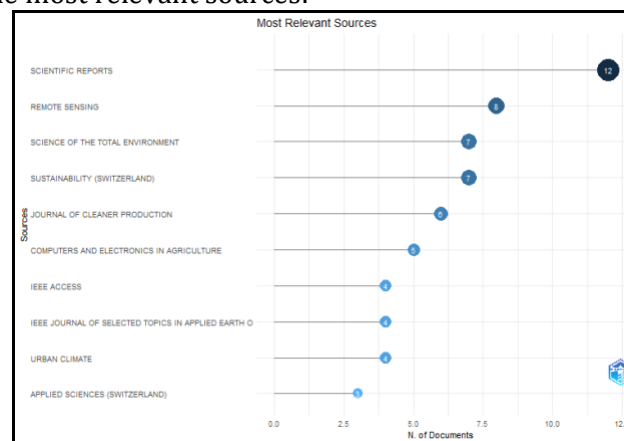


Figure 3. Most Relevant Sources.

Based on the mapping in Figure 3, a series of journals that are most significant in facilitating the integration of technology for climate mitigation can be identified. Scientific Reports leads as the primary publication platform with a total of 12 papers, followed by Remote Sensing (8 papers), as well as Sustainability and Science of the Total Environment, each contributing 7 papers. Analytically, the dominance of these multidisciplinary journals with high citation rates indicates that rural climate solutions are no longer the exclusive domain of pure computer science but rather an interdisciplinary field that unites technological innovation and sustainability in the agricultural sector. Research in these journals focuses on the use of satellite imagery processed using machine learning algorithms, which are now widely recognized as crucial tools for land monitoring and accurate microclimate prediction ([Parnes & Weiss, 2025](#)).

The scientific contributions of this journal’s analysis confirm a tangible convergence between intelligent computing and practical environmental science ([Reichstein et al., 2019](#)). The regular publication of papers on these globally renowned platforms demonstrates that the developed methodologies have met rigorous empirical validation standards for direct application to rural environmental management.

Although the Journal of Cleaner Production ranks fifth with 6 papers, this journal has an extraordinary intellectual impact. One of its key articles on regional ozone prediction by Wang et al., (2020) has garnered 86 citations, while another study on rural waste management has reached 74 citations (Mihai & Ingrao, 2018). This confirms the journal's role as a knowledge hub for sustainable climate technology solutions.

The next journal with a substantial number of publications is Remote Sensing, which features a total of 8 selected studies. Research in this journal focuses on the application of remote sensing technology and the integration of machine learning for precise, large-scale environmental monitoring. Through this approach, researchers can address spatial data challenges in vast regions, such as mapping climate zones or urbanization patterns that impact natural resources. A significant example of this application is a study that utilizes VIIRS and MODIS satellite data to accurately map land cover a critical factor for resource management and disaster mitigation in the era of climate change (Chen et al., 2023). The integration of this spatial data makes an important scientific contribution by transforming raw remote sensing data into measurable adaptation policy tools for agricultural regions (Sitokonstantinou et al., 2021).

Meanwhile, the Journal of Cleaner Production includes 6 studies in this dataset; however, the articles within it have garnered a highly significant citation impact (a total of 182 citations). The research focus in this journal examines how Deep Learning-based prediction models can be applied to monitor atmospheric pollutants that directly impact human health and climate change. One key finding shows that a hybrid sequence-to-sequence approach is capable of providing accurate regional predictions of ground-level ozone concentrations, which serve as an early warning system for environmental policymakers (Chaoyong et al., 2024). The following is Figure 4 on country scientific production.

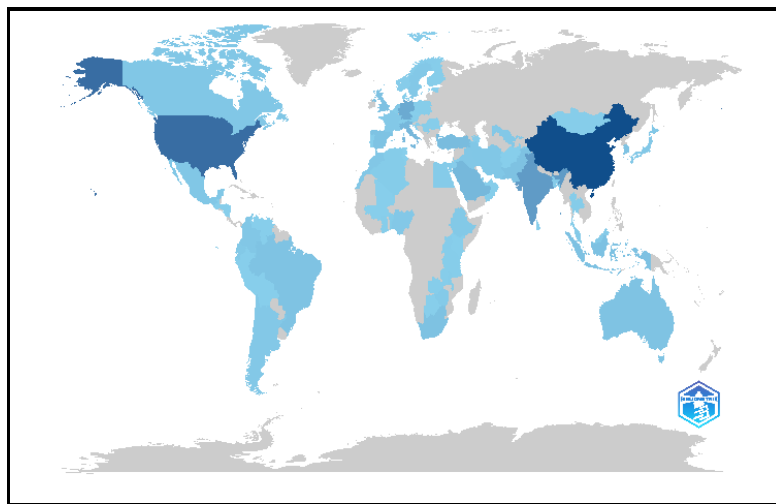


Figure 4. Country Scientific Production

Mapping the geographic distribution in Figure 4 identifies the countries that contribute most actively to the literature on AI-supported climate resilience in rural areas. China was the largest contributor, with 62 publications, followed by the United States with 46 publications. The prominence of these two countries may be associated with their broader AI research ecosystems and established infrastructures for Earth observation and data-intensive environmental research. At the broader AI level, China has become a major producer of scientific publications, while the United States maintains a particularly strong presence in highly cited AI research (Stanford Institute for Human-Centered Artificial Intelligence, 2025). In China, the development of the China High-resolution Earth Observation System (CHEOS) has expanded access to high-resolution Earth-observation data for applications including modern agriculture, disaster prevention, and environmental monitoring, providing an institutional and technological context that may support research at the intersection of AI and climate resilience (Wei et al., 2023). In the United States, federal research programs similarly support the integration of AI, machine learning, remote sensing, and satellite imagery for crop and soil monitoring, environmental management, and agricultural decision

support, while collaboration between NASA and the USDA has strengthened the use of Earth-observation technologies in agricultural research (Fieuzal et al., 2017).

An interesting trend is also evident in the output from Saudi Arabia, with 17 publications, and Pakistan, with 9 publications. The emergence of these countries among the leading contributors indicates that AI-based climate resilience research has become a crucial tool for regions facing the threats of extreme drought and water crises. This is reinforced by research highlighting the need for accurate water prediction models for sustainable agricultural development in regions with limited water resources. This global distribution demonstrates that while AI technology is developed in major technology hubs, its applications are now actively addressing pressing local issues across diverse rural landscapes worldwide (Monavvar Sabegh et al., 2026). This shift indicates a significant scientific contribution stemming from the maturity of this research field, in which global AI frameworks have been successfully adapted to address unique sociogeographic vulnerabilities at the local level (Adger et al., 2003).

Structural Map of Knowledge and Thematic Clusters

A keyword co-occurrence analysis was conducted to map the conceptual structure and identify the main themes dominating the AI literature in the context of climate change in rural areas. Based on the network visualization, several major clusters were identified that represent the pillars of knowledge in this field. Figure 5 shows the authors' keywords that co-occur with one another.

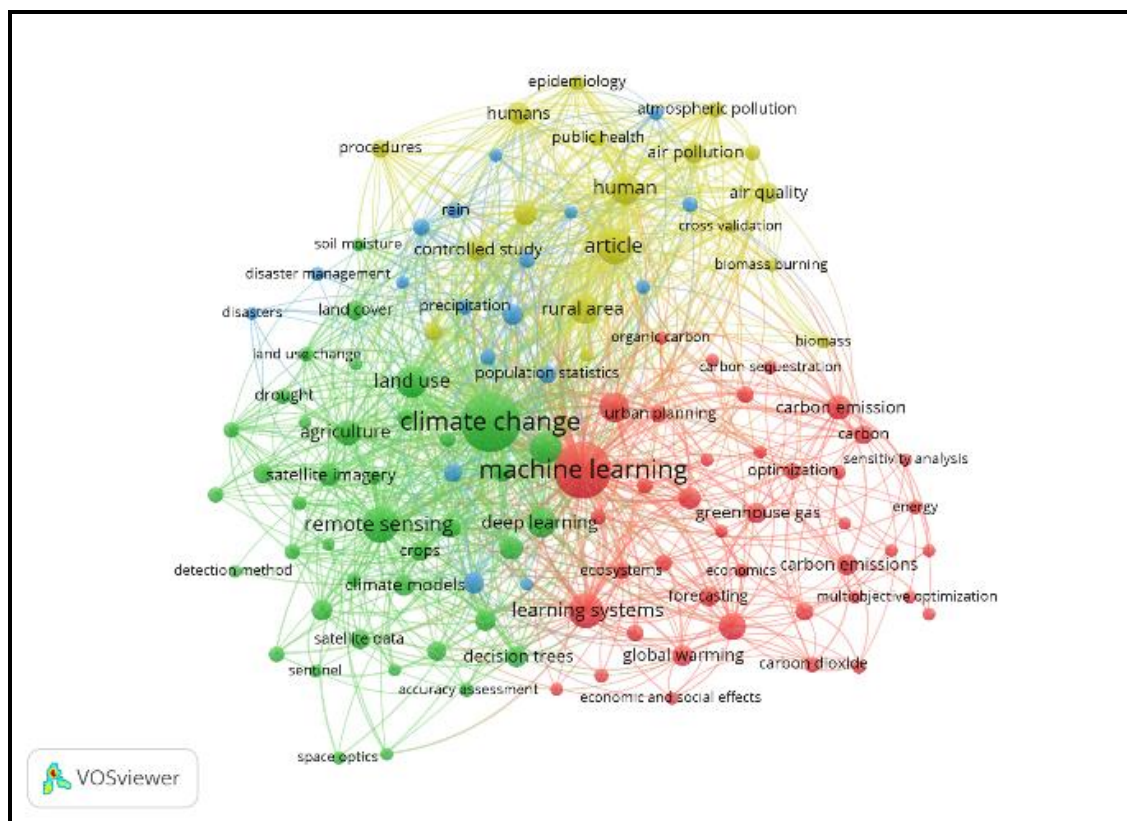


Figure 5. Co-occurrence of Author Keywords

Figure 5 visualizes a co-occurrence network of author keywords, mapping the intellectual structure and dominant themes in this field of research. Node size represents keyword frequency, while the thickness of the connecting lines indicates how often the two topics are discussed together in a single publication. This visualization reveals a strong integration between advanced computing technologies and environmental sustainability issues. To clarify the scientific contributions of each sub-analysis to the development of this field, the knowledge structure is systematically divided into four main thematic clusters based on the network's color coding.

The green cluster contains keywords centered on technical methodological aspects, such as "Deep Learning," "Climate Change," "Remote Sensing," and "Satellite Imagery." This cluster represents a concentration of research focused on developing air pollution and greenhouse gas emission monitoring systems as crucial tools for mitigating global climate change. This grouping indicates that researchers rely heavily on predictive algorithms and remote sensing data to process the complexity of environmental data. The primary focus here is the development of high-precision models to monitor Earth's biophysical parameters in real time, as applied in satellite-based crop yield estimation (Fieuzal et al., 2017). The integration of artificial intelligence technology in this cluster serves not only as a monitoring tool but also as a strategic platform for identifying specific sources of carbon emissions at various regional scales to support the implementation of more effective and measurable decarbonization policies (Pramulya et al., 2025). Scientifically, this cluster makes a significant contribution by providing an analytical framework based on high-level spatial data representation, which enables advanced feature extraction algorithms to recognize patterns of land cover change and climate anomalies on a massive scale (Zhu et al., 2017).

Meanwhile, the red cluster highlights application domains at the site level, with key terms including "Machine Learning," "Learning Systems," "Carbon Emissions," and "Optimization." This cluster represents the practical implementation of AI technologies in rural areas to address agricultural challenges. The close relationship between these keywords and technology clusters underscores that digital innovations do not stand alone but are specifically applied to improve water resource efficiency and land productivity amid weather uncertainty (Kleemann et al., 2017). The use of machine learning algorithms such as Random Forest and Support Vector Regression has become a central theme for predicting crop hydrological needs and water use efficiency in dryland areas. In this context, research shows that biologically inspired machine learning approaches can integrate terrestrial meteorological data with remote sensing indices to significantly improve the accuracy of evapotranspiration predictions (Monavvar Sabegh et al., 2026). The primary scientific contribution of this cluster is the optimization of agricultural operations to minimize crop failures and energy waste at the farmer level (Kim et al., 2019).

On the other hand, the blue cluster represents the macro-environmental context, characterized by the terms "Climate Effect," "Disasters," "Climate Models," and "Risk Assessment." The emergence of these keywords specifically evaluates the vulnerability of rural populations to climate change and environmental risks. This is clearly evident in a study on renewable energy optimization aimed at creating environmentally friendly energy self-sufficiency for rural communities (Nurunnabi et al., 2019). The integration of artificial intelligence in this cluster is used to map how climate affects human health and mobility, thereby generating adaptation strategies based on community protection. Accurate monitoring is an absolute prerequisite for "disaster risk reduction and sustainable development amid global climate change" (Pan et al., 2026). This aligns with efforts to develop a framework capable of supporting climate adaptation strategies in water-constrained agricultural regions, ultimately placing human safety at the center of artificial intelligence technological innovation.

The yellow cluster, with the keywords "Air Pollution," "Air Quality," "Human," and "Rural Area," specifically highlights the critical correlation between local activities in rural areas and declining air quality, which impacts climate change and public health. The primary focus of research in this cluster is the use of intelligent models to monitor air pollution generated by activities such as biomass burning and land-use changes in rural areas. This analysis is crucial because rural areas often serve as emission hotspots that are rarely monitored yet contribute significantly to regional pollution loads (Ma et al., 2026). Although often associated with urbanization, this cluster demonstrates that air quality in areas surrounding rural regions is influenced by cross-scale dynamics that require machine learning models to understand the dynamics driving these risks (Liu et al., 2025). The scientific

Methodologically, density visualization serves to measure the level of concentration and intellectual saturation of relationships between keywords within a bibliometric network. Through this density analysis, the strength of a research field's cognitive structure can be evaluated based on the frequency of co-occurrence of closely related terms, with high-density areas indicating well-established and extensively explored core topics. The network density visualization in Figure 5 shows that the discourse on the integration of artificial intelligence for rural climate resilience is centered on several areas with very high research intensity. The region with the highest density, marked in bright yellow in the center, is absolutely dominated by the keywords "Machine Learning," "Climate Change," and "Remote Sensing." Analytically, this pattern indicates that these three topics serve as both conceptual anchors and the fundamental foundation of the entire body of literature currently under development. This massive concentration in the field of Machine Learning confirms a tangible shift in the research paradigm: from one that initially relied on conventional passive observation to one that has now transformed toward predictive modeling aimed at preventively mitigating environmental impacts. This synergistic combination of satellite sensors and advanced intelligent algorithms has become a crucial tool for successfully monitoring land dynamics and ensuring the accuracy of climate predictions across various global agricultural regions (Fieuzal et al., 2017). The following is Image 5: Density Visualization of AI in Climate Change in Rural Areas.



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for early detection of drought risk (LeCun et al., 2015). Still in the low-density area, the decarbonization and climate techno-economics zone defined by the terms “Carbon Emissions” and “Optimization” contributes to the formulation of mathematical optimization models for designing efficient decarbonization strategies for agricultural regions (Fawzy et al., 2020). Finally, the environmental health and social impact parameter zones at the outermost peripheral boundary were identified through “Air Pollution” and “Public Health” as an emerging frontier that helps link physical climate variability to indicators of the epidemiological burden on rural communities (Adger et al., 2003). Overall, this peripheral distribution demonstrates that the application of interdisciplinary hybrid models has become the new standard for formulating targeted environmental policies at the rural level (Wang et al., 2020).

Analysis of Thematic Evolution and Emerging Trends

An analysis of trends in this research topic was conducted to map the dynamics of intellectual evolution and shifts in scientific interest regarding the use of artificial intelligence technologies to mitigate climate change in rural areas over the past two decades. By identifying keywords that emerged significantly during a specific time period, this section reveals how the global focus of research has undergone a radical transformation. The visualization of research topic trends in Figure 7 captures a paradigm shift from what was initially conventional static environmental mapping, now moving toward advanced predictive modeling. In the early stages of the research, academic discourse was dominated by fundamental terms such as “expert systems” and “decision support systems” for mapping natural resources, as well as “environmental protection,” which became prevalent around 2018–2019. The systematic evolution, term frequency, and chronological shifts of these core research themes over the analyzed period are visually mapped in Figure 7.

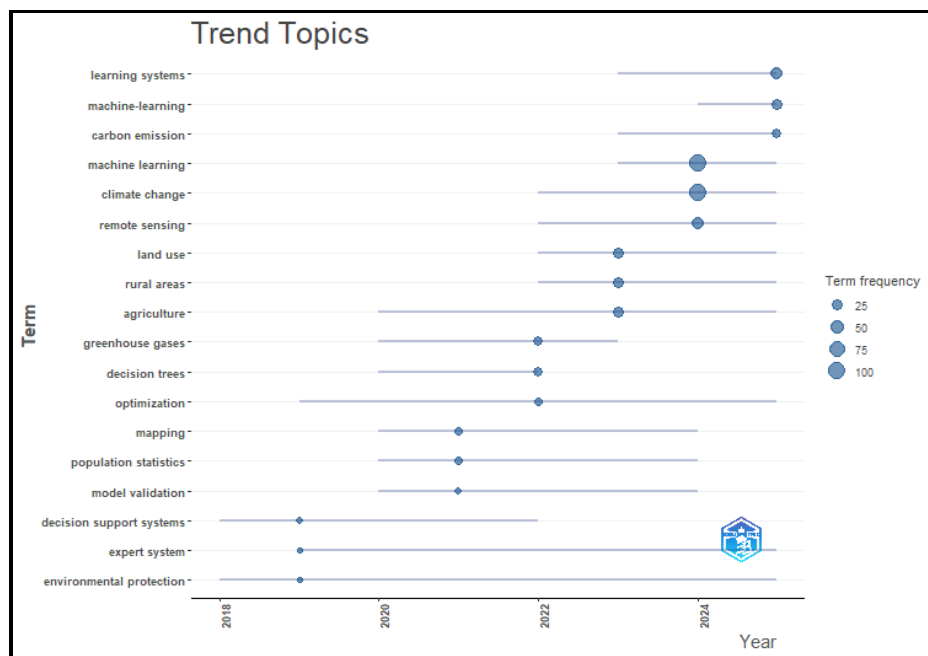


Figure 7. Discussion on Trends in Developed Countries

However, entering the post-2020 period, there was a massive surge in cutting-edge computational terminology such as “deep learning” and “artificial neural networks.” The emergence of these new topics indicates that the scientific community is now focused on using intelligent algorithms to project complex climate phenomena with a high degree of precision. This reinforces the argument that machine learning can be a powerful tool in reducing greenhouse gas emissions while helping local communities adapt to climate change, with the technology having now evolved into a strategic platform to support more effective and measurable decarbonization policies. The systematic evolution, frequency of terms, and chronological shifts in these core research themes are visually mapped in Figure 7. One of the most prominent recent trends in the past few years has been the emergence of topics closely related to energy sustainability, such as renewable energy and

[illegible]

The overlay visualization map in Figure 8 above shows a highly significant thematic shift during the period from 2022 to 2024. The research focus has shifted sharply from the initial focus centered on mapping the potential of AI for use and basic food security issues and has now moved toward the formulation of global decarbonization strategies. Although the early phase of the research was exploratory, focusing on mapping the basic capacity of rural land, in the most recent period, specific topics such as carbon emissions and artificial neural networks have emerged with great intensity. This shift signals an evolution toward the use of more complex computational architectures to address rural climate mitigation challenges in depth. Beyond its technical sophistication, the implementation of a responsible AI framework is considered crucial for protecting the well-being and livelihoods of farmers in the field (Upadhyay & Kamble, 2024). Through this hybrid modeling approach, the scientific community is now able to generate highly accurate regional predictions regarding the distribution of atmospheric pollutants, vegetation cover, and local weather anomalies. The thematic evolution shown in Figure 8 indicates increasing attention to data-driven and computational approaches for addressing climate-related challenges in rural areas. The emergence of topics such as carbon emissions and artificial neural networks suggests a growing convergence between advanced computational methods and environmental monitoring. Rather than demonstrating the operational performance of these technologies, the bibliometric patterns reflect how research priorities have increasingly incorporated data-driven approaches into discussions of rural climate resilience. Previous studies on deep learning and remote sensing provide broader methodological context for this development (Zhu et al., 2017).

Discussion

The integration of artificial intelligence into research addressing the impacts of climate change in rural areas has undergone a notable transition, with increasing attention to data-driven and predictive approaches for environmental resilience. This development is reflected in the acceleration of research output in the present dataset, which recorded an annual growth rate of 17.69%, with publications increasing from 33 documents during 2015–2020 to 221 documents during 2021–2025. Rather than demonstrating the practical adoption of AI technologies, this increase indicates growing scholarly attention to their potential role in addressing climate-related challenges. Previous research has similarly highlighted the growing relevance of machine-learning approaches for climate-change mitigation and adaptation (Rolnick et al., 2023). A comparable pattern has also been reported in adjacent research domains. Lewis et al. (2024), for example, identified substantial growth in the global intersection of AI and climate-change research, while Pervez et al. (2026) reported an annual growth rate of 12.69% for AI research in sustainable agriculture and noted particularly rapid expansion after 2020. Taken together, these similarities suggest that the growth observed in the present study is part of a broader post-2020 expansion of data-intensive research across climate and agricultural sciences rather than an isolated development within the rural literature.

More importantly, the findings suggest that this expansion has been accompanied by changes in the thematic orientation of the field. Earlier research in the dataset was more closely associated with terms such as “expert systems,” “decision support systems,” and “environmental protection,” whereas post-2020 publications increasingly featured “deep learning” and “artificial neural networks.” More recent themes also include carbon emissions, renewable energy, and microgrids. The keyword co-occurrence analysis further identified Machine Learning, Climate Change, and Remote Sensing as central conceptual anchors, with Deep Learning and Satellite Imagery forming part of a closely connected technological-environmental research cluster. This progression is broadly consistent with Rejeb et al. (2024), who identified successive phases in the development of precision-agriculture research and highlighted the increasing importance of data-driven enabling technologies. Similarly, Pervez et al. (2026) identified Machine Learning, Deep Learning, and precision agriculture among prominent themes in AI-based sustainable-agriculture research. The increasing prominence of machine learning is also consistent with broader developments in precision agriculture, where data-driven techniques have progressively been used for agricultural monitoring, prediction, and decision support (Sharma et al., 2021).

Despite these similarities, the conceptual structure identified in the present study differs in an important respect. AI-related terms are connected not only with agricultural production and optimization but also with climate change, carbon emissions, air pollution, disaster risk, climate models, and environmental monitoring. This distinction becomes clearer when the findings are compared with Xu et al. (2024), whose bibliometric analysis of 344 publications on sustainable agriculture in the digital era identified major clusters related to digitalization and sustainable agriculture, geospatial analysis, smart agriculture and biodiversity conservation, technological approaches to agricultural challenges, and farmer adoption. Although the present study shares several technological themes with that literature—particularly Remote Sensing, Machine Learning, and environmental monitoring—it places greater emphasis on climate-specific concepts such as carbon emissions, climate models, risk assessment, air pollution, and adaptation. This difference suggests that rural climate-resilience research is not simply a narrower version of digital or precision agriculture. Rather, it represents an intersection between agricultural digitalization and climate-risk research, in which computational technologies are increasingly examined in relation to environmental vulnerability, mitigation, and adaptation. The increasing visibility of carbon-related themes also connects this literature to the broader climate-mitigation agenda described by Fawzy et al. (2020), which encompasses technological, energy, and land-based mitigation strategies.

The increasing association between computational methods and spatial environmental information provides further context for this thematic development. The prominence of Remote Sensing and Satellite Imagery alongside Machine Learning and Deep Learning suggests that spatially resolved environmental data have become an important component of the intellectual structure of this literature. Previous work demonstrates the analytical potential of high-resolution environmental datasets; for example, (Wei et al., 2023) developed high-resolution pollution mapping capable of representing fine-scale spatial variation in PM_{2.5} exposure. Such studies provide substantive context

for the bibliometric relationships observed here, but they should not be interpreted as evidence that the technologies represented in the clusters have already been widely or successfully implemented in rural settings. Instead, the co-occurrence patterns indicate that computational and Earth-observation approaches are increasingly discussed together within research addressing climate-related environmental problems.

The geographic distribution of research provides a further point of comparison. China emerged as the largest contributor in the present dataset with 62 publications, followed by the United States with 46 publications, while Saudi Arabia and Pakistan also showed visible contributions. The dominance of China and the United States is consistent with [Lewis et al. \(2024\)](#), who likewise identified Chinese research institutions as the largest contributors to global AI–climate research, followed by institutions in the United States. However, the relatively visible presence of Saudi Arabia and Pakistan in the present rural-focused dataset is noteworthy because it differs somewhat from the geographical pattern reported in broader AI–sustainable-agriculture research, where [Pervez et al. \(2026\)](#) identified India and China as the leading contributors. This difference may indicate that the geographic structure of rural climate-resilience research is shaped not only by general AI research capacity but also by the relevance of climate-sensitive agricultural and environmental challenges in particular regions. Because the current bibliometric analysis does not directly examine national research funding, climate exposure, or policy drivers, these factors should be regarded as plausible contexts for future investigation rather than established causal explanations.

In addition to computational developments, the thematic results indicate increasing attention to resilient and sustainable energy systems in rural areas. The emergence of renewable energy and microgrids among more recent research topics suggests that the literature is gradually connecting AI-supported environmental analysis with questions of rural energy resilience. The optimization of hybrid renewable-energy systems in rural areas has been discussed in previous research as a potential means of reducing dependence on fossil fuels and improving local energy resilience ([Nurunnabi et al., 2019](#)). Within the context of the present bibliometric findings, however, the importance of this literature lies primarily in showing an expansion of the research agenda beyond agricultural monitoring toward interconnected climate, energy, and environmental challenges. This thematic diversification further distinguishes rural climate-resilience research from narrower precision-agriculture frameworks.

The authorship landscape also reveals a relatively collaborative research environment, with an average of 5.07 authors per document and an international collaboration rate of 37.4%. These indicators suggest substantial cross-national participation in the scientific literature, although they should not be interpreted as direct evidence of large-scale technology transfer. International collaboration is also emphasized in broader AI–agriculture research. [Pervez et al. \(2026\)](#), for example, reported increasing interdisciplinary and international cooperation while simultaneously identifying substantial geographical inequalities in research productivity, particularly the underrepresentation of Africa and South America. This comparison highlights an important implication of the present findings: although AI-based rural climate-resilience research is increasingly international, the concentration of publication output in a relatively small number of countries raises questions about whether the existing knowledge base adequately represents the diverse environmental, infrastructural, and socioeconomic conditions of rural communities worldwide. Responsible AI therefore remains relevant not merely as an ethical principle but as an important future research direction, particularly in relation to data availability, contextual applicability, and equitable technological development ([Upadhyay & Kamble, 2024](#)).

Taken together, the contribution of this study lies in showing how several research streams that have largely been mapped separately in previous bibliometric studies converge within the specific context of rural climate resilience. [Lewis et al. \(2024\)](#) mapped AI–climate research at a global and cross-sectoral level; [Xu et al. \(2024\)](#) examined digital sustainable agriculture; [Rejeb et al. \(2024\)](#) focused on precision agriculture; and [Pervez et al. \(2026\)](#) examined AI for sustainable agriculture. The present study adds a rural-specific perspective by simultaneously mapping publication development, geographic and collaboration patterns, conceptual clusters, and thematic evolution at the intersection of AI, climate-related challenges, and rural environments. Its contribution therefore does not rest on claiming that AI–climate or AI–agriculture research is new, but on demonstrating that their intersection within rural climate resilience exhibits a distinctive combination of

computational, environmental-risk, spatial-monitoring, carbon-related, and emerging energy themes that is less visible when these broader research domains are examined separately.

LIMITATIONS

This study has several limitations that should be considered when interpreting its findings. First, the bibliometric analysis was conducted using only the Scopus database. Although Scopus provides extensive coverage of peer-reviewed international literature, relevant publications indexed in other databases such as Web of Science, Dimensions, IEEE Xplore, or Google Scholar were not included. As a result, the knowledge structure presented in this study may not fully represent the entire body of research on artificial intelligence for climate resilience in rural areas.

Second, the dataset was limited to English-language, open-access journal articles. Consequently, valuable scientific contributions published in other languages or available through subscription-based journals may have been excluded, potentially introducing language and publication bias into the analysis.

Third, the findings are based on bibliometric metadata, including publication records, author keywords, citations, and collaboration networks. While these indicators effectively reveal research trends, intellectual structures, and collaboration patterns, they do not evaluate the methodological quality or empirical performance of the artificial intelligence models reported in the selected studies. Therefore, the results should be interpreted as describing the evolution of the research landscape rather than assessing the effectiveness of specific AI techniques in practical climate adaptation and mitigation.

Finally, although keyword standardization was performed using Microsoft Excel and OpenRefine to reduce duplication and merge synonymous terms, variations in terminology across publications may still have influenced the clustering results and thematic network visualizations. Such semantic inconsistencies are inherent in bibliometric studies and may affect the interpretation of relationships among research topics.

CONCLUSION

This study provides an up-to-date bibliometric overview of the global research landscape on the application of Artificial Intelligence to climate resilience in rural areas. The findings indicate a substantial increase in scholarly attention to this topic, particularly after 2021, and identify Machine Learning, Climate Change, and Remote Sensing as central conceptual themes within the literature. The thematic analysis further shows that research has evolved from earlier topics related to expert systems, decision support, and environmental protection toward more recent themes involving Deep Learning, artificial neural networks, carbon emissions, renewable energy, and environmental monitoring. These patterns suggest an increasing convergence between computational approaches and climate-related research in rural contexts, rather than demonstrating the operational implementation or effectiveness of specific AI technologies.

The study contributes by providing a rural-specific mapping of publication development, geographical contributions, international collaboration, conceptual clusters, and thematic evolution at the intersection of AI and climate resilience. Four major thematic clusters were identified, together with areas of high keyword concentration that reflect the intellectual structure of the field. By distinguishing rural climate resilience from broader AI-climate, digital agriculture, and precision-agriculture research, this study offers a more focused understanding of how computational, environmental-risk, spatial-monitoring, carbon-related, and emerging energy themes are connected within the literature. The findings may help researchers identify underexplored topics, avoid unnecessary duplication, and develop more context-sensitive research agendas. Future studies should complement these bibliometric findings with empirical research that evaluates the practical effectiveness, accessibility, and responsible implementation of AI-based approaches in diverse rural settings.

AUTHOR CONTRIBUTIONS

DA contributed to the conceptualization of the study, formulation of the research objectives and bibliometric research framework, definition of the search strategy and inclusion criteria, data collection from the Scopus database, and preparation of the original manuscript. FT contributed to the development and validation of the bibliometric methodology, data cleaning and curation, bibliometric analysis using Biblioshiny and VOSviewer, visualization and interpretation of publication trends, geographic contributions, keyword co-occurrence, and thematic evolution. Both authors contributed to the interpretation and synthesis of the findings, discussion of the intellectual and thematic structure of research on artificial intelligence and climate resilience in rural areas, and formulation of the research implications. Both authors critically reviewed and revised the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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