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Agricultural Modeling Under Climate Change: Mapping the Transition from Crop Simulation to Artificial Intelligence-Based Decision Systems

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ABSTRACT: This study examines the knowledge evolution of agricultural modeling under climate change through a bibliometric science mapping approach. The analysis is performed based on 860 documents published between the years 1992-2025 and indexed in the Scopus database, which are processed with the Bibliometrix package in R. A PRISMA-based screening procedure was applied to ensure thematic relevance and transparency. The study identifies publication dynamics, the leading sources, productive authors, country level contributions, collaboration patterns, as well as thematic development. The results show a sharp increase in research activity after 2020, indicating that this domain has moved from a limited technical niche to a rapidly expanding interdisciplinary field. The most active publication outlets are concentrated in environmental, agricultural, water management, and digital technology-oriented journals, with Science of the Total Environment emerging as the most productive source. Thematic mapping shows four large conceptually defined directions: climate change; agriculture; crops; and learning systems. These clusters show that the field is moving from process-based crop and resource models toward spatial, data-driven, and AI-assisted systems. The findings also reveal an important imbalance. Environmental, crop-oriented, and digital themes are expanding quickly, while their economic interpretation remains less developed. For agricultural economists this would be beneficial for future research to directly link the knowledge and understanding of the climate and ecosystem needs of agriculture with the contribution of food security and market resilience to scarcity, adaptation costs, investment priorities, and risks related to agri-food supply-chains.

Keywords: Agricultural modeling, Climate change adaptation, Bibliometric analysis, Artificial intelligence, Crop simulation models.

I. INTRODUCTION

Over the past several decades, scientists and policymakers worldwide [1] have given greater attention to the complex and pressing issue of climate change. This term refers to the ongoing changes [2] in the Earth's climate system, including changes in temperature and rainfall [3]. Climate variations have always occurred naturally. The distinctive feature of the present period is the rapid warming of the Earth system

[4, 5]. This warming is mainly attributed to greenhouse gas emissions [6], including carbon dioxide (CO_2) [7], methane (CH_4) [8], and nitrous oxide (N_2O) [9]. They are created by using fossil fuels [10], doing industrial activities [11], deforestation [12], and unsustainable agricultural practices.

It took decades for climate change [13] to be recognized as a major threat to people worldwide. In the latter part of the 20th century, advances in science demonstrated that Earth's warming was mainly caused by human activities [14]. A major institutional shift occurred with the adoption of the United Nations Framework Convention on Climate Change in 1992. This was followed by the Kyoto Protocol [15]. Later climate commitments emphasized the need to keep global temperature rise below 2°C and, where possible, below 1.5°C [16]. Such commitments are not only declaratory; they also demonstrate that countries recognize that climate-related risks harm the world's food [17], water [18], public health [19-21], and nature. Agriculture is both highly vulnerable [22] and sensitive [23] to global warming. Farming [24] mainly relies on the stability of weather [25], including rainfall [26], heat [27], and soil quality [28]. Agriculture itself is also a significant factor in climatic shifts because of deforestation [29], gases from livestock [30-32], and emissions from fertilizer use [33-34]. Being central to climate change and at the same time affected by it, agriculture becomes a main subject for both research and policy changes.

To address these problems, it is important to recognize that it requires more than intuition or trial-and-error approaches. Thus, this demands a clear evidence-based approach, and it is in this area that modeling is essential. In general, a model is a simplified representation that shows or explores how complex systems behave. In reality, models are used to forecast weather [35] and economic trends, as they help us predict the future using known facts and assumptions. With modeling, scientists can try situations that would be too risky, too expensive, or impractical in the real world. For example, a model may show what would happen to crop yields in Kazakhstan if rainfall [36] changes by 20% (either up or down), or if farmers gain access to improved irrigation technologies.

In mathematical modeling, variables are shown by using formulas [37], equations, functions [38], and algorithms. In agriculture, mathematical models are used to link temperature and rainfall [39-41] to the growth of crops, track the rate of evaporation, optimize irrigation settings, or project drought's consequences on the economy. Back in the mid-20th century, the earliest use of mathematical modeling in farming was to predict yields based on rainfall and soil quality. Thanks to new and improved computing and data-gathering technologies, models have become more complex. What started as simple linear regressions evolved into an area of study that draws on reactions from biological, chemical, and economic domains. At present, widely used crop models, including DSSAT [42], AquaCrop [43], EPIC, and APSIM [44], simulate how plants grow, use water, cycle nutrients, and emit greenhouse gases, depending on the climate and the ways farmers manage them. Researchers mostly use them and specialists working in policy creation, supporting climate risk management, and decision-making on the farm. Recent methodological development has moved beyond process-based crop simulation. AI- and machine-learning-assisted systems are now used to analyze complex, uncertain, and data-intensive climate-agriculture interactions. The approaches are increasingly helping to facilitate adaptive decision-making, resource optimization, and sustainability-oriented management in a changing climate.

Thus, agricultural modeling is no longer just a technical tool for simulating the growth of crops or for estimating the demand for water. It is a knowledge infrastructure that is progressively used to help researchers understand production vulnerability, resource scarcity, adaptation options and future trajectories of agri-food systems under climate warming pressure. However, the rapid expansion of this literature has quickly become fragmented conceptually. Process-based crop models, spatial and remote sensing applications, irrigation management optimization, machine learning, digital farming and supported decision systems are mentioned separately in the literature and although these approaches are often articulated as independent research lines, they are now connected and represent a single and unified methodological field.

Existing reviews and bibliometric studies typically only consider limited fields, such as crop simulation, agroecology, irrigation technologies, food-system resilience, machine learning applications, or digital agriculture. These studies provide valuable insights, yet do not fully capture the evolution of agricultural simulation as a whole ensemble of knowledge in the context of climate stress. In particular, the narrative of process based models transitioning to spatial, data-driven, and AI-based systems, and how these fit into the wider sustainability, adaptation, and agricultural economics logic has not received a lot of attention.

For this reason, the present study applies bibliometric science mapping as a knowledge evolution framework. This study uses bibliometric analysis as an instrument to reconstruct the conceptual map of the field instead of counting papers, authors, sources or countries. The difficult task of identifying shifts in the literature from earlier themes concerning climate impacts and yields in crop production, to the focus of sustainability-oriented, predictive, and AI-driven systems, is achieved by identifying co-word clusters, thematic mapping, and thematic evolution analysis. This standpoint enables the research to view the use of farm models in a changing climate as an emerging field of interdisciplinary study.

Researchers address this gap by applying bibliometric analysis, a quantitative method. Through bibliometrics, it is possible to inquire about the growth in the number of studies over time. Moreover, bibliometric analysis helps to answer the questions such as: What are the most published research subjects? Who are the most relevant authors, the 5W1H questions (who, when, where, what, why, and how) in general [45]. Experts such as Kositzyn et al. [46], Nie, & Valero et al. [47], and Ranjan [48] argue that mapping the evolution of model-based analysis is essential to advancing sustainable agri-food systems. In other areas, such as renewable energy, sustainable finance, and public health, bibliometric research [49] has enabled understanding of the field's development at both broad and detailed levels [50].

The study examines publication trends, influential sources, productive authors, and leading contributing countries. It also reconstructs the conceptual structure of the field through co-word clustering, strategic thematic analysis, and thematic evolution across subperiods. By doing so, the article contributes to the existing bibliometric studies by demonstrating the internal structures of the field and how its hegemonic topics have evolved into sustainability-driven, digitally-enabled, and systems-based learning. In line with this, the key contribution of this research is offering an organized interdisciplinary review of agricultural simulation in the context of climate stress as a developing field of research as opposed to a collection of isolated technical implementations. Such a view can be used to explain the conceptual architecture of the field, emphasize the emerging methodological direction, and pinpoint gaps that are pertinent to future research, policy development, and climate resilient agricultural decision-making.

To conduct this bibliometric research on mathematical analytical approaches in agricultural economy under climate stress, the work was structured into six main sections. In Section 2, a Literature Review had been revealed with a structural analysis of documents related to the research field. Section 3 describes the construction of the bibliographic dataset and the details of the Scopus search strategy [51], including search field, Boolean logic [52], time limits, and subject-area filters and PRISMA-based screening procedure. This procedure was carried out in a manner that achieved conceptual relevance and thematic accuracy. After that, the core findings of the research, the trends in publishing, the dominant sources and authors, and the geographic dispersion were presented, followed by statistical definitions and bibliometric laws, such as Lotka's and Bradford's laws, in Section 4. Section 5 subsequently amplifies these results by commenting on the observed trends, evaluating the epistemological and methodological trajectories, and identifying shortcomings and regional discrepancies. Section 6 concludes the study by offering final reflections on the main findings and core contributions of the research, and by identifying gaps that need to be addressed through recommendations for collaboration in policymaking and research on sustainable crop simulation.

The main contribution to this work is a thematic reconstruction of the field. Through a mixture of co-word clustering, a strategic thematic diagram, and thematic evolution across subperiods, the article reveals the conceptual architecture within which the research area is currently structured. Specifically, the four large thematic clusters identified, including climate change, agriculture, crops and learning systems, allow perceiving the field as a structured, developing and interdisciplinary study.

II. RELATED WORK

1. CLIMATE CHANGE, SUSTAINABILITY, AND THE REPOSITIONING OF AGRICULTURE

Recent studies increasingly consider agri-food sector as less an area of production and more of a system that is being influenced by climate risk, ecological limits, and sustainability demands. Such a change matters since it alters the analysis purpose of agricultural research per se: the key question is no longer how to scale up production, but how agricultural systems can be productive, adaptive, and ecologically viable to ongoing environmental stresses.

In this approach, the analytical approaches and sustainability-related research started to unite around the resource efficiency, resilience and reorganization of the systems. Ginaldi et al. [53] demonstrated that crop models are now being utilized to analyze water and nitrogen efficiency, management trade-offs and adaptation to climate stress. In turn, Nikiema et al. [54] associated agroecology literature with the concepts of biodiversity, food sovereignty, and agricultural productivity, implying that sustainability in farming systems is being redefined as an external limitation.

This generalized repositioning is also reflected on the level of agri-food system. Tamasiga et al. [55], Ho and Lwesya [56], and Slepetiene et al. [57] have shown that agricultural studies on the climate aspect are then becoming more interwoven with food security, carbon management as well as long term resilience. Altogether, these researches suggest that the intellectual base of the subject area is shifting towards combining climate adaptation, ecological sustainability, and agricultural decision-making. The agri-food sector is therefore being redefined. It is no longer viewed only as a production space, but as an ecologically sensitive socio-economic system. Its future depends on the ability to align productivity, environmental sustainability, and adaptive resilience [58].

2. EVOLUTION OF AGRICULTURAL MODELING APPROACHES, DIGITAL AGRICULTURE, AI, AND PREDICTIVE SYSTEMS

The literature review revealed that model-based analysis in agroecosystems in the context of agroclimatic instability has not been developed as a unified methodological approach. It has gone through a series of successive phases, that are interdependent and each have transformed how climate-agriculture interactions are described, quantified and understood. This shift can be interpreted as a transition from process-based, models of crop and resource to spatial and data-driven systems, towards AI-supported and hybrid crop and resource decision-making support.

2.1. Process-based Crop and Resource Models

The first major stage is associated with process-based crop and resource models. These models are expected to capture the biophysical logic of agricultural systems by incorporating various components of an agricultural system, including crop growth, soil properties, water availability, nutrient cycles, weather variability, and management. In this group, DSSAT, APSIM, AquaCrop, EPIC, and similar models occupy an important place because they offer an agronomically interpretable structure for assessing productivity and resource-use efficiency under changing climatic conditions.

Crop-system models are still very much relevant to understanding the production response, water-use characteristics and climate adaptation, as shown by Asseng et al. [59] and Sarkar et al. [60]. Besides predicting they are important for causal explanation. Under variable climatic and soil factors, and varying rainfall, variable temperature, irrigation and soil conditions, the process-based models are not of less use if the researcher wants to understand why the particular crop system acts in a particular manner. Their drawback is that they will only be useful if the data they are taking in is detailed and context specific and if they are calibrated carefully. They have a strong capability in explaining the agronomic aspects but are less flexible in a task that is both large scale monitoring of data and data that are spread out across space and requires real-time decision making.

2.2. Spatial and Data-Driven Approaches

The second stage is related with growth in the spatial, monitoring approach and to data centred approach. Both these techniques are found to be developed and cultivated as farming entered the stage of relying more heavily on remote sensing, GIS, evapotranspiration calculation, monitoring of irrigation, resource assessment of soil, and data fusion from various sources. Advantages of spatial and data-driven approaches over the classical process-based approaches are that they are more useful when observing cropping systems over extensive areas and patterns not easily recognized with only field level process modelling.

The use of remote sensing, GIS, smart irrigation analysis and land-resource monitoring has grown increasingly important and significant for the study of climate sensitive agroecosystems, as demonstrated by Pang et al. [61], Ahmed et al. [62], Du et al. [63] and Vagelas and Leontopoulos [64]. These are techniques that increase the analytical scale of the field. They enable the mapping of regional water stress, soil degradation, irrigation performance and landscape level vulnerability to local production processes. They are strongest on the spatial cover and operational visibility. Spatial interpretation capability, on the other hand, depends on the linkage of spatial indicators and their agronomic, environmental and economic interpretation.

2.3. AI-Driven and Digital Systems

The third phase is connected with the fast development of machine learning, AI, deep learning, digital agriculture, IoT, robotics, blockchain, and big data analysis. The application of machine learning and forecasting models in climate research, forecasting precipitation, and predicting the occurrences of crop pests and diseases is becoming commonplace, as demonstrated by Niculae et al. [65] and Aydin and Kilar [66] and Goyal et al. [67]. Also, Mesías-Ruiz et al. [68], Montalvo et al. [69], Degila et al. [70], Papa et al. [71] and Hussein et al. [72] identified a trend of using AI, cyber-physical systems, digital agronomy, traceability technologies and big data analytics to support crop protection, smart farming, livestock monitoring, and agri-food system coordination. These systems are also less reliant on pre-defined agronomic equations than process-based systems, and much more reliant on the large amount of data, how algorithms learn, sensor infrastructure, and computational capacity. They are strong on responsiveness, scalability and predictiveness. The challenge is a decreased level of transparency, particularly if algorithms are opaque and cannot be checked.

2.4. Hybrid Decision-Support Logic

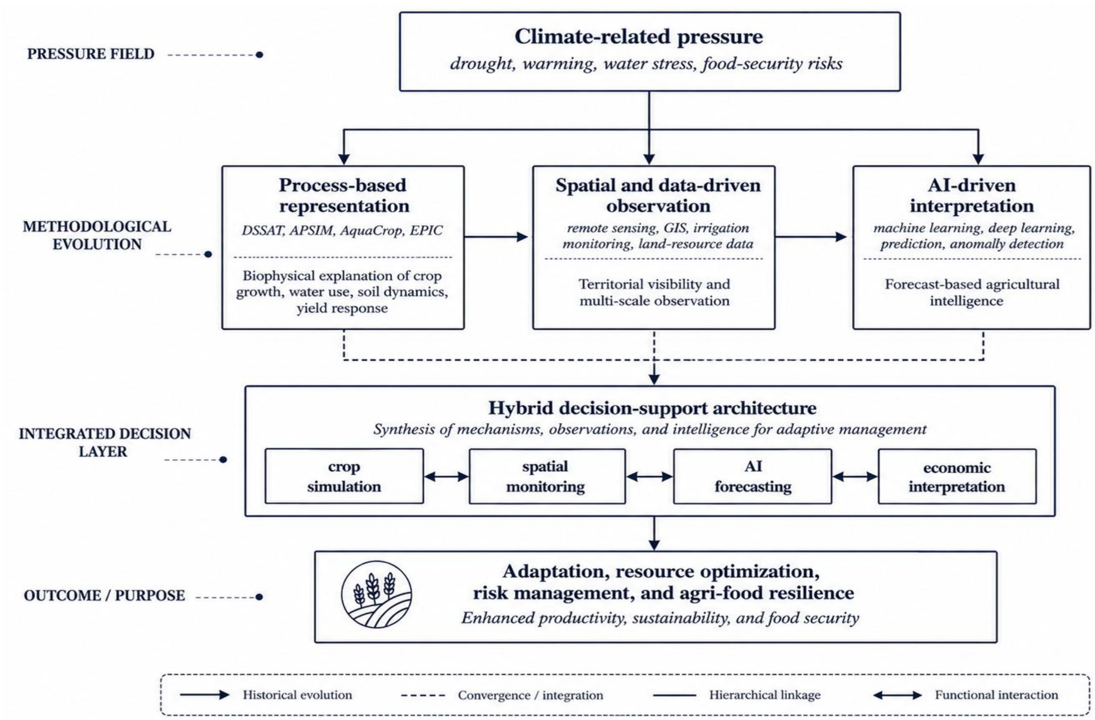
The literature indicates a transition to Hybrid Decision Support Systems (HDSS) over time. According to this logic, process-based models are agronomic and biophysical explanatory models, spatial models can provide insight into a territory, and models based on artificial intelligence can be adaptive and predictive. Thus, the most promising direction is not strictly process-based, spatial, or algorithmic. It is integrative.

Such hybridization is important for climate-related agricultural research for many reasons, including the multidimensional nature of climate risks. For example, drought cannot be considered simply as a problem of agricultural production. It also affects irrigation needs, soil moisture levels, product prices, food market supply, logistics, and the sustainability and adaptability of food systems. Thus, the need for future agricultural optimization will largely depend on a combination of crop simulation, remote sensing, artificial intelligence forecasting, decision support system, and economic interpretation.

This integration underpins the transition from isolated technologies to a broader knowledge system for combating agroclimatic instability, optimizing resources, and managing agricultural processes in a sustainable manner. This methodological development is also the conceptual basis for the current bibliometric analysis. The study examines not only agricultural modeling in the context of climate uncertainty as a set of disparate methods. This study sees this field as an ever-changing knowledge architecture based on three interrelated stages: from process-based representation to space- and data-centric observation, and from observation to decision support through artificial intelligence.

2.5. The Methodological Trajectory

The methodological approach presented above can be summarized in a conceptual framework (Figure 1). The resulting structure describes the field as a sequence of knowledge levels or a trajectory. Representation is the necessity that arises in response to pressure from climate. Process-based models are then used to describe the responses of the crop and resources by using a biophysical logic. This logic is extended, from the field level to the territorial level, by the use of spatial and data-driven approaches. AI systems bring predictive intelligence by turning disparate data into predictions, classifications and adaptive responses. The next frontier is the hybrid decision-support architecture, where crop simulation, spatial monitoring, AI forecasting and economic interpretation are all integrated into one, with a view to climate adaptive agricultural decision making.



Source: Authors' own elaboration based on the literature review and bibliometric science mapping logic.

FIGURE 1. Conceptual framework of methodological evolution in agricultural forecasting under global warming.

This framework also elucidates the gap that is filled in the present study. The present review may consider different parts of this process individually, including crop simulation, irrigation technologies, remote sensing, machine learning and digital agronomy. What is still not clear is how these fragments are integrated into one dynamic research area. The existing syntheses are therefore described, and the remaining gaps in the literature are indicated.

3. EXISTING SYNTHESES AND THE REMAINING GAP

Despite the fact that there are already bibliometric and review studies, they are still disjointed in subfields. Ginaldi et al. [53] were interested in crop-model spatialization, Nikiema et al. [54] in agroecology adoption, Pang et al. [61] in smart irrigation, Niculae et al. in machine learning in climate research, Tamasiga et al. [55] in food value chains, and Montalvo et al. in cyber-physical systems in smart farming. The rest of the studies covered cattle traceability, soil carbon, evapotranspiration, pest prediction, and digital agroindustry in developing countries. Consequently, convergence of crop simulation, irrigation, agroecology, food-system resilience, digital agroecosystems, and AI has already been confirmed in the literature, but is yet to be given a dedicated bibliometric synthesis as a coherent interdisciplinary field in its own right. This is the gap that is considered in the current study.

III. MATERIAL AND METHOD

The set of procedures in the R environment and package 'Bibliometrix' (version 5.0.0) was used as the bibliometric toolset for the study. Apart from creating citation and co-authorship maps, the software supports analysis of the content itself, revealing the field's main concepts and methods. This type of analysis helps track knowledge evolution by detecting structural changes across a large set of scientific documents [73].

Database selection and search design were central to building a reliable and thematically coherent bibliographic dataset. Scopus was chosen as the source database for this study because of its comprehensive coverage of journals in environmental sciences, agricultural systems, and applied crop simulation. Scopus provides accurate details on authors, keyword indexing, and structural metadata, all of which make the research more precise. The robustness of the analysis mostly depends on how the Scopus search strategy is created.

Restricting the search to titles alone would exclude important articles whose main themes are placed in the abstracts or keywords. On the contrary, looking at the entire content of the articles could have yielded many irrelevant results, since the main ideas may appear only in passing. Thus, in many cases, when the key concepts are what the publication is mainly about, this field is best suited to capture those. Boolean logic was also applied in searches. The expression "AND" links important subjects in this research and ensures that all these subjects appear in the metadata of every document. For instance, for "mathematical" AND "modeling," the search returns only articles that highlight both the mathematical structure of the approach and its modeling function or description. As a result, the ideas were aligned, and the data was relevant. The "OR" operator was also used throughout the query to ensure that different ways of expressing ideas across fields were included. For example, although certain pieces of content may present the phrase "mathematical modeling", "machine learning", "crop simulation", and "predictive modeling", while the operator "AND" was used to keep only those records that addressed "agriculture" and "climate change". Using this search, conclusions are drawn regarding both thematic terms and their components, which are present in the final dataset (Figure 2).

Under this framework, articles that discuss the same concept with slightly different formulations are not skipped. Moreover, proper use of parentheses and operators is respected so that the expressions are checked according to the precedence. Since "AND" has a higher logical order in database queries, the engine can misunderstand the intended meaning if terms are not put in parentheses together. Making the search term group in this manner ensured that the results included data on agriculture, climate change, and mathematical modeling.

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( TITLE-ABS-KEY ( "mathematical modeling" ) OR TITLE-ABS-KEY ( "machine learning" ) OR TITLE-ABS-KEY ( "crop simulation" ) OR TITLE-ABS-KEY ( "predictive modeling" ) ) AND TITLE-ABS-KEY ( agriculture ) AND TITLE-ABS-KEY ( "climate change" ) ) AND PUBYEAR > 1989 AND PUBYEAR < 2026 AND ( LIMIT-TO ( LANGUAGE , "English" ) ) AND ( LIMIT-TO ( SUBJAREA , "ENVI" ) OR LIMIT-TO ( SUBJAREA , "EART" ) OR LIMIT-TO ( SUBJAREA , "AGRI" ) )
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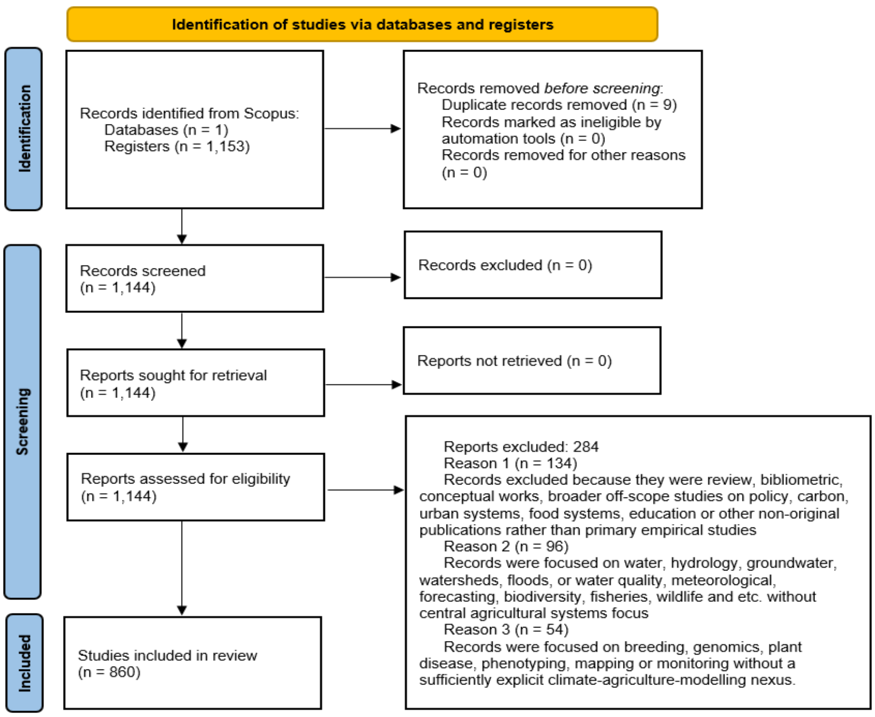
Source: Authors' own elaboration

FIGURE 2. Scopus database search query.

The use of time filters and discipline-based filtering was another important addition to the search design [74]. Only publications found from 1992 to 2025 were reviewed. The search filter was installed to

1990, but the earliest publication was discovered only in 1992. This should not be interpreted as a statement that earlier research on agriculture, modelling, and climate-related issues does not exist beyond the final corpus. Rather, 1992 is the starting point for the dataset analyzed in this bibliometric study.

Given the dominance of English amongst topic-related articles in the Scopus database, documents included in the final dataset were limited to English-language publications. The subject-area filters Environmental Science (ENVI), Earth and Planetary Sciences (EART), and Agricultural and Biological Sciences (AGRI) were applied to preserve thematic coherence. These filters helped exclude records that used similar terminology but did not address climate-agriculture interactions, including some publications indexed mainly under mathematics or computer science.



Source: Authors' own elaboration using [75].

FIGURE 3. PRISMA 2020 flowchart implemented in this research.

Each element of the search string was selected to preserve thematic relevance. This included the searched fields, Boolean operators, time limits, language restriction, and subject-area filters. Focusing on the methodological component of the Scopus search strategy enables the study to accurately interpret thematic trends, changes, collaborations, and ideas in the scientific field.

The keyword match network was created using the combined keyword field (KW_Merged) from the final set of Scopus keywords in the Bibliometrix/Biblioshiny software. A thematic map was created containing 250 terms (with a frequency limit of 4 words). No stemming was applied. The Louvain clustering algorithm was used to identify thematic communities. To interpret the map, Callon centrality and Callon density were used: centrality reflects the degree of connection between the topic and the field of study.; the density reflects the internal development of the topic. These parameters were chosen in such a way as to preserve the basic conceptual structure of the field, but avoid low-frequency noise from the keyword network. This was done using the PRISMA verification process to document the changes made to the original Scopus data in the final bibliometric corpus (Figure 3). The first search yielded a complete list of all potentially relevant records [76]. Duplicate entries were deleted, and the remaining ones were selected using the title, annotation, and keywords. Written documents that did not explicitly cover agricultural systems, climate change, and model-based analysis were not included. Other exceptions were also made related to records containing only general information about climate, environmental processes with no agricultural applications, purely technical computer science applications, and general discussions without an obvious element of agricultural modeling. A total of 860 documents were included in the final compilation for 1992-2025.

Table 1. A descriptive review of a set of bibliometric data (1992-2025).

Description	Results
Timespan	1992:2025
Sources (Journals, Books, etc)	377
Documents	860
Annual Growth Rate %	17.07
Document Average Age	3.55
Average citations per doc	21.41
Authors	3945
Authors of single-authored docs	37
Single-authored docs	39
Co-Authors per Doc	5.36
International co-authorships %	40.58
article	596
book chapters, conference papers	162
review	102

Additional exclusions covered bibliometric reviews, purely conceptual publications, off-scope hydrological or environmental studies, and records in which agricultural production systems were not the primary focus of analysis.

IV. DATA ANALYSIS

As a result, as shown in Table 1, the dataset contains 860 documents published between 1992 and 2025. At the end, 377 different journals, books, and conference proceedings were used to source these documents, which reflects a broad level of diversity. The number of studies published each year in this area is increasing by 17.07%, indicating a rapid rise in scholarly attention. The final dataset has an average document age of 3.55 years, suggesting a strong orientation toward recent scientific output in the field. A large number of citations, on average 21.41 per document, indicates a relatively high level of academic interest across the dataset. On average, there are 5.36 co-authors per document, underscoring the high level of cooperation in this field.

International co-authorship accounted for 40.58% of the dataset. This confirms the global character of the research field. Most of the documents are journal articles (596), with 162 conference papers and book chapters and 102 review articles. The research approach in this study was influenced by the guidelines given in the Leiden Manifesto for Research Metrics and San Francisco Declaration on Research Assessment (DORA) [77]. They both stress interpreting numbers in the right context, balancing numbers with expert opinions, and rejecting the use of journal impact factors as a universal measure of research quality [78]. For this reason, the study prefers to examine scientific topics, shifts in interest, and organizations' contributions rather than focusing solely on raw outputs to ensure accuracy and ethical soundness. Figure 4 combines two dimensions of field development: publication activity and citation impact over time. Figure 4a captures the expansion of annual scientific production across six-time intervals, while Figure 4b shows how average citation indicators changed across the same publication periods.

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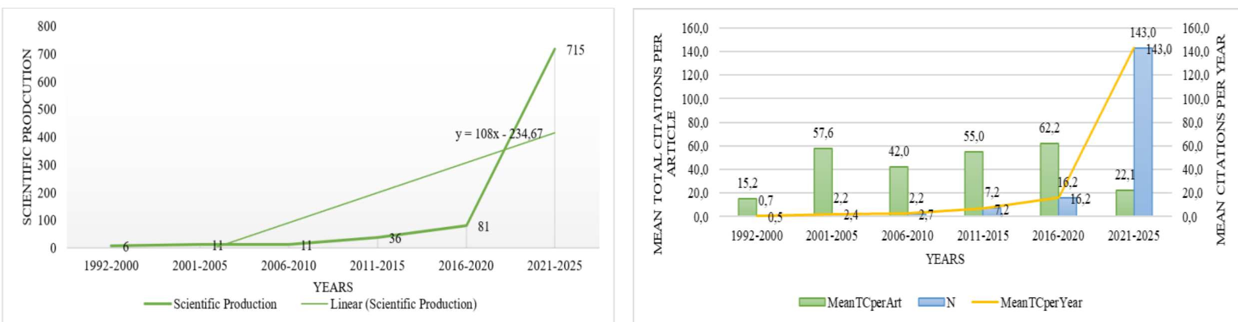
Scientific production remained limited in the early periods, with 6 publications in 1992-2000, 11 in 2001-2005, and 11 in 2006-2010. Subsequently, the volume of publication started to grow more significantly, to 36 in 2011-2015 and 81 in 2016-2020. The most dramatic growth was in the last period, 2021-2025, where 715 publications were registered. This trend indicates that the discipline has ceased to be a relatively limited research niche but a fast-growing interdisciplinary field with the visibility of the scholarly community sharply increasing. The linear regression shown in the figure (y = 108x - 234.67) also reflects a growing academic importance of this research domain.

Figure 4b illustrates how citation rates have changed over time. It demonstrates three features: the mean total citations per article (green bars), the mean annual citation rate (orange line), and the number of citable years (dark green line). The mean citation impact per article was highest in 2016-2020 (62.2), 2001-2005 (57.6), and 2011-2015 (55.0), which means that articles published during these years had the best citation convergence. In comparison, the first period, 1992-2000, had less citation intensity, with 15.2 average total citations per article and 0.5 average citations/year. The last period, 2021-2025, stands out with the highest volume of publications (143.0) per average annual output, although the average impact of citations per article is lower (22.1), which is anticipated due to the fact that these studies have not been able to gather numerous citations. Simultaneously, the rate of citation is the highest in the past year, which implies that the newly published works are becoming more visible faster than ever.

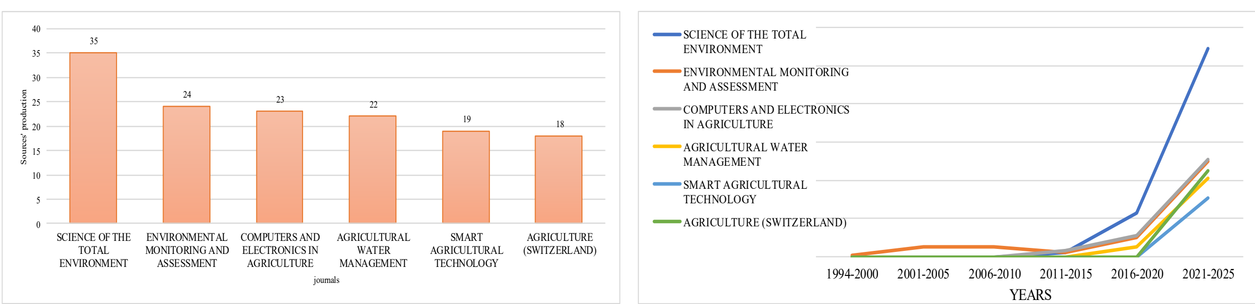


a) b)

Source: Authors' own elaboration

FIGURE 4. Annual scientific production and average citations per year.

Figure 5 links source productivity with the temporal concentration of publication activity. Figure 5a identifies the most productive sources, while Figure 5b shows how their output developed across the analyzed period. b)



Source: Authors' own elaboration.

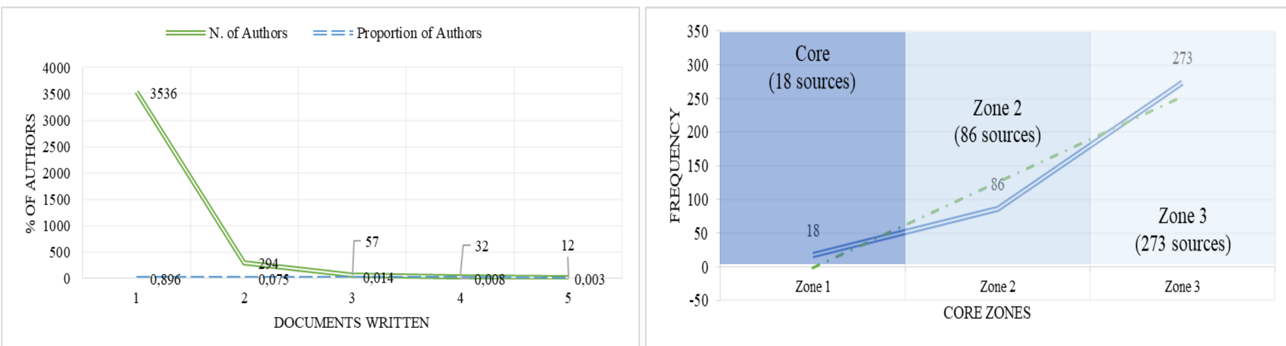
FIGURE 5. Sources' production over time and most relevant sources.

The leading publication outlets indicate where the field has found its main interdisciplinary platforms. Among all sources, the journal Science of the Total Environment was the main contributor, putting out 35 articles. It shows that the journal's interdisciplinary approach fits well with the complex nature of climate-related model-based analysis in agroecosystems. Other top documents are found in Environmental Monitoring and Assessment (24), Computers and Electronics in Agriculture (23), Agricultural Water Management (22), Smart Agricultural Technology (19), and Agriculture (Switzerland) (18). Each journal focuses mainly on systems analysis, environmental research assessment, and climate research. The growing number of scientists citing these journals links agro-policy understanding to environmental sciences.

Figure 5b concentrates on how the output of the leading sources changes with time. In the earlier subperiods, the activity of publication was extremely low, and highly fragmented. There was a noticeable growth after 2011-2015, and the most outstanding growth was experienced by 2016-2020 and 2021-2025. Science of the Total Environment showed the strongest growth in the latest period. Environmental Monitoring and Assessment, Computers and Electronics in Agriculture, Agricultural Water Management, and Smart Agricultural Technology also recorded visible growth.

These tendencies indicate the shift of the field away towards the piecemeal contributions to more coherent concentration around a few high-visibility interdisciplinary outlets. The growing popularity of journals devoted to environmental systems, agricultural technologies, and water management are also indicators of the expansion of the methodological approach in climatic shifts and agricultural model-based analysis. Further explanation of the concentration of the publication activity in few sources can be explained via Bradford's Law.

Bradford's Law describes the tendency of the distribution of scientific articles throughout the journals unevenly. According to Bradford's logic, a small core of journals usually contains a disproportionate share of publications on a given topic. The remaining studies are distributed across wider peripheral zones of sources. This can be clearly observed in the current dataset as presented in Figure 6a.



a) b)

Source: Authors' own elaboration

FIGURE 6. Core sources by Bradford's law and author productivity through Lotka's law.

The Bradford's Law distribution of the sources in the current dataset is shown in Figure 6a. There are 18 sources located in the core zone, 86 sources in Zone 2 and 273 sources in Zone 3. This tendency proves a high level of concentration of research activity in comparatively few journals, whereas most of the sources do not contribute such a significant portion of publications. This distribution is similar to the Bradford's Law that is often found in the emerging interdisciplinary areas, where only a few journals are usually used as the main sources of publication of the new findings. Simultaneously, Lotka's Law offers a classical model to see the distribution of scientific productivity among authors. The simplest version of the law is that the majority of authors write a single article, and only a very small fraction of the authors writes many articles. This trend can be seen in the current data in Figure 6b. Figure 6b indicates that the majority of authors contributed one document (3,536 authors) with a substantially smaller percentage of two (294), three (57), four (32), and five (12) documents. This is roughly equivalent in proportions to 89.6 per cent of those having one publication, 7.5 per cent with two, 1.4 per cent with three, 0.8 per cent with four and 0.3 per cent with five. This confirms the appearance of a wide pool of contributors to the field, yet a rather small number of them stay active over time. Combined, Bradford's and Lotka's Laws indicate that the field is both concentrated in sources and dispersed in authors: increasing numbers of the research are concentrated in a small number of journals, and authorship is diffused in numerous occasional contributors.

Reading the combination of Bradford's and Lotka's laws gives us a clear view of the way documents are organized in bibliometrics. A certain number of journals help officially disseminate scientific results, while authorship is widely dispersed across occasional contributors. This pattern is common in research sectors that are still on the rise or where help from related fields is needed. As tools used in climate-smart agroindustry improve, it is becoming evident that both publication outlets and scholarly communities are beginning to unite. However, to detail this distribution and specify the leading sources, authors, and countries, it is advisable to refer to the quantitative metrics presented in Tables 2-4.

Tables 2-4 report the main bibliometric indicators used to describe sources, authors, and countries. The h-index indicates the number of publications that received at least h citations. The g-index gives additional weight to highly cited publications [79]. The m-index normalizes the h-index by the number of active publication years. TC refers to total citations, NP to the number of publications, and PY_start to the first publication year recorded in the dataset [80-81]. TC per active year was calculated as total citations divided by the number of active years in the dataset (2025 - PY_start + 1). For country-level analysis, SCP refers to single-country publications, MCP to multi-country publications, and MCP % to the share of internationally co-authored documents within a country's output.

With 35 articles, the journal Science of the Total Environment has the highest productivity and impact, with h-index = 17, g-index = 35, TC = 1305, and m-index = 1.42. Computers and Electronics in Agriculture (23 articles) and Global Change Biology (16 articles) follow with high citation performance, as well. The other valuable sources are Remote Sensing, Smart Agricultural Technology, Agricultural Water Management, Agriculture (Switzerland), Agronomy, Environmental Monitoring and Assessment, and Environmental Research Letters. At the same time, the inclusion of a time-normalized citation indicator indicates a more nuanced pattern. Although Science of the Total Environment is still ranked high in terms of cumulative impact, Smart Agricultural Technology (130.25 citations/active year) and Science of the Total Environment (118.63) have the greatest annualized citation impact, followed by Global Change Biology (117.53), Environmental Research Letters (90.73), Agriculture (Switzerland) (84.25), and Remote Sensing (65.71). This indicates that new journals are becoming influential at a far higher rate in comparison. Collectively, these journals suggest that the field is spread in environmental, agricultural and technology-focused publication sources, with a specific focus on interdisciplinary and applied model-based analysis studies [82].

Table 2. Top ten sources in the field of knowledge.

Source	H_index	G_index	M_index	TC	TC per active year	NP	PY_start
Science of the total environment	17	35	1.42	1305	118.63	35	2015
Computers and electronics in agriculture	14	23	1	770	59.23	23	2013
Global change biology	13	16	0.8	1763	117.53	16	2011
Remote sensing	10	15	1.25	460	65.71	15	2019
Smart agricultural technology	9	19	1.8	521	130.25	19	2022
Agricultural water management	8	18	0.9	332	41.50	22	2018
Agriculture (switzerland)	8	18	1.6	337	84.25	18	2022

Agronomy	8	18	1	335	67	18	2021
Environmental monitoring and assessment	8	18	0.3	327	12.58	24	2000
Environmental research letters	8	10	0.67	998	90.73	10	2015

Source: Authors' own elaboration.

In Table 3, it is depicted that most researchers do not have sustained productivity and citation impact, even though many of them have a positive contribution to the field. Li Y is the top ranked author, having published 21 articles, h-index = 11, and 1139 total citations, then Zhang X (15 publications) and Zhang Y (11 publications). Wang Y is the author with the largest m-index (1.67) among the listed ones, and it is possible to conclude that the growth of publications is very rapid within a brief recent time. Nevertheless, across a normalized citation performance by active period of publication, a more distinct image occurs. Zhang X has the largest time-normalized citation impact (80.0 citations per active year) and then comes Wang Y (72.0) and Li Y (71.19). What this means is that certain more recent contributors are gaining scientific impact at a greater pace than can be seen in the aggregate number of citations. Simultaneously, other authors, including both authors Asseng S and Chen H show that with a smaller yet respectable collection of publications solid citation influence can be obtained. Overall, the distribution of authors implies a mixture of highly prolific authors and newer rapidly growing researchers.

In Table 4, the most productive countries in science are shown. China ranks first with 133 articles (15.46%), followed by India with 114 (13.25%) and the United States with 75 (8.7%). The number of multi-country publications (MCP = 50) is also the highest in China, and the highest proportion of international collaboration is registered in Pakistan (MCP % = 76.47). Australia (65.2%), Morocco (62.5%), and Iran (55%), also have high collaboration ratios.

Table 3. Top ten authors in the field of knowledge.

Author	H_index	G_index	M_index	TC	TC per active year	NP	PY_start
Li Y	11	21	0.64	1139	71.19	21	2010
Zhang X	10	15	1.11	640	80	15	2018
Zhang Y	9	11	0.8	466	46.6	11	2016
Wang X	7	10	0.77	496	62	10	2018
Chen J	5	7	0.8	90	18	7	2021
Chen L	5	6	1.25	174	58	6	2023
Liu L	5	6	0.45	245	24.5	6	2016
Wang Y	5	9	1.67	144	72	9	2024
Asseng S	4	6	0.36	303	30.3	6	2016
Chen H	4	5	0.28	233	17.9	5	2013

Source: Authors' own elaboration.

Table 4. Top ten countries by corresponding author's country.

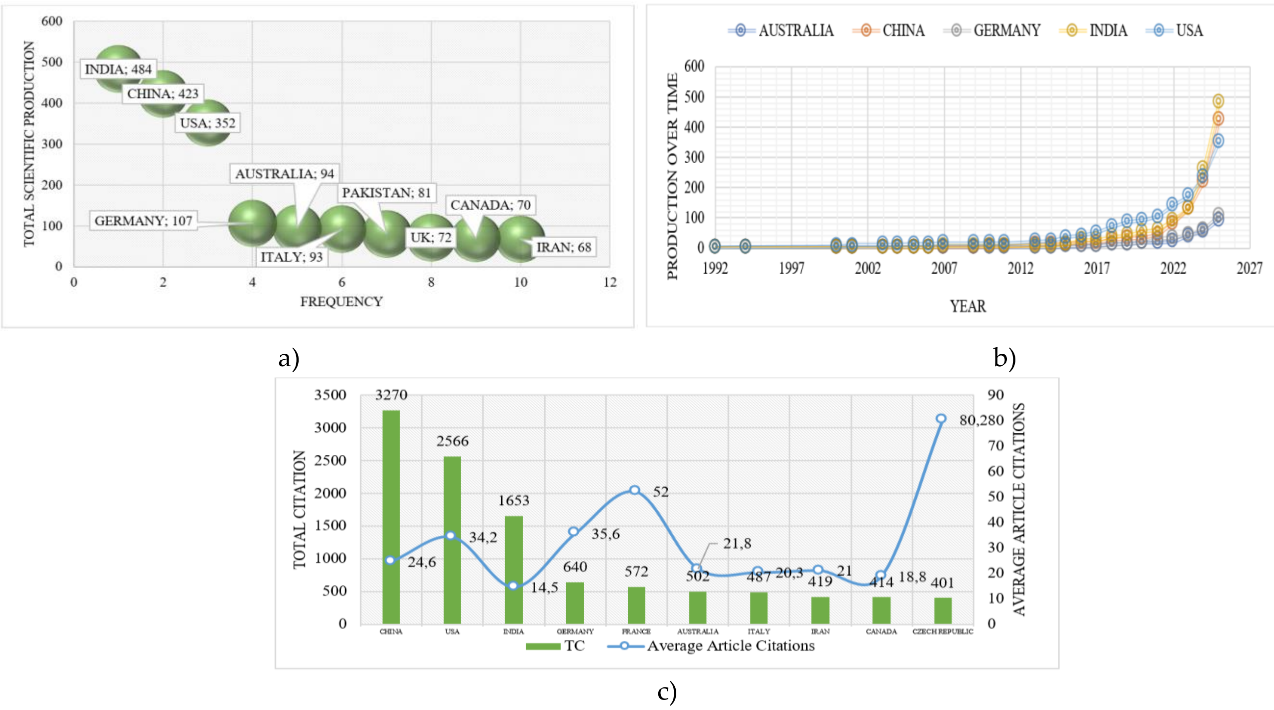
Country	Articles	Articles %	SCP	MCP	MCP %
China	133	15.46	83	50	37.59
India	114	13.25	91	23	20.18
Usa	75	8.72	48	27	36
Italy	24	2.79	14	10	41.67
Australia	23	2.67	8	15	65.22
Canada	22	2.56	11	11	50
Iran	20	2.32	9	11	55

Germany	18	2.09	10	8	44.44
Pakistan	17	1.97	4	13	76.47
Morocco	16	1.86	6	10	62.5

Source: Authors' own elaboration.

These findings imply that, despite the continued concentration of scientific productivity in a small number of nations, international cooperation is becoming more and more vital in enhancing visibility and connectivity of research in the area.

Table 4 and Figure 7a report different country-level indicators. Table 4 presents the distribution of documents by the corresponding author's country, including SCP and MCP values. In contrast, Figure 7a reflects countries' scientific production over time based on author affiliation data. Accordingly, Table 4 should be read as a corresponding-author indicator, while Figure 7a should be read as an affiliation-based country production indicator.



Source: Authors' own elaboration.

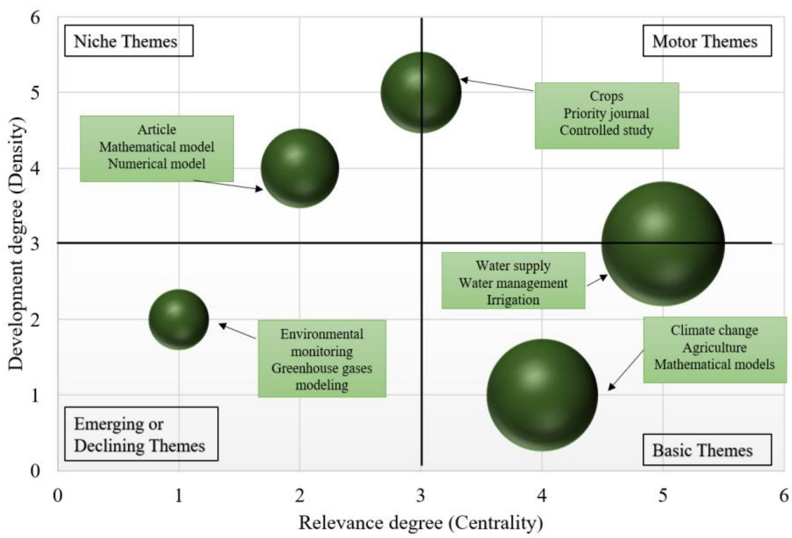
FIGURE 7. Affiliation-based country scientific production, production dynamics, and citation impact.

Figure 7 summarizes country-level scientific output through three indicators: publication volume, production dynamics over time, and citation impact among the leading contributing countries. In combination, these indicators mirror the quantitative presence as well as a comparative scientific impact of the countries in the sphere.

The publication output of the most active countries is presented in Figure 7a. India tops the list with 484 publications, China comes second (423) and third is the United States (352). These are followed by Germany (107), Australia (94), Italy (93), Pakistan (81), the United Kingdom (72), Canada (70), and Iran (68). This distribution suggests that scientific output in the research area is largely concentrated in few countries with much contribution of higher magnitude between Asia and North America.

Figure 7b traces the production dynamics of the five leading countries from 1992 to 2025. Publication growth remained limited during the earlier years and accelerated markedly after 2015. The most dramatic growth over the recent years, particularly post 2020, is in India and China, and the United States also has a powerful and maintaining upward trend. Australia and Germany rank lower than the three most developed countries in absolute output but exhibit nonstop growth in the long-term. In general, the figure indicates that the discipline has passed into a phase of international proliferation, whereby publication activity is becoming more and more commanding a handful of actively working national research systems. Figure 7c is a comparison of the total Citation Counts (TC) and average article citation per country of highest frequent citation. The largest number of citations is registered in China (3270) and then the United States (2566) and India (1653). However, when citation impact is taken on a per-article scale the situation alters. Czech Republic records the largest average number of article citations (80.28), France (52.0), Germany (35.6) and the United States (34.2) respectively. In comparison, other countries like India (14.5), Canada (18.8), Iran (21.0), and Italy (20.3) have lower average citation values even though they continue to be visible in terms of publication activity. This comparison shows that the volume and impact of publications do not necessarily correlate: certain countries have a larger total output, but others have a higher average impact of a publication.

Collectively, these three panels demonstrate that the field is multidimensional. Scientific visibility is also based on longitudinal patterns of growth and proportional contribution of the national research output. The findings indicate that the field is characterized by a small number of highly productive countries, and citation power is more unequally represented in the global arena. A co-word clustering approach was used to examine the relationships between research topics. The results were plotted in a two-dimensional strategic diagram based on Callon centrality and Callon density (Figure 8). Centrality reflects the connection between a theme and the broader research field. Density reflects the internal development and coherence of that theme.



Source: Authors' own elaboration.

FIGURE 8. Keyword co-occurrence thematic map of conceptual structure on the basis of Centrality vs. Density analysis.

As a result, the thematic map shown in Figure 8, the strategic diagram, splits the thematic space into four different quadrants:

- The Motor Themes, which are situated in the upper right quadrant are well developed and well interrelated to the field [83].

- Basic Themes, depicted in the lower right quadrant are of significance to the field too, although they are still in the development stage [84].
- Niche Themes, which is in the upper left quadrant is very elaborate internally but not so much in the outside.
- Emerging or Developing Themes, displayed in the lower left quadrant, are also low density and low centrality, meaning that they are less matured and less related to the centrality of field [85].

This mapping indicates that the beneficial conceptual framework of the field is arranged with four major thematic clusters: climate change, agriculture, crops, and learning systems. The cluster connected to changing climatic conditions seems to be one of the most central and developed ones, uniting such words as climate change, machine learning, prediction, models, irrigation, soil moisture, and remote sensing. This proves that the climate dimension is one of the key axes of the current studies and concerns the simulation systems and analytical applications in a close correlation. The agriculture cluster includes broader terms related to sustainability, land use, food, environment, ecosystem, and temperature displaying that agricultural simulation systems are being more and more connected with resource utilization, environmental strains, and broader sustainability arguments. Crops cluster represents a more instrumental research focus and consists of other words referencing crop yield, productivity, decision support, adaptation, and farm-level management. Lastly, the learning systems cluster shows the increased significance of precision farming, sustainable development, machine learning, prediction, and adaptive analytical tools, demonstrating a visible change towards a data-driven and intelligent model-based approach.

Such thematic arrangement is one of the principal analysis contributions of the work. Instead of a mere listing of common keywords, the strategic map allows one to re-create the way the sphere is conceptualized, what thematic clusters are placed at the core or at its periphery, and how the methodological and substantive priorities interplay with the larger picture of the research. The four-cluster structure thus gives more than a descriptive overview: it offers an interpretive structure of how agricultural crop simulation under climate-related risks is changing as an interdisciplinary body of knowledge. The thematic map identifies four thematic clusters, each describing a clear subdomain: Quadrant I: Motor Themes.

- Cluster #3 (Crops): crops, crop production, crop adaptation, and crop decision.
- Quadrant II: Niche Themes
- Cluster #1 (Climate Change): climate change, machine learning, prediction, irrigation, soil moisture, and remote sensing.
- Quadrant III: Emerging or Developing Themes.
- Cluster: #4 (Learning Systems): agriculture, sustainable development, predictive systems, and machine-learning-based methods.
- Themes: Basic Themes.
- Cluster # 2 (Agriculture) - agriculture, land use, environment, food, sustainability and ecosystem.

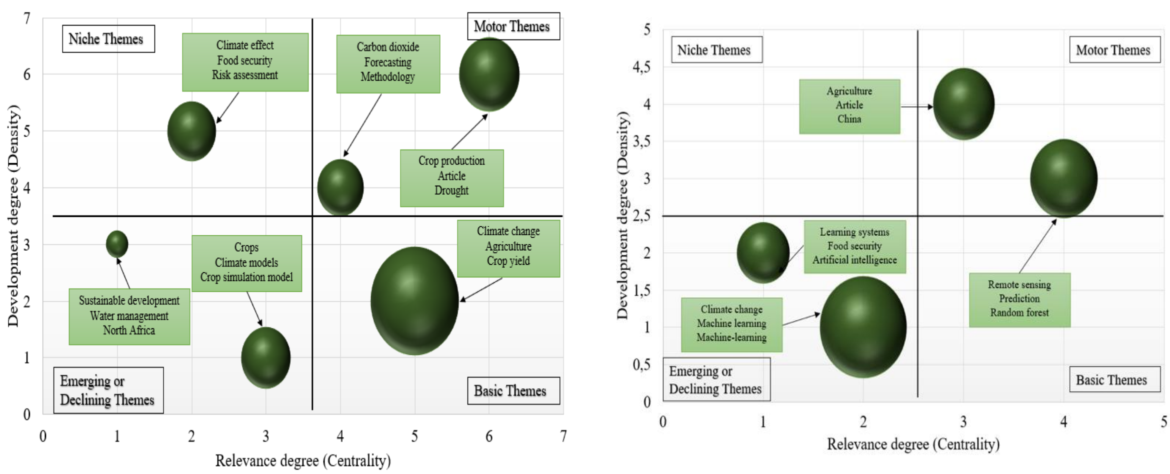
It is the various analyses carried out by each group that determine the value of this four-cluster structure. The climate change cluster is a pressure field: It reflects the instability of the environment, which requires model-based analysis. An agricultural cluster is a system domain, and land use, food systems, ecosystems, and sustainability are the broader context of interpretation. The crop cluster serves as a field for translating common climate and resource scarcity issues into specific production-related issues, including yield, productivity, adaptation, and decision support. The learning systems cluster is an area of intelligent research in which forecasting, machine learning, remote sensing, and adaptive analytical systems are changing the way uncertainty is managed in agriculture. The map shows the understanding of these levels of the same knowledge system: pressure, system, production response, analytical intelligence.

The cluster structure highlights the growing interaction between climate-focused simulation systems and intelligent learning systems. The dependence on the use of mathematical simulation systems, model-based analysis, predictive tools, and environmental management concepts proves that this area is influenced by very interdisciplinary and quantitative philosophy.

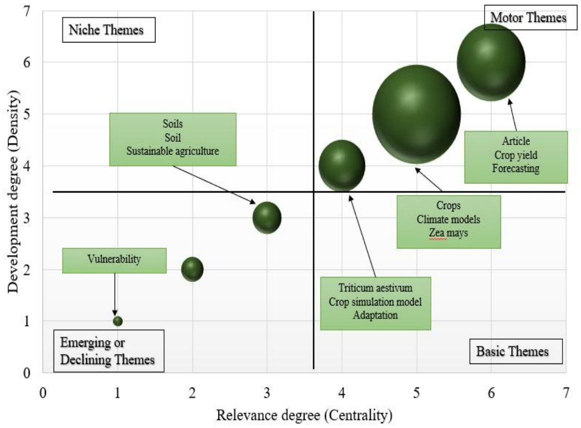
Clusters climate change and agriculture highlight one of those times where environmental stress is shaping an agriculture and agroecological land use issue in the fields, a land use food security, water resource and sustainability issue. The connection between agriculture and crop production provides insight into the dynamics of this systemic pressure and leads to continual use of resources while extending into crop management, yield or productivity and adaptation. Crop-growing and learning systems are connected; this connection validates the trend of increasingly engaging in forecasting, classification, and optimization at the crop level in decision making. It is especially relevant for the study of climate-risk relationship as it shows a methodological turn, namely the introduction of remote sensing, machine learning, forecasting and artificial intelligence-based tools into the forecasting of climate risks. This happens in the overlaps. The overlaps are where the field becomes the vehicle for the production of agricultural intelligence and information from environmental uncertainty.

1. THEMATIC EVOLUTION ACROSS SUBPERIODS

The thematic development of the field was also explored in three sub-periods (1992-2015 (Figure 9a), 2016-2020 (Figure 9b), and 2021-2025 (Figure 9c) to supplement the general thematic map. The first period was condensed in a wider formative phase since the number of publications during the initial years was insufficient to produce consistent and explicable thematic frameworks. This combination allowed comparing the thematic development of periods in a more solid way. During the foundational period (1992-2015), climate effects, food security, risk assessment, carbon dioxide, forecasting, crop production, drought, and the overall climate change-agriculture-crop yield nexus dominated the field. This implies that the initial phase of the literature was majorly focused on the environmental and production-related impacts of climate variability. The thematic structure was more differentiated in the second period (2016-2020) with more focus on soils, sustainable farming, vulnerability, crop and climate models, forecasting, and adaptation The most recent period (2021-2025) does exhibit a more definite move toward climate change, machine learning, artificial intelligence, learning systems, food security, remote sensing, prediction, and random forest, with the field having a distinct thematic anchor in food systems. Collectively, these sub-periods demonstrate that the field has developed around a limited climate-impact and production-focused foundation into a more expansive and more digitally focused area that connects sustainability, forecasting and intelligent analytical systems.



a) b)



c)

Source: Authors' own elaboration.

FIGURE 9. Keyword co-occurrence thematic map across sub-periods of conceptual structure based on centrality vs. density analysis.

V. DISCUSSION

1. DEVELOPMENT OF THE FIELD AND PRACTICAL IMPLICATIONS

The present bibliometric study confirms that, agricultural forecasting for changing agroclimatic conditions is no longer a relatively small group of technical activities. It has emerged as a very rapidly growing interdisciplinary research field [86]. This is not the only growth factor. It signals a more fundamental paradigm change in the applications of models in agricultural research for climate sensitivity. Until recently, it was primarily employed to simulate crop development, irrigation needs, soil conditions or environment. It is now being used increasingly as a tool for adaptive planning, resource allocation and decision making for agroindustry resilience at the present stage. In such a way, modeling systems are increasingly used as operational tools to respond to climatic pressures [87-89].

1.1. Relevance for Agricultural Economics

Such a change is particularly significant for agricultural economics. The field is no longer just about the forecast of crop land, water demand, or impacts of global warming. It is slowly getting towards a system of anticipation, meaning that potential future economic disruptions in farming could be identified earlier. This potential as an anticipating force, however, is not equally harnessed. The bibliometrics structure reveals a definite kernel of concern with climate change, sustainability, machine learning, and prediction as technologies in environment. Meanwhile, the economic dimension of these results based on the models is less prominent.

1.2. Translation into Economic Categories

This gives rise to a certain problem for agricultural economists. The knowledge derived from climate and production must be converted into economic terms: vulnerability, efficiency, adaptation costs, priorities for investments, constraints on resources, and resilience in the market. If this translation is not received, the field may continue to be technologically developed and financially uninterpreted. The mathematical and computational models are thus gaining relevance for the decision-making of agribusinesses. They can provide input optimization, water-use efficiency, yield prediction, risk management in production and distributing limited resources under climate stresses.

1.3. Beyond the Farm Level

These models may also be used to inform production planning and minimize production uncertainty as climate shocks occur increasingly in force. Their significance is beyond the farm level. Tools for forecasting and optimization can complement the supply stability, market coordination and cross-border agri-food flow response to climate-induced disruptions. The theme's evolution in emphasis is shifting from water management and crop productivity to water-based systems with predictive capabilities, implying that the analytical components of the field are increasingly moving closer to what we can define as a model-based approach more closely related to the economic efficiency and strategic adjustment in the agro-industrial sector.

2. DIGITAL SUPPLY CHAINS, COLLABORATION, AND TRANSITION TO INTELLIGENT SYSTEMS

One other important fact is the expanding significance of collaboration. It is becoming more international with co-authorship, cross-country visibility, and focus within a small number of important journals and research systems within the countries. Yet collaborative efforts do not have to be confused as a bibliometric scoring metric. Operational meaning is also part of the story with climate related risks, as there is a need for coordinated action of various actors in the agricultural modelling, including producers, technology suppliers, logistics actors and research institutes, and finally policy makers.

2.1. Digital Supply Chains as Decision-Support Environments

In the newer days, green and data-oriented supply chains are gradually integrating digital models into their work. In such systems, forecasting, monitoring, traceability, and inter-organizational coordination are a key part of the work of making business activities climate-adaptive and sustainable. Considered from this angle, the sector is stepping on the road of further developing the decision support system, extending its boundaries well from the farm.

Coordination between the different groups of stakeholders in the agricultural value chain could be enhanced through the use of forecasting models, digital agronomy infrastructures, and artificial intelligence tools [90, 91]. This is due to the fact that the chances of climate risks being confined to farm level are slim. They could impact on market stability, input availability, export flows, processing and storage. Sustainability in digital agroecosystems needs to be perceived beyond technological modernization. Whether or not digital tools can strengthen resilience and adaptive capacity in the context of climate stress makes a difference in its importance. Making forecasts, monitoring, and using infrastructure-linked analytics digitally can mitigate uncertainty, improve interventions' accuracy, and speed up reactions to environmental volatility.

2.2. Conditional Effect of Digitalization

Concurrently, these impacts are not automatic. Digitalization can contribute to sustainable agricultural production only when it is integrated with other institutional, infrastructure and socio-economic systems. Even the most sophisticated digital tools can be underutilized or disjointed without this underpinning.

2.3. Climate Shocks and Coordinated Response. Organizational Collaboration and Eco-Innovation

This is particularly a factor when there is a climate shock. Under these circumstances, the reaction of agroindustry will be determined by the capacity of supply chains to anticipate risks and to prevent disruptions, while also optimizing resources [92, 93]. As a result, agricultural optimization is increasingly relevant for agri-food chain management, agricultural innovation/ecosystem innovation and uncertainty management at the collective level.

Cooperation between organizations could be an enabler element in this transition. It enables agricultural actors to integrate internal/external resources, speed-up eco-innovation and enhance adaptation of the climate-resilient value chains [94]. In this regard, collaboration is a key aspect of the successful implementation of digital agricultural systems. The development of the field also undergoes a change, seen in the thematic development. Previous studies had a close relationship to irrigation, crop response, and computational process analysis. Recent studies are more strongly linked with machine learning, predicting, digital tools and analyzing the learning. Agricultural forecasting is therefore shifting from relatively "static" models of biophysical systems. It's becoming the space that is being adapted for analytical integration of different data streams and for real-time decision-making. The field is increasingly associated with forecasting, monitoring, automation, and coordination using digital systems, unlike when it was strongly linked with crop models like Decision Support System for Agrotechnology Transfer and Agricultural Production Systems Simulator.

3. UNEQUAL IMPLICATIONS OF DIGITAL AGRICULTURAL MODEL-BASED ANALYSIS, SUSTAINABILITY TRANSITIONS, AND RESILIENCE

Trends toward predictive systems, machine learning and digital agricultural tools are not automatically a transition toward sustainability. These tools can enhance decision timelines, resource delivery, and climate-risk monitoring, plus improve forecasting and resource optimization. Their contribution to sustainability, however, relies on their contributions to long term viability, ecological stability and inclusive adaptation in various agricultural contexts.

3.1. Strength in Prediction, Weakness in Transformation

Current forecasting approaches are usually better for models of short- and medium-term processes of transition, optimization processes and efficiency-based analysis compared to their ability to model deeper processes of transition. Less research has focused on how repeated climate shocks affect amongst other things, agricultural systems over time, in terms of adaptive capacity, biodiversity conservation, ecosystem restoration and repetitive climate shocks.

3.2. Uneven Sustainability Coverage

This disproportionality indicates rapid progress in methodological aspects but still under-developed approach to wider sustainability transition(s). This translates to a fundamental fact: that technical features don't always equate to the depth of sustainability. A model could be accurate and useful for its purpose but may not provide much insight into ecological regeneration or social inclusion or long-term resilience goals.

3.3. Data Dependence and Technological Asymmetry

This same imbalance is reflected in the socio-economic level. Forecasting systems that are used to make data intensive forecasts can rely on existing datasets, sensor networks, computing power, and institutional support. Consequently, they might prefer areas, regions or production systems that already feature a more advanced technological infra-structure. There is likely to be differential representation of smallholders, less connected areas and less digitalized farming systems in both the scientific landscape and the hands-on impacts of model innovation. In this sense, model-based analysis can help facilitate transitions toward sustainability, but can also leave out of the picture the infrastructures needed in order to induce the transition, further perpetuating existing inequalities.

3.4. Technological Dependency as a Risk

Technological dependence is also an important issue. Traditional questions about the accuracy of models are far from the only problem; as solutions increasingly depend on proprietary platforms and third-party analytical tools, their agricultural forecasting systems are becoming automated. It is also important whether it is accessible, transparent, adaptable and relevant to local realities. Therefore, when developing and applying model-based systems, new agricultural projection should take into account sustainability (resilience, biodiversity, socio-economic inclusivity, institutional autonomy). This is especially true for arid areas of the world, small-scale farming, and the vulnerability of farming to global warming.

4. THEMATIC CLUSTER DEVELOPMENT AND CONCEPTUAL MEANING

Time cluster analysis reveals a timeline in the organization of the topic area that was not implemented from the very beginning. It took some time to form it, and it was compiled in stages. In the early years (1992-2015), the literature was mainly devoted to climate impacts, food security, risk assessment, carbon dioxide, forecasts, crop production, drought, and the general relationship between climate stress, agroecosystems, and crop production. At this stage, the field of research was rather narrow. The main focus was on biophysical and risk-based interpretations of agricultural systems. Global warming was mainly considered as a factor to which food production, food security, and environmental stability must adapt. The second period cluster, 2016-2020, brought more clarity to this area. Special attention was paid to soils, sustainable agriculture, vulnerability, crop and climate patterns, forecasting and adaptation. The development of an "adaptation-oriented" language reflects the growing efforts to "formalize" knowledge about climate risk in the form of more formalized decision-making tools in agronomy. More recently, in the period 2021-2025, there has been a clear methodological and conceptual shift. The main topics were agricultural systems, while climate-related risks, machine learning, artificial intelligence, learning systems, food security, remote sensing, forecasting, and random forests were more prominent. This indicates the growing adoption of data-driven, predictive, and intelligent analytical systems in addition to traditional models for solving agricultural modeling tasks.

4.1. From Thematic Growth to Knowledge Evolution

The temporal evolution therefore shows a movement from climate- and production-oriented research toward sustainability, adaptation, and digital learning-based systems. This shift is not only a change in keywords. It reflects a broader transformation in the way the field understands the relationship between climate risk, agricultural production, data, and decision-making.

4.2. Four Clusters as Conceptual Architecture

In terms of analysis, this thematic reconstruction is significant as it demonstrates that the field is not growing in a random way. It is in the process of reorganization based on a comparatively stable conceptual center. The four key clusters of the strategic diagram climate change, agriculture, crops and learning systems are the four main axes of knowledge production.

4.3. Meaning of Each Cluster

Cluster labels were assigned interpretatively. In the Bibliometrix output, keyword groups were first grouped based on their overlap and position in the strategic chart. These groups then got acquainted with the conceptual approach described in the literature review: from crop and resource models to various approaches based on space and data, and, as a final step, decision support systems based on artificial intelligence. Thus, the terms climate change, agriculture, crop production, and learning systems are not just synonyms for the most common words. They summarize the importance of each cluster in the industry structure. The cluster related to climate change reflects the external pressure that is driving the industry.

The broader systemic context is represented by an agricultural cluster. The crop cluster is an example of establishing a link between climate, resource load, and production-level problems. Forecasting, machine learning, remote sensing, and intelligent analytical tools are of particular importance in the cluster of learning systems. The relationship between these clusters is also important. Agriculture and climate change intersect at the point of environmental impact, leading to issues of sustainability and production.

In the case of farming and crop production, it is at these points that the pressure of the system is reflected in crop management decisions. Taking into account that farming systems arise simultaneously with training systems, when problems arising on farms become objects of forecasting and optimization. There is a relationship between climate change and learning systems in the context of using artificial intelligence, remote sensing, and forecasting tools to address climate-related risks.

4.4. Beyond Statistical Grouping

This is an internal dynamic that partially defines agricultural modeling as an interdisciplinary knowledge system in the context of agroclimatic stress. The importance of cluster analysis will lie in the fact that, due to the ever-growing interconnectedness of clusters, agricultural areas, climatic conditions, yield levels, and intelligent analytics will become more and more intertwined.

The clusters clearly indicate the field has become restructured and there is a new analytical chain in operation. Climate pressure is what necessitates explanation: context is provided by agricultural systems; climatic pressure is translated at the crop level into measurable production problems; learning systems transform these problems in some model of prediction, optimization and decision support. The theme of this map stems from this chain of ideas. It demonstrates the need to shift from single-purpose technical applications of agricultural models to an integrated knowledge system to promote climate adaptation, resource management and intelligent decision making in the agri-food sector.

5. AI, GOVERNANCE, AND THE LIMITS OF AUTOMATED MODELING

With the advent of machine learning and artificial intelligence, advanced forecasting and management-related learning systems, a broader problem is emerging. However, with the increasing automation, reliance on data and operation embeddedness of agricultural models, their applicability cannot be judged solely from predictive efficiency. Transparency, interpretability and stakeholder trust also affect the usefulness of these systems. Digital simulation software that is highly autonomous can offer benefits in terms of efficiency, but can also lead to opacity, particularly when the decisions made by the software are hard to audit due to complex decision rules or model assumptions or training logic. Hence, in the future agricultural digital modeling will be designed responsive.

5.1. Models in Policy and Planning

The relevance of this is noted specifically if the models are applied for policy recommendations, regional planning or coordinated supply-chain decision making. The more important models reshape both adaptation strategies and the allocation of resources and methods used for risk mitigation, the more crucial is the need to keep them understandable and accountable. Thus, the development of enlightened autonomy is relevant in this context. Model-based systems should be complex enough to facilitate complex decision making, but transparent enough that people can continue to have control and trust in the system [95]. This is particularly crucial in climate-sensitive agricultural systems where automated recommendations can influence the allocation of resources, the adoption of technologies, and adaptation pathways.

5.2. Economic And Governance-Related Gap.

The bibliometric data also indicate that explicit economic and governance-related terminology remains less visible than environmental and technical terms. It is revealing that there is one significant gap. While a lot has been learnt in the field in relation to the economic links between climate related agricultural risks, crop systems, sustainability and the role of smart tools, the economic considerations, supply-chain governance and responsibility of the decisions have been less well integrated.

Future research is thus needed to build up better connections and linkages between the biophysical decision-support programmes with the agribusiness strategy, resource economics and responsible digital governance. Alarmingly, if farming systems are made technically robust with AI, they will depend on institutions, without which they are institutionally weak. There's also an added Environmental, Social, and Governance element to this transition. Artificial intelligence is heavily influencing the efficiency of agronomy systems, the coordination of agriculture systems, and the quality of governance in decision-making processes as AI tools are more frequently cited in agricultural assessment systems.

6. LIMITATIONS

While the aim of this study is to provide a comprehensive and broad bibliometric adoption of agricultural modeling in the presence of climate-related changes, several limitations were observed. It has three limitations, firstly being based only on Scopus database. This database is comprehensive and has complete and explicit metadata, but no single database can contain all relevant scientific literature. As a result, it is possible that some publications cited in other databases are not included in the final data. Secondly, the results are affected by the search approach, language filter and subject-area limitations. By restricting analysis to the English-language publications, comparisons of materials are made possible, however other local knowledge and regional studies in different languages may be excluded. The environment sciences, earth sciences and agricultural sciences were included in the selection to help maintaining the thematical coherence. This time, it could have missed out on mathematics, computer science, engineering, economics or other relevant books that were cataloged under these subdisciplines. The results from the bibliometric study are also dependent on search terms and Boolean operators. Even the most well-structured query may not result in a complete coverage of the studies undertaken using alternative vocabulary.

Third, it is a metadata-based study as opposed to a full text study of all the documents. This method works for massive science mapping at the level of bibliography but not to reflect the empirical, methodological or theoretical content of the studies. This may also result in the summarization of certain facts and findings about applied models, theories, and research strategies prevailing in bibliometric classification. Because of this, some details of modeling strategies, theory and findings from applied modeling may also be summarized or simplified in bibliography classification. This is particularly important in a field where the same words can be used to describe different modeling logics, data structures, and/or decision-support applications.

VI. CONCLUSION

This bibliometric review shows that agricultural mathematical analysis in relation to climate dynamics is becoming a rapidly expanding and increasingly interdisciplinary field of research. These temporal, geographical, and thematic trends confirm that modeling has taken a leading position in sustainable agrifood research, especially in relation to climate adaptation, water management, crop levels, and data-driven analytical systems. Thematic reconstruction of the field by co-word clustering and strategic mapping is one of the key contributions of the study. The determination of four key thematic groups: climate change, agriculture, crops, and learning systems show that the study of the research area is structured around a familiar conceptual framework, as opposed to a haphazard mix of disconnected applications. This observation is useful in explaining the course of the present methodological revolution.

A central implication is that scenario-based agricultural forecasting should become more closely integrated into agricultural economics. Rather it ought to be one of the fields which actively redefines the interpretation and application of simulation outputs. The future research should shift to the economic question of the meaning of these modeled changes on farms, markets, resources, investment, and policy decisions rather than the technical question of the extent to which models capture climate-agricultural processes. Such a change would enable agricultural predictive assessment to operate as a forecasting instrument, as well as a warning-bell analytical instrument to identify future economic stress-points within climate-sensitive agricultural systems.

Meanwhile, the results show that this area is still characterized by high concentration and obvious gaps. The research results are published in several reputable journals and countries, and the thematic organization offers more environmentally friendly, crop-oriented, and intelligent analytical methods than explicitly economic or management-oriented prediction. These patterns imply that the field has reached a higher level of maturity, but it needs more thorough conceptual implementation at the biophysical, digital and economic levels, as well as increased regional coverage of future research. In this regard, bibliometric analysis helps to identify not only gaps in thematic coverage, but also new areas of interdisciplinary intersection.

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Author Contributions

Conceptualization, P.F.M. and A.M.; methodology, P.A.M. and A.M.; software, D.M.; validation, P.A.M., A.M. and D.M.; formal analysis, D.M.; investigation, A.M.; resources, P.A.M.; data curation, D.M.; writing – original draft preparation, D.M.; writing – review and editing, P.A.M; visualization, P.F.M. and A.M.; supervision, A.M.; project administration, A.M.; funding acquisition, A.M. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

1. Nasir, M. A., & Morgan, J. (**2023**). Paradox of stationarity? A policy target dilemma for policymakers. *Quarterly Review of Economics and Finance, 87*, 142–145.
2. Bradley, R. S., Keimig, F. T., & Diaz, H. F. (**2004**). Projected temperature changes along the American cordillera and the planned GCOS network. *Geophysical Research Letters, 31*(16), L16210.
3. Kassem, Y., & Gökçekuş, H. (**2021**). Do quadratic and Poisson regression models help to predict monthly rainfall. *Desalination and Water Treatment, 215*, 288–318.
4. Maharana, P., Kumar, D., Das, S., Tiwari, P. R., Norgate, M., & Raman, V. A. V. (**2024**). Projected changes in heatwaves and its impact on human discomfort over India due to global warming under the CORDEX-CORE framework. *Theoretical and Applied Climatology, 155*(4), 2775–2786.
5. Olesen, J. E., Carter, T. R., Díaz-Ambrona, C. H., Fronzek, S., Heidmann, T., Hickler, T., Holt, T., Minguez, M. I., Morales, P., Palutikof, J. P., Quemada, M., Ruiz-Ramos, M., Rubæk, G. H., Sau, F., Smith, B., & Sykes, M. T. (**2007**). Uncertainties in projected impacts of climate change on European agriculture and terrestrial ecosystems. *Climatic Change, 81*(Suppl. 1), 123–143.
6. Vavrus, S., Ruddiman, W. F., & Kutzbach, J. E. (**2008**). Climate model tests of anthropogenic influence on greenhouse-induced climate change. *Quaternary Science Reviews, 27*(13–14), 1410–1425.
7. Sukhoveeva, O. E. (**2020**). Problems of modeling carbon biogeochemical cycle in agricultural landscapes. *Uchenye Zapiski Kazan University, Series Natural Sciences, 162*(3), 473–501.
8. Pressman, E. M., & Kebreab, E. (**2024**). Microbial and nutritional elements for mechanistic modeling of rumen fermentation. *Frontiers in Microbiology, 15*, 1488370.
9. Kebreab, E., Clark, K., Wagner-Riddle, C., & France, J. (**2006**). Methane and nitrous oxide emissions from Canadian animal agriculture. *Canadian Journal of Animal Science, 86*(2), 135–158.
10. Bach, H., Mäkitie, T., Hansen, T., & Steen, M. (**2021**). Sustainability transitions in Norwegian coastal shipping. *Energy Research & Social Science, 74*, 101957.
11. Basterrechea, D. A., Rocher, J., Parra, L., & Lloret, J. (**2020**). Development of optical sensor to detect industrial oil in irrigation systems. In *Proceedings of the Global Mosharaka Congress on Electrical Engineering* (pp. 65–70). IEEE.
12. Medvigy, D., Walko, R. L., & Avissar, R. (**2012**). Links between deforestation and extreme cold events. *Journal of Climate, 25*(11), 3851–3866.
13. Barinova, G. M., Krasnov, E., & Gaeva, D. V. (**2015**). Climate change in the South Baltic region. In *Handbook of climate change adaptation*. Springer.
14. Pineda-Martinez, L. F., Carbajal, N., Campos-Ramos, A. A., Noyola-Medrano, C., & Aragón-Piña, A. (**2011**). Wind-induced dust transport in semi-arid regions. *Atmospheric Environment, 45*(27), 4652–4660.
15. Oh, S., Greene, J., Honegger, M., & Michaelowa, A. (**2025**). Economics and policies of carbon dioxide removal. *Renewable Energy Reports, 12*(1).
16. Kirchengast, G., & Pichler, M. (**2025**). A traceable global warming record and clarity for the 1.5 °C and well-below-2 °C goals. *Communications Earth & Environment, 6*(1).
17. Fujimori, S., Wu, W., Doelman, J., Frank, S., Hristov, J., Kyle, P., Sands, R., van Zeist, W. J., Havlik, P., Domínguez, I. P., Sahoo, A., Stehfest, E., Tabeau, A., Valin, H., van Meijl, H., Hasegawa, T., & Takahashi, K. (**2022**). Land-based climate change mitigation measures can affect agricultural markets and food security. *Nature Food, 3*(2), 110–121.

18. Omar, M. E. D. M., Moussa, A. M. A., & Hinkelmann, R. (**2021**). Impacts of climate change on water quantity, water salinity, food security, and socioeconomy in Egypt. *Water Science and Engineering, 14*(1), 17–27.
19. Liu, L., Guo, Z., Huang, G., & Wang, R. (**2019**). Water productivity evaluation under climate projections in oases. *International Journal of Environmental Research and Public Health, 16*(10), 1706.
20. Rastogi, R., Maheshwari, S., Garg, P., Rastogi, M., & Kumar, P. (**2022**). Analysis of agriculture production and climate change impacts. In *Intelligent Systems Reference Library* (Vol. 210, pp. 41–65).
21. Springmann, M., Mason-D'Croz, D., Robinson, S., Garnett, T., Godfray, H. C. J., Gollin, D., Rayner, M., Ballon, P., & Scarborough, P. (**2016**). Global and regional health effects of future food production under climate change. *The Lancet, 387*(10031), 1937–1946.
22. Duan, J., Xu, Y., & Jiang, H. (**2021**). Trade vulnerability assessment in grain-importing countries. *PLoS ONE, 16*(10), e0257987.
23. Gunawardena, M. A., & Lokupitiya, E. (**2024**). Conventionally vs organically grown pineapple. *Cleaner Environmental Systems, 14*, 100219.
24. Al-Tulaibawi, A., de Faria Madrazo, P., & Martínez Cervantes, P. A. (**2024**). Advantages of contract farming. *Journal of Ecohumanism, 3*(8), 617–629.
25. Riaman, Sukono, Supian, S., & Ismail, N. (**2022**). Mathematical modeling for estimating farmers' loss risk. *Computation, 10*(8), 140.
26. Anwar, M. R., O'Leary, G., McNeil, D., Hossain, H., & Nelson, R. (**2007**). Climate change impact on rainfed wheat. *Field Crops Research, 104*(1–3), 139–147.
27. Sachdev, T., Gaba, V. K., & Tiwari, A. K. (**2021**). Comparative thermal analysis of applications using novel solar air heater with U-shaped longitudinal fins. *Journal of Thermal Engineering, 7*(5), 1174–1183.
28. Smouni, I., Baroudi, M., Alia, M., Elmansouri, A., Labzai, A., & Belam, M. (**2025**). Spatiotemporal stability analysis of soil-borne disease dynamics in tomato plants. *Modeling Earth Systems and Environment, 11*(2).
29. Kirby, J. T., & Durrans, S. R. (**2007**). Modeling the combined effects of forests and agriculture on water availability. *Journal of Hydrologic Engineering, 12*(3), 319–326.
30. Delandmeter, M., de Faccio Carvalho, P. C., Bremm, C., dos Santos Cargnelutti, C., Bindelle, J., & Dumont, B. (**2024**). Integrated crop and livestock systems increase climate adaptation and mitigation capacities. *Science of the Total Environment, 912*, 169061.
31. Patel, R., Upasana, Pattanaik, A., Kumar, D., Afaq, A., & Bag, S. (**2024**). Optimizing livestock feed formulation for sustainable agriculture. In *Mathematical modeling in agriculture*. Wiley.
32. Tedeschi, L. O., Greenwood, P. L., & Halachmi, I. (**2021**). Advancements in sensor technology and decision support tools in livestock farming. *Journal of Animal Science, 99*(2), skab038.
33. Abd-Elaty, I., Pugliese, L., Zelenakova, M., Mesaros, P., & El Shinawi, A. (**2020**). Simulation-based solutions for reducing soil and groundwater contamination. *International Journal of Environmental Research and Public Health, 17*(24), 9373.
34. Barbieri, F., Barbi, S., Bertacchini, A., & Montorsi, M. (**2023**). Effects of LED light and fertilizers on lettuce growth: Modeling approach. *Applied Sciences, 13*(15), 8687.
35. Deeptha, R., Veeramani, R., Bama, B. S., & Karthikeyan, U. (**2023**). Development of non-parametric model for weather prediction. In *Proceedings of the International Conference on Applied Artificial Intelligence and Computing* (pp. 1604–1609).
36. Ghafarian, P., Gholami, S., Owlad, E., & Gerivani, H. (**2016**). Rainfall–runoff variability and anthropogenic effects. *Journal of Earth System Science, 125*(6), 1299–1311.
37. Berdennikov, E. A., & Tarasov, E. N. (**2021**). Applicability of Lamet formulas in agricultural repair enterprises. *IOP Conference Series: Earth and Environmental Science, 624*(1), 012059.
38. Zaatri, A. (**2024**). Estimation of AM2 model parameters using empirical functions. *European Journal of Sustainable Development Research, 8*(3).
39. Ragunath, R., Dhamodharavadhani, S., & Rathipriya, R. (**2023**). Forecasting rainfall using neural networks and traditional models. *Communications in Computer and Information Science, 1798*, 592–608.
40. Sagero, P. O., Pratap, A., Magiri, R., Ongoma, V., & Okello, P. (**2024**). Validation of rainfall data over the South Pacific region. *Meteorology and Atmospheric Physics, 136*(4).
41. Senapati, D., Narendra, M., Kumar, A., & Rath, S. (**2023**). LSTM algorithm for rainfall prediction. *Lecture Notes in Networks and Systems, 401*, 243–252.
42. Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., & Ritchie, J. T. (**2003**). The DSSAT cropping system model. *European Journal of Agronomy, 18*(3–4), 235–265.
43. Amiri, E., Bahrani, A., Irmak, S., & Roshan, N. M. (**2022**). Evaluation of irrigation scheduling using AquaCrop model. *Water Supply, 22*(1), 602–614.
44. Sarkar, S., Dey, S., Dhar, A., Chaki, A. K., Goswami, R., Gaydon, D. S., Garai, S., Brahmachari, K., & Mainuddin, M. (**2025**). Bibliometric analysis of APSIM-driven agricultural research. *International Journal of Biometeorology*.
45. Romanelli, J. P., Gonçalves, M. C. P., de Abreu Pestana, L. F., Soares, J. A. H., Boschi, R. S., & Andrade, D. F. (**2021**). Challenges in bibliometric reviews. *Environmental Science and Pollution Research, 28*(43), 60448–60458.
46. Kositzyn, A., Serdechnyy, D., Korchagin, S., Pleshakova, E., Nikitin, P., & Kurileva, N. (**2021**). Modeling flight paths of unmanned aerial vehicles. *Mathematics, 9*(17).
47. Nie, Y., Hicks, B., Nassehi, A., & Valero, M. R. (2025). Aligning sustainable development goals and stakeholders' needs in food supply chains: a comprehensive review and mapping. *International Journal of Production Research*, 1-43.

48. Ranjan, R. (**2013**). Mathematical modeling of drought resilience in agriculture. *Natural Resource Modeling, 26*(2), 237–258.
49. Akman, E., Akman, Ç., & Aksu, D. (**2022**). Bibliometric analysis of sustainable development research. *Present Environment and Sustainable Development, 16*(2), 183–193.
50. Fatima, S., Tandon, P., & Singh, A. B. (**2024**). Sustainability and innovation in finance: A bibliometric review. *International Journal of System Assurance Engineering and Management, 15*(5), 1591–1614.
51. Vagelas, I., & Leontopoulos, S. (**2023**). Bibliometric analysis of soil and climate interactions. *AgriEngineering, 5*(1), 581–610.
52. Lordelo, S. A. V., Nogueira, S. M. S., de Farias Filho, J. R., Costa, H. G., Barbosa, C. L., & Calado, R. D. (**2021**). Kaizen and healthcare: A bibliometric analysis. *IFIP Advances in Information and Communication Technology, 631*, 314–322.
53. Ginaldi, F., Bajocco, S., Bregaglio, S., & Cappelli, G. (**2019**). Spatializing crop models for sustainable agriculture. In *Innovations in sustainable agriculture* (pp. 599–619). Springer.
54. Nikiema, T., Ezin, E. C., & Kpenavoun Chogou, S. (**2023**). Bibliometric analysis of agroecology adoption. *Sustainability, 15*(21), 15616.
55. Tamasiga, P., Ouassou, E., Onyeaka, H., Bakwena, M., Happonen, A., & Molala, M. (**2023**). AI and food security: A bibliometric analysis. *Journal of Agriculture and Food Research, 14*, 100819.
56. Ho, Y. S., & Lwesya, F. (**2024**). Food security research: A bibliometric analysis. *World Food Policy, 10*(1), 143–161.
57. Slepetiene, A., Belova, O., Fastovetska, K., Dinca, L., & Murariu, G. (**2025**). Carbon storage in agricultural soils. *Agriculture, 15*(23), 2489.
58. Rajput, A., Kumar, P., Singh, G. A., & Tiwari, S. (**2026**). Agriculture, sustainability, and climate change. In *Climate-responsive plant biology* (pp. 135–165). Springer.
59. Asseng, S., Zhu, Y., Basso, B., Wilson, T., & Cammarano, D. (**2014**). Simulation modeling: Applications in cropping systems. In *Encyclopedia of agriculture and food systems*. Elsevier.
60. Sarkar, S., Dey, S., Dhar, A., Chaki, A. K., Goswami, R., Gaydon, D. S., Garai, S., Brahmachari, K., & Mainuddin, M. (**2025**). Mapping APSIM-driven agricultural research. *International Journal of Biometeorology, 69*(7), 1599–1615.
61. Pang, Y., Marinello, F., Tang, P., Li, H., & Liang, Q. (**2023**). Bibliometric analysis of trends in smart irrigation for smart agriculture. *Sustainability, 15*(23), 16420.
62. Ahmed, S. M., Biro Turk, K. G., Ahmed, A. E., Elbushra, A. A., Aldhafeeri, A. A., & Darrag, H. M. (**2025**). Evapotranspiration estimation in the Arab region. *Water, 17*(18), 2702.
63. Du, X., Yang, G., Yuan, H., Wu, Y., Lv, Z., Du, C., Jian, J., Wang, Q., Huang, L., & Chen, W. (**2025**). Terracing effects on water resources under climate change. *Water, 17*(8), 1125.
64. Vagelas, I., & Leontopoulos, S. (**2023**). Soil organic matter and climate interaction: A bibliometric analysis. *AgriEngineering, 5*(1), 581–610.
65. Niculae, A. M., Oprea, S. V., Văduva, A. G., Bâra, A., & Andreescu, A. I. (**2024**). Machine learning in climate research publications. *Sustainability, 16*(24), 11086.
66. Aydin, O., & Kilar, H. (**2025**). Artificial intelligence in precipitation modeling: A bibliometric analysis. *Theoretical and Applied Climatology, 156*(11).
67. Goyal, A., Singh, A., Raghuraman, M., Ghosh, P., & Jadhav, A. (**2025**). Forecasting models for crop pest and disease outbreaks. *International Journal of Tropical Insect Science*.
68. Mesías-Ruiz, G. A., Pérez-Ortiz, M., Dorado, J., de Castro, A. I., & Peña, J. M. (**2023**). Precision crop protection and agriculture 5.0. *Frontiers in Plant Science, 14*, 1143326.
69. Montalvo, A., Camacho, O., & Chavez, D. (**2025**). Cyber-physical systems for smart farming. *Sustainability, 17*(14), 6393.
70. Degila, J., Tognisse, I. S., Honfoga, A. C., Houetohossou, S. C. A., Sodedji, F. A. K., Avakoudjo, H. G. G., & Assogbadjo, A. E. (**2023**). Digital agriculture in West Africa. *Agriculture, 13*(5), 1067.
71. Papa, M., Robson de Medeiros Oliveira, S., & Bergier, I. (**2024**). Technologies in cattle traceability. *Computers and Electronics in Agriculture, 227*, 109459.
72. Hussein, J. B., Workneh, T. S., Kassim, A., Ntsowe, K., Melesse, S. F., & El-Mesery, H. S. (**2025**). Big data analytics in agriculture and food systems. *Applied Food Research, 5*(2), 101234.
73. Martín-Cervantes, P. A., Ziarati, P., de Frutos Madrazo, P., & Gigauri, I. (**2025**). Digital marketing and circular economy. *Sustainability, 17*(11).
74. Stefanis, C., Giorgi, E., Tselemponis, G., Voidarou, C., Skoufos, I., Tzora, A., Tsigalou, C., Kourkoutas, Y., Constantinidis, T. C., & Bezirtzoglou, E. (**2023**). Terroir and bibliometric analysis. *Stats, 6*(4), 956–979.
75. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P., & Moher, D. (**2021**). The PRISMA 2020 statement. *BMJ, 372*, n71.
76. Faggiolani, C. (**2015**). The Leiden manifesto for research metrics. *AIB Studi, 55*(3), 427–438.
77. San Francisco Declaration on Research Assessment. (**2013**). *San Francisco Declaration on Research Assessment*.
78. Chaturbhuj, S., & Motewar, N. R. (**2021**). Scientometric analysis of university research productivity. *DESIDOC Journal of Library and Information Technology, 41*(6), 438–447.

79. Borgohain, D. J., Lund, B., & Verma, M. K. (**2026**). A mathematical analysis of the h-index and study of its correlation with some improved metrics: A conceptual approach. *Journal of Information Science, 52*(1), 244–252.
80. Mallick, S., Vashistha, R., & Vashistha, B. (**2023**). Research indices and evaluation metrics. In *Translational radiation oncology* (p. 713). Elsevier.
81. Singh, P. K. (**2022**). t-index and citation entropy analysis. *Scientometrics, 127*(1), 637–660.
82. Han, J., Chen, H., Ren, Z., Zhang, X., Shao, Z., Wei, Q., & Li, Z. (**2025**). Environmental research on triclosan and triclocarban. *Frontiers in Environmental Science, 13*.
83. Folharini, S., Vieira, A., Bento-Gonçalves, A., Silva, S., Marques, T., & Novais, J. (**2023**). Wildfires and protected areas: A bibliometric study. *Sustainability, 15*, 18536.
84. Ghura, A. S., Sharma, G. D., Pereira, V., Islam, N., & Chopra, R. (**2022**). Corporate entrepreneurship research mapping. *International Journal of Entrepreneurial Behavior and Research, 28*, 2151–2181.
85. Verma, S. (**2022**). Sentiment analysis in public services. *Government Information Quarterly, 39*, 101708.
86. Bibliometric analysis of climate smart agriculture research. (**n.d.**). *Moroccan Journal of Chemistry, 10*, 488–499.
87. Dzhumabayev, K. D., Dzhumabayev, A. K., Jamalov, S. A., Kydykbaeva, E. K., & Kyzy, T. A. (**2023**). Investment in agricultural cooperatives in Central Asia. In *Food security in the economy of the future* (pp. 123–136). Springer.
88. Kimathi, E., Mudereri, B. T., Abdel-Rahman, E. M., Niassy, S., Tonnang, H. E. Z., & Landmann, T. (**2022**). Monitoring Striga risk using environmental variables. *Environmental Monitoring and Assessment, 194*.
89. Zavadskiy, V., & Revalde, G. (**2024**). Water deficit and green hydrogen in Central Asia. *Engineering for Rural Development, 23*, 921–926.
90. Singels, A., Annandale, J. G., De Jager, J. M., Schulze, R. E., Inman-Bamber, N. G., Durand, W., Van Rensburg, L. D., Van Heerden, P. S., Crosby, C. T., Green, G. C., & Steyn, J. M. (**2010**). Crop growth modeling in South Africa. *South African Journal of Plant and Soil, 27*, 49–65.
91. Zoogah, D. B., & Rigg, J. S. (**2014**). Bibliographic analysis in strategic management research. *Research Methodology in Strategy and Management, 10*, 189–213.
92. Bapat, D., & Vashisht, D. (**2024**). Financial services experience: A bibliometric analysis. *Journal of Financial Services Marketing, 29*, 904–921.
93. Román-Vázquez, J., Carbonell-Bojollo, R. M., Veroz-González, Ó., da Silva Piletti, L. M., Márquez-García, F., Cabeza-Ramírez, L. J., & González-Sánchez, E. J. (**2025**). Conservation agriculture and climate change research trends. *Agronomy, 15*, 249.
94. Manioudis, M., & Meramveliotakis, G. (**2022**). Sustainable development and political economy. *New Political Economy, 27*(5), 866–878.
95. Misra, V. P., Mishra, P. K., & Sharma, A. (**2023**). Artificial intelligence in education. In *Proceedings of the IEEE Asia-Pacific Conference on Computer Science and Data Engineering*. IEEE.