Research Trends in Machine Learning Applications for Predicting Ecosystem Responses to Environmental Changes

Fairuz Iqbal Maulana[1*], *Puput Dani Prasetyo* Adi[2], *Chasandra* Puspitasari[1], and *Agung* Purnomo[3]

[1]Computer Science Department, School of Computer Science, Bina Nusantara University, Jakarta, Indonesia 11480
[2]Telecommunication Research Center, National Research and Innovation Agency, Jakarta, Indonesia 11480
[3]Entrepreneurship Business Creation, BINUS Business School, Bina Nusantara University, Jakarta, Indonesia 11480

Abstract. This research discusses the trends in machine learning (ML) applications for predicting ecosystem responses to environmental changes. A keyword search was conducted in the WoS database using Boolean operators to identify relevant peer-reviewed articles. The search focused on English-language documents published between 2014 and 2023, while excluding non-original articles. Bibliometric data, including publication trends, citation counts, author collaboration patterns, and keyword analysis, were extracted from 554 retrieved articles. The data was then analyzed and visualized using R and VOSViewer. The study highlights the significant growth in annual scientific production, reflecting a growing interest in this interdisciplinary field. Core concepts such as “climate change,” “biodiversity,” and “ecological responses” continue to receive significant attention, while contemporary themes like “variability,” “time-series analysis,” and “organic matter” are emerging. Co-authorship networks demonstrate extensive collaborations across countries, with the United States and China playing prominent roles. The research topics have evolved from “ecological responses” and “community” to a focus on “model,” “optimization,” and “performance,” with an emphasis on fine-tuning models to incorporate climate variability.

1 Introduction

Machine learning (ML) has gained significant traction in the ecological and environmental science communities for its empirical modeling and predictive capabilities [1,2]. Ecologists and environmental scientists have increasingly turned to ML to model nonlinear and high-dimensional systems, leading to improved predictability in understanding complicated ecosystems. This trend is evident in the intensive study and modeling of rivers, one of the earth's key ecosystems, through the application of ML [3].

Furthermore, ML has been employed in ecosystem service research for describes data and predictive modeling, showcasing its versatility in addressing environmental challenges [4,5]. The use of ML in predicting ecosystem responses to environmental changes is further exemplified by its application in understanding the environmental controls on ecosystem photosynthesis, which is essential for comprehending the impact of environmental changes on ecosystems. Advanced data analysis approaches, such as machine learning, have become indispensable tools for revealing hidden patterns or deducing underlying structures in complex datasets [6,7].

Supervised learning techniques, including classification and regression, have been widely used in environmental sciences for predicting ecosystem responses. Unsupervised learning techniques, such as clustering and ordination, have also been employed in the analysis of ecological communities. Deep learning techniques, like convolutional neural networks, have enabled species classification from remote sensing data, further demonstrating the potential of ML in environmental sciences [8,9].

Machine learning has been used to predict ecosystem responses to environmental changes by analyzing the effects of climate change on individuals and species, with particular emphasis on the effects on phenology and physiology of organisms as well as changes in community composition [10]. ML has also been applied to study the impact of land use changes on ecosystem services, highlighting its potential in understanding the effects of human activities on ecosystems. Moreover, ML has been used to predict the distribution of invasive species, helping to inform conservation efforts and management strategies [11,12].

The ability of ML algorithms to uncover patterns and make predictions from vast and multifaceted data sets is particularly beneficial for understanding the dynamics of ecosystems under environmental stressors [13]. This study aims to map the research landscape using bibliometric analysis, identifying key methodologies, algorithms, and application areas that have shaped the current state of the field.

* Corresponding author: fairuz.maulana@binus.edu

2 Materials and Method

2.1 Search Strategy and Article Selection

This study employed a comprehensive literature review utilizing the Web of Science (core collection) database to gather journal articles and reviews published between 2014 and 2023. The search aimed to identify international academic papers pertaining to the research topic by employing specific keyword combinations with Boolean operators [14]. The keywords used were “Machine Learning” OR “Predictive Modeling” AND “Ecosystem Responses” OR “Ecosystem Dynamics” OR “Ecological Responses” AND “Environmental Changes” OR “Environmental Impact”. The search was limited to English-language documents published within the last decade (2014-2023).

To ensure the selection of relevant and informative articles, the focus of the selection process was narrowed down to original articles. This decision was made based on the understanding that original articles are more likely to present new insights. English-language articles were preferred due to their relevance and accessibility within the scientific community, as English serves as a widely used international language in scientific research. The prominence of English in the field of Machine Learning further emphasized the significance of English-language literature for this study [15]. After eliminating duplicates and non-relevant articles, a total of 554 articles were deemed suitable for inclusion.

2.2 Bibliometric Analysis

The bibliometric analysis in this study utilized two software tools, namely R and VOSviewer, which are commonly employed in bibliometric research, each offering distinct advantages. R is a specialized integrated development environment (IDE) specifically designed for the R programming language, renowned for its wide range of statistical and graphical functionalities. With a user-friendly interface and comprehensive editing, debugging, and visualization tools, R is favored by data scientists and statisticians, particularly in bibliometric studies. It facilitates seamless integration and processing of bibliometric data, featuring programs like 'biblioshiny' for efficient data cleaning and preparation, ensuring accuracy and reliability in bibliometric analysis. Notably, R excels in robust data visualization capabilities, enabling the creation of high-quality visualizations suitable for publication, such as citation maps and trend graphs [16].

VOSviewer, on the other hand, is a software application developed specifically for visualizing bibliometric networks, encompassing components such as journals, researchers, publications, and keywords. It offers functionalities including keyword co-occurrence analysis and the measurement of relationship intensity within a bibliometric network. VOSviewer's research capabilities extend to identifying frequently occurring keywords and applying clustering algorithms to unveil thematic patterns and associations [17].

3 Results and Discussion

3.1 Main Information

A total of 554 documents from 363 sources were obtained through data selection from the Web of Science database. The analysis of research trends in this field reveals notable patterns and trends. The selected time span from 2014 to 2023 provides valuable insights into both recent advancements and historical developments. Conducted as part of this study, the bibliometric analysis explores the utilization of machine learning in predicting ecosystem responses over the past decade, yielding two key metrics: annual scientific production and average citations per year from 2014 to 2023, as illustrated in Figures 1 and 2.

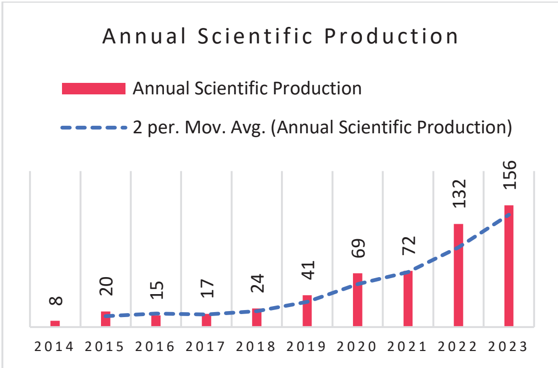

Fig. 1. Annual Scientific Production

Figure 1 illustrates the number of documents published each year from 2014 to 2023 in the field of machine learning applications for predicting ecosystem responses to environmental changes. From 2014 to 2023, there is a significant increase in annual scientific production. In 2014, there were only 8 documents, whereas in 2023, the number increased to 156 documents. This indicates a growing interest and increased recognition of the importance of machine learning in ecological research. The graph shows an almost exponential growth in the number of publications, particularly in recent years. The sharp increase from 132 documents in 2022 to 156 in 2023 confirms a strong growth trend.

The dashed blue line represents the two-period moving average, which is used to smooth annual fluctuations and highlight long-term trends. This trend line shows a consistent and stable increase over time, without any significant decline. The graph also demonstrates some annual fluctuations in the number of publications. For example, there is an increase from 15 to 24 between 2016 and 2017, but only a small increase from 41 to 47 between 2018 and 2019. The consistency in the growth trend suggests a potential continuous increase in research in this area, possibly driven by an increased awareness of climate change and the need for a better understanding of how ecosystems respond to these changes. This research may become more relevant as machine learning technology advances and environmental data becomes more available and accurate.

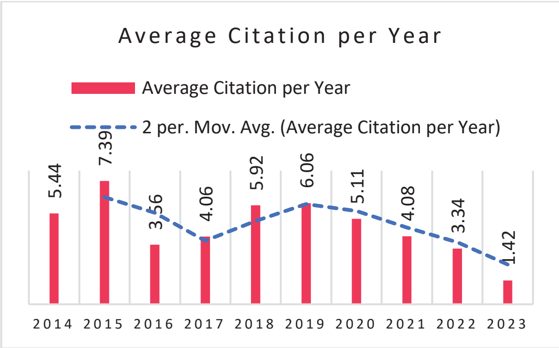

Fig. 2. Average Citation per Year

Figure 2 depicts the mean number of citations received by documents published each year from 2014 to 2023 in the field of machine learning applications for predicting ecosystem responses to environmental changes. The average citations per year started relatively high in 2014, with each document receiving an average of 5.44 citations. This could indicate that the foundational work published in the early years was highly referenced, possibly because it laid the groundwork for future research. There is a noticeable declining trend in the average number of citations per document over time, reaching the lowest point in 2023 with an average of 1.42 citations per document. This decline could be due to several factors, such as a larger number of publications diluting the citation count or recent articles not having had enough time to accumulate citations.

The dashed line represents the two-period moving average of the average citations per year. This trend line smooths out fluctuations and helps to see the overall trend more clearly. The moving average also shows a downward trend, which suggests that, on average, publications in this field are receiving fewer citations over time. The graph shows variability from year to year in the average citations, with some years like 2018 and 2020 seeing a slight increase in citations from the previous years. These fluctuations could be related to the publication of particularly influential papers or external factors affecting the field's research interest. The decreasing trend in average citations could indicate that the field is becoming more specialized, with studies being cited by a narrower segment of the research community. It might also suggest a saturation of the literature, where newer publications find it harder to stand out. The recent decline in average citations per year might not fully reflect the impact of those publications, as citations generally accumulate over several years. Therefore, the citation potential of papers published in the last few years might not yet be fully realized.

3.2 Three Fields Plot

The provided image depicts a three-field plot, commonly referred to as a Sankey diagram, which is frequently employed in bibliometric analysis to visually represent the interrelationships among authors, references, and keywords [18]. Within this plot, the middle column presents a list of individual authors who have made contributions to the field, with the width of the connecting bands indicating the strength of their association. Authors with wider bands are likely to have more influential works or a higher number of publications within the dataset.

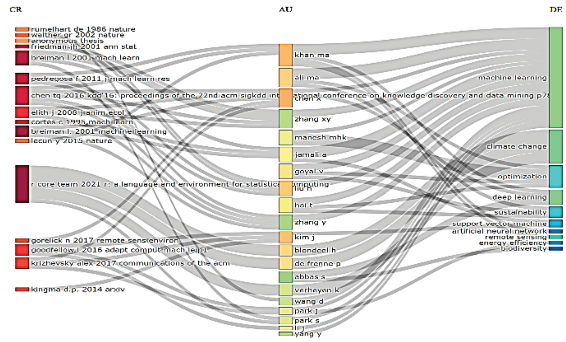

Fig. 3. Thee Fields Plot

The left column showcases key references cited within the existing body of literature, encompassing seminal papers, influential researchers, and foundational theories in the field. Noteworthy works such as those authored by “rumelhart de 1986” and “lecun y 2015” suggest the presence of foundational research in the domain of neural networks and deep learning, which are being referenced by current studies. On the right column, descriptors or subjects associated with the publications are presented, with the widest band corresponding to the topic of “Machine learning,” indicating its prevalence within the dataset. Other notable topics include “climate change,” “optimization,” “deep learning,” and “sustainability,” indicating their significance as focal areas in current research endeavors.

The connections observed between authors and keywords provide valuable insights into the most active or influential researchers in specific areas of machine learning applications for ecosystem response prediction. Moreover, this diagram effectively highlights the interdisciplinary nature of the field, as evidenced by the keywords spanning across technical aspects such as “support vector machine” and “deep learning,” as well as application areas like “climate change” and “biodiversity.”

The linkages analysis between authors and references makes it possible to identify potential mentor-mentee relationships, collaborations, or prevailing schools of thought within the field. Notably, a strong connection between recent references and current authors suggests a rapid evolution of the field, with new research building directly upon the latest findings. The keywords associated with both authors and references shed light on the thematic areas that currently drive research, as well as potential gaps or emerging trends within the field.

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3.3 Most Cited Sources and Articles

In the investigation of bibliometric patterns within the domain of machine learning applications for ecosystem response prediction to environmental changes, a scrutinized analysis of the most cited sources has yielded insightful revelations. As shown in figure 4, the journal 'Remote Sensing' stands at the forefront with a substantial citation count of 420 across 14 documents, underscoring its pivotal role in advancing research in this arena. Notably, 'Nature Sustainability' commands attention with an extraordinary citation density, accumulating 412 citations from merely two documents, indicating the groundbreaking nature of its publications.

Moreover, 'Scientific Reports' exhibits a robust citation total of 388, attributed to six documents, reflecting the significance and widespread influence of its scholarly contributions. The inclusion of 'Construction and Building Material' with 384 citations from four documents highlights the intersection of construction materials science with ecological sustainability, an aspect of growing interest in the context of environmental machine learning research.

The 'Journal of Cleaner Production' is recognized for its focus on sustainable production processes, evidenced by 345 citations for three documents, marking it as an authoritative source within the field. The presence of 'Remote Sensing Environment' with 282 citations for two documents further corroborates the integral application of remote sensing technologies in environmental change studies.

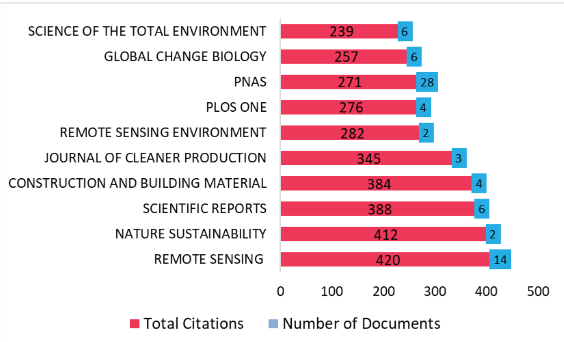

Fig. 4. Increased Research growth in the last ten years

'PLOS ONE' is also featured prominently, with 276 citations across four documents, showcasing the journal's role in the widespread dissemination of research findings. The 'Proceedings of the National Academy of Sciences of the United States of America' (PNAS) presents the most extensive array of documents, totaling 28, and a cumulative citation count of 271, indicating its comprehensive coverage and interdisciplinary reach.

Additionally, 'Global Change Biology' and 'Science of the Total Environment' with citation totals of 257 and 239 for six documents each, respectively, are indicative of their substantial contributions to the understanding of biological and environmental systems.

Collectively, these journals delineate a multifaceted research landscape wherein machine learning serves as a nexus, drawing together diverse fields in an effort to elucidate and predict ecological responses to a changing environment. The high citation metrics not only reflect the relevance and impact of the published research but also suggest the degree to which these findings inform and shape ongoing scientific discourse.

Table. 1. Most Cited Articles

Authors	Title	Year	Citation
Cordier T [19]	Predicting the Ecological Quality Status of Marine Environments from eDNA Metabarcoding Data Using Supervised Machine Learning	2017	109
Cordier T [20]	Supervised machine learning outperforms taxonomy-based environmental DNA metabarcoding applied to biomonitoring	2018	86
Connolly DP [21]	Assessment of railway vibrations using an efficient scoping model	2014	69
Ribeiro AMNC [22]	Short-Term Firm-Level Energy-Consumption Forecasting for Energy-Intensive Manufacturing: A Comparison of Machine Learning and Deep Learning Models	2020	10
Karka P [23]	Digitizing sustainable process development: From ex-post to ex-ante LCA using machine-learning to evaluate bio-based process technologies ahead of detailed design	2022	6
Peng YM [24]	Analyzing the mechanical performance of fly ash-based geopolymer concrete with different machine learning techniques	2022	31
Connolly DP [25]	Scoping prediction of re-radiated ground-borne noise and vibration near high speed rail lines with variable soils	2014	59
Jung SW [26]	Can the algicidal material Ca-aminoclay be harmful when applied to a natural ecosystem? An assessment using microcosms	2015	12
Yao Q [27]	Palynological reconstruction of environmental changes in coastal wetlands of the Florida Everglades since the mid-Holocene	2015	34
Rammer W [28]	Coupling human and natural systems: Simulating adaptive management agents in dynamically changing forest landscapes	2015	59

Table 1 shows the most cited articles on machine leaning for predicting ecosystem response researches.

Within the domain of bibliometric analyses, which specifically target the expanding intersection between machine learning and ecosystem response forecasting, there exists a notable collection of foundational publications that exemplify the robust interdisciplinary discourse and the creative utilization of data-centric methodologies.

Within this scholarly landscape, the works of Cordier T. have garnered notable attention, with a 2017 publication delving into the predictive potential of eDNA metabarcoding data via supervised machine learning, accruing 109 citations. This is closely followed by a subsequent 2018 study, also by Cordier T., which amassed 86 citations for its comparative analysis underscoring the superiority of machine learning over traditional taxonomy-based methods in eDNA applications for biomonitoring.

Connolly DP.'s 2014, with its pragmatic focus on the assessment of railway vibrations through an efficient scoping model, illustrates the pragmatic fusion of machine learning with environmental engineering, as reflected in its 69 citations. This integrative trend continues with Ribeiro AMNC.'s 2020 contribution to the field, cited 10 times, that elucidates the efficacy of machine learning and deep learning models in the arena of short-term, firm-level energy consumption forecasting within the manufacturing sector.

The nascent yet impactful work of Karka P. in 2022, though cited 6 times, signals a shift towards the pre-emptive application of machine learning in sustainable process development, particularly through the lens of life cycle assessments in bio-based technologies. Complementing this forward-looking approach, Peng YM.'s 2022 study on the mechanical performance of fly ash-based geopolymer concrete, referenced 31 times, underscores the transformative potential of machine learning in advancing sustainable construction materials.

Further underlining the diversity of application, Connolly DP.'s second study within the same year examining ground-borne noise and vibration against the backdrop of high-speed rail lines, cited 59 times, and Jung SW.'s 2015 microcosm-based assessment of algicidal materials, with 12 citations, reflect the environmental risk assessment dimension of machine learning.

Yao Q.'s 2015 palynological reconstruction of environmental changes, cited 34 times, ventures into the domain of historical ecology, leveraging machine learning to distill insights from coastal wetland data spanning the mid-Holocene. Similarly, Rammer W.'s 2015 article, receiving 59 citations, explores the coupling of human and natural systems through machine learning simulations, offering a window into the adaptive management of dynamically changing forest landscapes.

Collectively, these scholarly contributions map the trajectory of machine learning applications from theoretical underpinnings to practical environmental assessments, marking a pivotal transition in ecological research methodologies. The diversity of these studies, both in thematic concentration and methodological execution, showcases the expanding footprint of machine learning techniques in ecological and environmental sciences, heralding a new epoch of predictive modeling and data-centric environmental stewardship.

3.4 Keywords Occurences Analysis and Trend Topics

The visualization provided (Figure 5) is keyword co-occurrence network generated by VOSviewer, a tool commonly used for bibliometric analysis. VOSViewer graphically represents the relationships between terms used in a body of literature. In this case, it illustrates the interconnectedness of keywords in research papers related to machine learning applications for predicting ecosystem responses to environmental changes. This network visualization serves as a strategic tool for identifying the most influential concepts within the field, understanding the structure of the research domain, and potentially guiding future research to fill gaps or expand on key themes. The network categorizes keywords by color to show related topics, and the line thickness between them indicates how often they are mentioned together in research, indicating a stronger relationship or relevance [29,30].

The most prominent nodes, such as "algorithm," "environmental impact," "species," "change," and "ecosystem," indicate these are central themes in the current research landscape. Their size and the density of connections to these nodes suggest they are frequently discussed topics within the literature. The network shows a strong link between machine learning terms like "algorithm," "ml-model," and "random forest classifier" with environmental and ecological terms like "biodiversity," "climate change," and "ecosystem." This implies an interdisciplinary approach where machine learning techniques are applied to ecological data. The presence of specific machine learning methods like "random forest classifier," "dnn" (deep neural networks), and "ann model" (artificial neural networks) alongside "prediction accuracy" and "classification" suggests that these techniques are particularly valued for their precision in predicting ecological outcomes. The cluster of terms including "environmental impact," "energy," "building," and "concrete" indicates a research subdomain concerned with the sustainability of human-made structures and their ecological footprints.

The occurrence of "satellite," "landsat," and "gis" (Geographic Information Systems) reflects the importance of remote sensing and spatial data in environmental studies. Terms like "response," "effect," and "change" are central, showing the research is focused on understanding and predicting the reactions of various ecological entities—ranging from individual species to entire ecosystems—to environmental changes. Keywords such as "biodiversity," "species," "habitat," and "ecological response" highlight a concern for the biological aspects of ecosystems and how they are affected by and adapt to changes. Smaller, less connected nodes could represent emerging or niche topics within the field that might be gaining traction or represent specialized areas of study.

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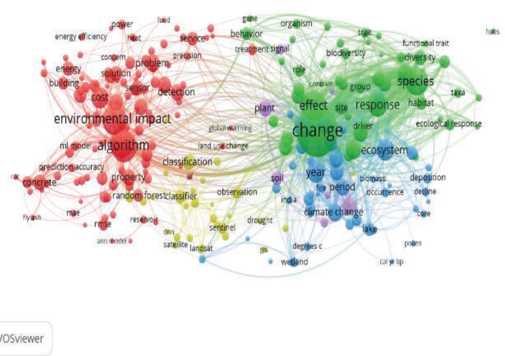

Fig. 5. Keyword Co-occurences

In Figure 6, the trending topics over time are depicted based on term frequency within the research field of machine learning applications for predicting ecosystem responses to environmental changes. The size of each circle indicates the frequency of the respective term in the literature, suggesting its prevalence and importance in the research field. The horizontal position of each circle indicates the year in which the term was trending, providing insights into the shifting research focus over time.

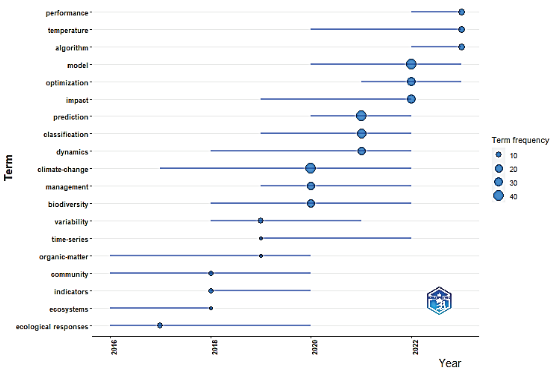

Fig. 6. Trend Topics

Keywords such as “model,” “optimization,” “performance,” “temperature,” and “algorithm” have their third quartile year in 2023, indicating that these topics are currently of high interest and likely to be actively researched. Terms like “climate-change,” “management,” “biodiversity,” “prediction,” and “classification” have their third quartile year in 2022, suggesting that while they remain important, the bulk of research may have stabilized, or the topics could be maturing. Keywords such as “ecological responses,” “community,” and “ecosystems” have a third quartile year earlier than 2020, which could imply that these were of early interest but may not be the central focus of the most recent research. “Climate-change” with a high frequency of 37 and a median year of 2020 suggests consistent relevance over recent years.

The trends depicted by this data can guide researchers to understand which topics have been historically significant, which are emerging, and which may be experiencing a decline in focus within the current research landscape. This knowledge can inform future research directions, identifying areas ripe for investigation or in need of renewed attention.

3.5 Author and Country Co-authorship Analysis

In evaluating the research landscape within a specific field, co-authorship research plays a crucial role. This section focuses on investigating the collaboration strength and research clusters in the utilization of intelligent techniques for predicting obstetric complications, considering both individual authors and countries. Co-authorship analysis is employed to examine the collaborative strength and research clusters in the field of machine learning for predicting ecosystem responses, considering individual authors and countries [31,32]. The creation of an individual co-authorship network is facilitated by the VOSviewer software. Before delving into the interpretation of the co-authorship network, it is important to clarify the distinction between co-authorship and co-citation. Co-authorship analysis aims to explore the extent of collaborative research within a specific field, while co-citation analysis focuses on relationships between articles rather than collaboration between authors.

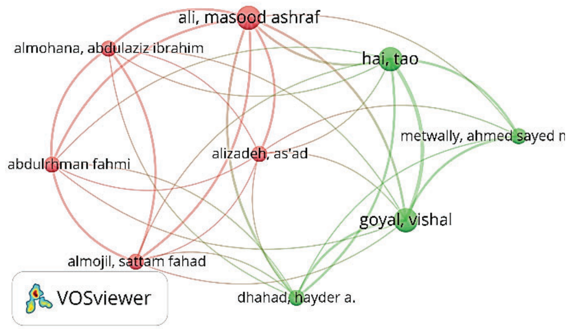

Fig. 7. Individual Co-authorship

The co-authorship network visualization, a construct of the bibliometric tool VOSviewer, delineates the collaborative landscape among researchers in the domain of machine learning for ecosystem response prediction. In this network, nodes represent individual scholars, with the node's size proportionate to the scholar's publication frequency or connectivity within the network. The interconnecting lines signify co-authored works, with the line thickness corresponding to the frequency of collaborative efforts. Notably, researchers such as “Goyal, Vishal” occupy a central node position, indicative of a pivotal role in this scientific community, likely acting as a nexus for various research collaborations.

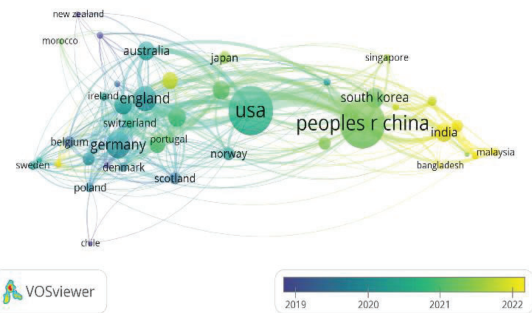

Fig. 8. Country Co-authorship

The visualization in figure 8 is a country co-authorship network map generated by VOSviewer, which illustrates the collaborative relationships between researchers from different countries in the field of machine learning for predicting ecosystem responses to environmental changes. Each node represents a country. The size of a node typically correlates with the number of publications or collaborations that country has in the dataset. The lines connecting the nodes represent co-authorship links between researchers in different countries. The thickness of these lines may indicate the volume or strength of collaborations between countries. The color gradient, which ranges from blue to yellow, represents the progression of time from 2019 to 2022.

Countries with nodes colored closer to the blue end of the spectrum were more active in earlier years, while those closer to the yellow end were more active in later years. Central nodes, such as the USA and China, with larger sizes and many connections, suggest these countries are central to the international research collaboration network. They likely have many researchers who are prolific in the field and collaborate with multiple other countries. The network may also reveal clusters of countries that tend to collaborate more with each other, which could be influenced by geographic proximity, shared languages, or historical and scientific ties.

4 Conclusion

This bibliometric analysis illuminated the expansive research landscape of machine learning applications in predicting ecosystem responses to environmental changes. Our inquiry began by highlighting the steep growth in annual scientific production, indicating a burgeoning interest and investment in this interdisciplinary field. We observed a pronounced focus on machine learning techniques, evidenced by frequent citation of foundational and contemporary works, underscoring the increased reliance on computational methods to address complex ecological questions.

The keyword co-occurrence data revealed a substantial and sustained emphasis on core concepts such as “climate change,” “biodiversity,” and “ecological responses,” with a notable pivot towards contemporary themes such as “variability,” “time-series analysis,” and “organic matter.” These shifts reflect the field's responsiveness to evolving environmental challenges and the increasing complexity of ecological data.

Co-authorship networks showcased an extensive and dynamic collaboration across countries, with prominent nodes representing the United States and China, indicative of significant contributions to the body of knowledge. The centrality of these countries, along with interlinked European nations, depicts a robust, interconnected community driving research advancements.

The evolution of research topics from earlier interests in “ecological responses” and “community” towards a recent focus on “model,” “optimization,” and “performance” suggests a trend of integrating sophisticated machine learning techniques to enhance predictive accuracy and efficiency. Additionally, the emerging interest in “temperature” and “algorithm” developments points towards fine-tuning models to incorporate climate variability with greater precision.

Despite the expansive growth and collaboration within this research domain, limitations inherent in the datasets and the methodological diversity necessitate cautious interpretation. Future research should aim to consolidate machine learning methodologies with ecological theory, ensuring that predictions are both computationally robust and ecologically valid. It is recommended that subsequent studies explore the application of machine learning models across varied ecosystems and scales, integrating multi-disciplinary data sources to enrich predictive frameworks.

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