

R LIBRARIES FOR SCIENTOMETRICS ON ARTIFICIAL INTELLIGENCE IN AGRICULTURAL MONITORING

R BIBLIOTEKE ZA SCIENTOMETRIJU O VJEŠTAČKOJ INTELIGENCIJI U POLJOPRIVREDNOM MONITORINGU

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ABSTRACT

The integration of artificial intelligence (AI) with adaptive crop monitoring has emerged as a crucial element in the environmental modeling of dynamic agricultural landscapes. AI-driven mapping has fundamentally transformed cartographic solutions across engineering, natural, and technical sciences by embedding automation into methodologies. This is particularly vital for Geographic Information Systems (GIS) where the automation of spatial data processing is critical. Given that agricultural landscapes undergo seasonal and yearly transformations, precise environmental forecasting becomes increasingly important. This study presents an overview of recent methodological advancements in three interdisciplinary areas: the environmental monitoring of agricultural landscape dynamics in soil studies, the application of AI in GIS through machine learning (ML) and deep learning (DL) techniques, and bibliometric analysis. The tools utilize the R-based libraries including Bibliometrix, Treemap, and Wordcloud, alongside the Mendeley reference system. The research explores the deployment of novel AI and ML methodologies in scalable data-driven analysis within agriculture and soil studies, addressing associated issues with their application. This review draws upon a comprehensive selection of over 100 papers from recognized databases such as Scopus, Web of Science (WoS), PubMed, and Google Scholar, providing an in-depth examination of AI applications in soil and environmental studies. Additionally, the study outlines future perspectives for AI in environmental analysis by identifying best practices for AI implementation in GIS and advocating for systematic benchmarking in remote sensing pertinent to soil studies.

Keywords: machine learning; artificial intelligence; agriculture monitoring; altmetrics; citations; quantitative analysis.

REZIME

Duboka integracija procesa vođenih vještačkom inteligencijom (AI) s adaptivnim dizajnom praćenja usjeva pojavila se kao ključna pokretačka snaga za modeliranje okoliša dinamičnih poljoprivrednih pejzaža. Mapiranje zasnovano na vještačkoj inteligenciji predstavlja fundamentalnu promjenu za kartografska rješenja u inženjerstvu, prirodnim i tehničkim naukama, jer ugrađuje automatizaciju u metodologije. Ovo je posebno važno za geografske informacione sisteme (GIS) gdje je automatizacija obrade prostornih podataka neophodna. Poljoprivredni pejzaži se transformišu sezonski i godišnje, što zahtijeva precizno predviđanje okoliša. U ovoj studiji dajemo pregled nedavnih metodoloških napredaka u tri interdisciplinarna područja: praćenje okoliša dinamike poljoprivrednih pejzaža u studijama tla, primjena vještačke inteligencije u GIS-u (tehnike mašinskog učenja (ML) i dubokog učenja (DL)) i bibliometrijska analiza korištenjem biblioteka zasnovanih na R-u (Bibliometrix, Treemap i Wordcloud) i Mendeley referentnog sistema. Istražujemo kako su nove metodologije vještačke inteligencije i strojnog učenja primijenjene na skalabilnu analizu zasnovanu na podacima u poljoprivredi i studijama tla i raspravljamo o pitanjima povezanim s njihovom primjenom. Ovaj pregled se zasniva na kritičkom skupu od preko 100 radova indeksiranih u priznatim bazama podataka Scopus, Web of Science (WoS), PubMed i Google Scholar za dubinsku analizu primjene umjetne inteligencije u studijama tla i okoliša. Iznosimo buduće perspektive za umjetnu inteligenciju u analizi okoliša, identifikirajući najbolje prakse za implementaciju umjetne inteligencije u GIS-u i sistematsko poređenje vrijednosti u daljinskom istraživanju tla.

Ključne reči: mašinsko učenje; vještačka inteligencija; praćenje poljoprivrede; altmetrika; citati; kvantitativna analiza.

INTRODUCTION

Agricultural mapping has advanced over time from the traditional Geographic Information System (GIS)-based mapping (Grüner et al., 2020; Klaučo et al., 2013, 2017; Lemenkova, 2022; Gokool et al., 2024) to sophisticated geospatial analysis, soft computing, big Earth data (Tong and Nikoloski, 2021), and machine learning applications (Ul-Haq et al., 2022; Wang et al., 2022; Zhang et al., 2025). The intricate nature of crop patterns and the heterogeneous mosaic of various cultivation types have highlighted the necessity for incorporating Artificial Intelligence (AI) techniques in the field of image classification. (Zhan et al.,

2024; Zhang et al., 2024). Apart from using satellite images, agriculture monitoring can also significantly benefit from the utilization of unmanned aerial vehicles (UAVs). The UAVs serve as a significant and innovative tool for collecting data and monitoring crop conditions from the air. This aerial perspective enhances the precision of agricultural practices, leading to improved decision-making for farmers. By leveraging UAV technology, farmers can achieve better insights into their fields, which supports more informed management strategies and potentially increases crop yields. (Radočaj et al., 2023; Khose and Mailapalli, 2024; Guimarães et al., 2023; Kebede et al., 2025; Qi et al., 2026) and hyperspectral imaging (HSI) (Zhou et al., 2025), which is capable

of solving uncertain and complex real-life problems of pattern recognition and object detection in large-scale maps of the agricultural fields (Matese et al., 2024).

Crop identification has been significantly enhanced through the implementation of advanced image analysis techniques. These methods allow for the accurate recognition and identification of plant features across various phenological stages, thereby facilitating a more precise understanding of crop characteristics and development (Xu et al., 2019; Newman & Furbank, 2021; Sun et al., 2024), as well as environmental changes related to seasonal climate dynamics (Zakarya et al., 2021; Lemenkova, 2023a; Melese et al., 2025). For instance, recent progress in remote sensing proposed methods of image segmentation (Rezvan et al., 2025; Lemenkova, 2023b), random forest (RF) (Banerjee et al., 2025; Lemenkova, 2024), support vector machines (SVM) (Awais et al., 2023; Ali et al., 2024), neural networks (El Hachimi et al., 2025; Jeong et al., 2022) and extreme gradient boosting (Afzal et al., 2025; Lemenkova, 2025a).

Remote sensing (RS) in agriculture necessitates the precise identification of the spectral reflectance of crops. This accuracy is essential to effectively distinguish between plants that exhibit similar spectral characteristics. By leveraging remote sensing techniques, agricultural practices can achieve enhanced monitoring and assessment of crop health and yield, leading to improved decision-making processes in farming management (Beila et al., 2025). Various methods can be employed to assess crop and vegetation health, taking into account diverse parameters that influence this evaluation. Among these parameters, canopy temperature and solar radiation serve as indicators of the climate conditions impacting vegetation mapping. In this context, vegetation indices are vital biophysical parameters that aid in evaluating plant health, as they effectively quantify the greenness of plant canopies, which is closely related to the chlorophyll content present in leaves (Radočaj et al., 2025; Banerjee et al., 2022; Lemenkova & Debeir, 2023). In addition, these methods have also demonstrated excellent performance in cartographic representation and GIS-based spatial analysis (Brandt et al., 2024).

The application of AI techniques, particularly machine learning (ML) and deep learning (DL), offers sophisticated approaches to conducting analytical tasks, which are essential for promoting sustainable agriculture. In addition to RS, AI technologies also enhance biological analyses, such as crop breeding and genomic selection, facilitating improvements in agricultural practices and productivity (Bayer et al., 2021), precision irrigation (Bwambale et al., 2022) and soil quality assessment (Barathkumar et al., 2024; Carbajal et al., 2024). Soil quality plays a vital role in agricultural practices as it directly influences crop productivity, regulates plant growth, and facilitates the availability of essential nutrients and water. Additionally, it underpins sustainable farming by maintaining a healthy ecosystem. Consequently, monitoring soil quality is essential for conducting comprehensive environmental analyses, as it enables the assessment of agricultural viability and environmental health (Catalano et al., 2023; Lindh & Lemenkova, 2022a, 2023a; Mandal et al., 2023). Monitoring soil quality involves analyzing both contaminants, such as heavy metals (HM), and assessing the structural integrity of soil. This process necessitates conducting statistical analysis that incorporates multiple influencing factors to provide a comprehensive evaluation (Lei et al., 2023; Lindh & Lemenkova, 2022b). Soil directly affects root development and other parameters of rhizosphere (Gao et al., 2022)

The performance of machine learning (ML) models varies based on several factors, including the algorithms employed, the size of the sample utilized, and the specific circumstances present in the environmental setting. This variation has prompted numerous

studies to conduct review analyses that compare the existing methods of ML and artificial intelligence (AI) in the context of agricultural monitoring. These studies aim to highlight the strengths and weaknesses of different approaches, thus providing insights into how best to implement these technologies in agricultural practices (Mesías-Ruiz et al., 2023; Ojo & Zahid, 2022; Roma & Catania, 2022; Alami Machichi et al., 2023; Sharma & Gawade, 2025). The quantitative scientometrics conducted on AI in agricultural monitoring demonstrated the effectiveness of these methodologies within the realms of RS and precision agriculture. This study highlights the feasibility and relevance of utilizing scientometric approaches to analyze the impact and application of AI technologies in enhancing agricultural practices through improved monitoring techniques (Arshad et al., 2023; Saha et al., 2025). Novel methodologies are continuously emerging parallel to the advancement of sophisticated algorithms and programming libraries tailored for particular research tasks. This evolution necessitates the execution of contemporary reviews that utilize extensive datasets from literature to identify state-of-the-art (SOTA) techniques in AI and ML specifically for agriculture and crop monitoring purposes.

This study aims to address the gap in the research by evaluating AI and ML applications specifically in the context of environmental soil studies and agricultural monitoring. The principal objective is to conduct a scoping analysis that showcases the utilization of ML and AI methodologies within the agricultural sector. This review includes a bibliometric analysis, examining various manuscripts from different regions, covering research published from 2016 to the present, thereby providing insights into the evolving landscape of technology in agriculture.

MATERIAL AND METHODS

The study employs a methodological approach grounded in bibliometrics theory, which has emerged as an effective tool for analyzing extensive bibliographic datasets containing hundreds of entries. The bibliometric method is increasingly popular for its capacity to elucidate patterns, trends, and developments within specific research domains. One of its key advantages is the ability to present findings in an objective, statistically impartial, and comprehensive manner. Recent case studies utilizing bibliometrics highlight its crucial role in SOTA reviews related to the technological advancement of Geographic Information Systems (GIS). The rapid progression in geoinformatics and cartography necessitates thorough literature analysis, providing a solid foundation for the continued evolution of sophisticated methods while simultaneously revealing their respective advantages and limitations.

Tools

Access to extensive scientific databases such as Web of Science (WoS), Dimensions, Scopus, Lens, and PubMed has enhanced the ability to conduct comprehensive and reliable systematic reviews in scientific research. However, the increasing volume of data, which can consist of thousands of entries, necessitates automated and statistically robust methods for processing this information. The evolution of bibliometric software has facilitated this automation. In the context of this review, the Bibliometrix package in R (version 4.5.1) was utilized to effectively organize, process, sort, and classify the data collected, as highlighted in the work of Aria and Cuccurullo (2017). The integration of various methodologies has enabled a systematic approach to identify a substantial dataset of pertinent publications across multiple disciplines related to environment and agriculture. This process facilitated the logical selection of a subset of relevant papers through the application of boolean queries with predefined parameters. The outcomes generated by combining tools such as

Mendeley, Elsevier, Bibliometrix, and R provide a robust basis for guiding future studies. They highlight current trends, uncover existing knowledge gaps, and point to potential avenues for further research development.

The bibliometric analysis was conducted in six main stages that include the following steps:

- defining research questions and keywords criteria;
- tracking literature through databases: Elsevier, WoS, and PubMed;
- collecting and organizing database;
- analysis of relevant documents in R;
- data visualisation and statistical analysis;
- results interpretation for detecting bibliometric trends.

The systematic review of the databases aimed at identification of major trends and knowledge gaps in papers related to the use of Artificial Intelligence (AI) and its sub-clusters Machine Learning (ML) and Deep Learning (DL) in the domains of Geographic Information System (GIS), cartography, and remote sensing (RS).

Search criteria

First step of the strategy involved defining keywords as search criteria, formulated through an interdisciplinary approach to shape the research objectives. These keywords facilitated the narrowing of search entries in the identification strategy, allowing a focused examination of relevant publications for a systematic analysis. The search process was systematically organized across various databases using groups of keywords that encapsulated the semantic coverage of the AI topic in geoinformatics. The interdisciplinary nature of the analyzed papers was categorized into two major groups. Boolean operators, such as "AND" and "OR", were employed to combine multiple search terms. The first group concentrated on geoinformatics and GIS, covering fundamental concepts of cartography, with keywords including "data visualization", "mapping", "GIS", and "geoinformatics".

The second group addresses the topics of AI, ML and DL methodologies. Hence, the keywords were organised in two major groups: the categories of AI concepts with definitions and the existing algorithms and known abbreviations. Hence, the first group included the following concepts: "Artificial Intelligence", "AI", "Machine Learning", "ML", "Deep Learning", "DL", "Artificial Neural Network", "ANN", "Supervised Learning", "Reinforcement Learning". The second group included the AI algorithms generally used in ML: "Support Vector Machines", "SVM", "Decision Trees", "Random Forest", "RF", "Multilayer Perceptron", "MLP", "K-Nearest Neighbors", "KNN", "Naive Bayes". Given the dominance of English in international scientific literature and its status as a universal technical language, the literature was selected among publications written in English. The chosen articles fall under the categories of 'article' and 'review article', as these types are prevalent across all databases and represent a meaningful collection of peer-reviewed scientific contributions.

Exploring the databases

The scientific databases aggregating scholarly records and content were defined. The strategy for creating the database involves integrating multiple databases that possess complementary characteristics, resulting in a vast pool of entries. This approach allowed us to explore various databases, leading to the formation of an extensive dataset for a systematic review: PubMed (National Library of Medicine), Lens, Dimensions and Scopus (Elsevier). Scopus is the most comprehensive and largest database of peer-reviewed articles covering interdisciplinary and specialised areas of knowledge in diverse scientific domains with over 20,000

journals. The PubMed comprises over 30 M citations for literature on life science published in journals and online books. Since bibliometrix supports only the "pubmed txt" file format, it was used for saving the search results.

The flowchart of the collected bibliographic entries used for reporting of systematic reviews was prepared using Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA). PRISMA software tool (Page et al., 2021) was employed to develop the workflow strategy due to its transparency, structural ease of use and clear visualization of the systematic review, Figure 2.

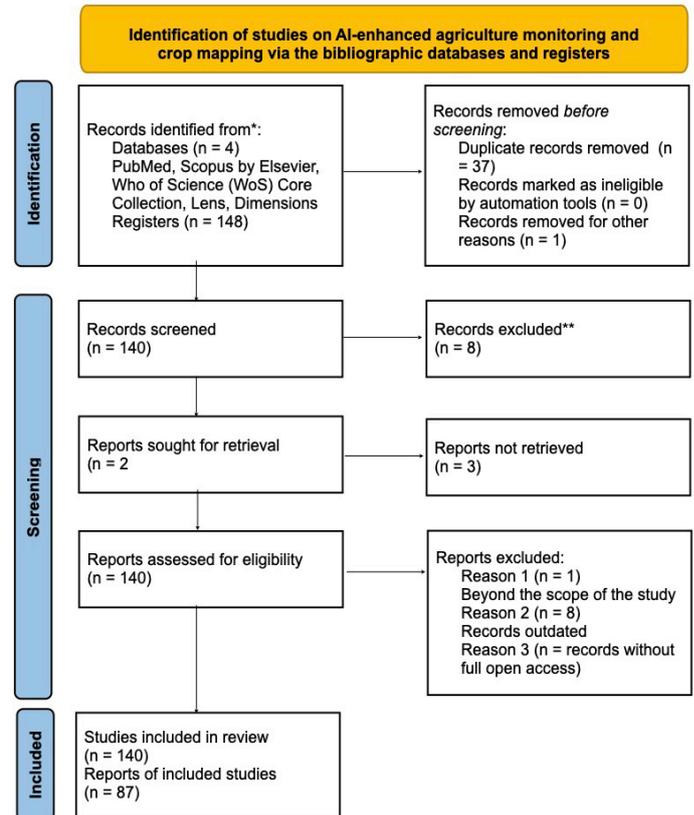


Fig. 1. Flowchart on the bibliography collection. Software: PRISMA 2020. Diagram source: author.

Mendeley: Collecting and organizing the database

The Mendeley reference manager was employed for the systematic collection and organization of bibliographic entries sourced from the Elsevier platform. Following this, the gathered database was imported into the R environment. The technological capabilities of Mendeley were utilized to evaluate evidence based on established criteria, allowing for the effective identification of patterns, trends, and insights within the current body of research. After the initial creation of the dataset in Mendeley, the data was exported into the Research Information Systems (RIS) format. Following this, the RIS file was accessed within the BibDesk environment. Subsequently, the data was converted into an EndNote .xml file, which was then further analyzed and processed using the Bibliometrix software.

R for bibliometric analysis: Bibliometrix package

The descriptive analysis of the bibliometric dataset was carried out based on the pool of the selected 548 publications. The data processed was performed using technical tools of the statistical language R, version 4.5.1. The files were exported via

BibTeX format (.bib) of LaTeX and checked for duplicates across the databases (identified 83 duplicates). The updated records were merged into an updated database. The data visualisation and statistical analysis were performed in RStudio platform of R statistical language.

Treemap and Wordcloud packages for data visualization

The Treemap and Wordcloud packages of R have been used for data visualization. A treemap is a type of visualization that effectively represents hierarchical structures by filling space in a two-dimensional format. This visualization method is particularly beneficial for displaying data that is organized in a tree-like structure, allowing for an intuitive understanding of proportions and relationships within the dataset, including bibliographic databases. The accompanying package provides significant versatility, enabling users to create various forms of treemaps tailored to specific data representations and analytical needs. This flexibility enhances the usability of treemaps in different contexts, catering to diverse requirements and preferences. This package necessitates a data frame (dtf) which includes one or more hierarchical index columns referred to as 'index'. Additionally, it should have a column representing the sizes of the rectangles, denoted as 'vSize'. There is also an optional column for specifying the colors of the rectangles, labeled 'vColor'. The coloration method for the rectangles is defined by the 'type' argument.

The Wordcloud package was used due to its functionality, which encompasses the creation of aesthetically effective word clouds, enabling users to visualize both differences and similarities between documents effectively. For bibliographic analysis, such functionality enables to highlight the most repetitive words and perform the frequency of keywords. Additionally, it addresses the challenge of over-plotting in scatter plots that incorporate text, enhancing clarity and readability in data presentation.

Table 1. Statistical report on published articles in the dataset: case studies on AI and ML applications in environmental soil studies and agricultural monitoring

Metadata and main information	
Timespan	2016 : 2025
Sources (Journals, Books, etc)	35
Documents	134
Annual Growth Rate, %	44.81
Document Average Age	2.57
Average citations per doc	3.2
Average citations per year per doc	1.4
References	5321
Category	
Authors	604
Author Appearances	722
Authors of single-authored docs	4
Single-authored docs	5
Documents per Author	0.222
Co-Authors per Doc	5.39
International co-authorships %	47.01
Author's Keywords (DE)	207
Keywords Plus (ID)	207
Document type	
journal article	115
journal article; research support, n.i.h., extramural	1
journal article; research support, non-U.S. governmental	12
journal article; review	5

RESULTS AND DISCUSSION

The comprehensive analysis of the datasets enabled identification of knowledge gaps and define future research directions in the domain of AI applications and methodologies of ML for GIS-based mapping and RS data classification. In the time span from 2016 to 2025, the annual growth rate of publications is almost doubled (44.81%), which illustrates the unprecedented rate of interest towards the AI topic in agriculture application, Table 1. This well illustrates that in recent years, the use of AI-based data modeling has significantly advanced precision agriculture, specifically in areas such as mapping and predictive assessment. This technological evolution empowers farmers to make more efficient use of their resources, significantly increase crop yields, and utilize predictive analytics for more informed decision-making. By leveraging advancements in technology, farmers can analyze data effectively, allowing for optimized agricultural practices that contribute to improved outcomes in farming productivity and sustainability (Zhou and Ismael, 2021; Sun et al., 2022; Sengupta, 2024). With the percentage of the international co-authorships of 47.01%, this indicates the high level of collaboration and the internationally acknowledged topic of ML and DL in crop identification. In the context of research collaboration, a notable trend has emerged where documents are produced by large groups of authors, as highlighted in Table 1. Specifically, it has been observed that the number of co-authors per document often exceeds five individuals. This phenomenon underscores the complexity of contemporary research topics, which necessitate collaborative efforts and the integration of expertise from diverse scientific disciplines to effectively address the issues at hand. Such collaboration is essential for tackling the multifaceted problems that arise in today's research landscape.

Furthermore, the analysis of literature based on 115 journal articles revealed that various methods for agricultural monitoring have been proposed for crop analysis (Moharana et al., 2024; Prins, and Van Niekerk, 2020; Radočaj et al., 2021), and these methods vary in terms of data availability, employed algorithms, and ease of use. While the literature reports diverse AI and ML techniques, certain algorithms found to be more effective in agriculture applications due to the regional context and specific soil properties (Sun et al., 2025; Chen et al., 2024). For instance, ML models can be used for estimating soil total nitrogen content (Dong et al., 2025) or crop loss identification (Hiremath et al., 2021).

According to the dataset analysis, China, India, and Iran are identified as the most productive countries for publishing research on AI applications in the agriculture sector and engineering. This trend is largely attributed to the critical role of agriculture in these nations, particularly in China, which boasts the largest agricultural sector globally by volume, production rate, and food output, contributing to a quarter of the world's agricultural production. However, the agricultural economy in China is currently confronted with significant challenges such as climate change and urbanization. These issues have prompted an increase in research efforts aimed at enhancing agricultural sustainability, boosting production levels, and securing yield through effective resilience and control management strategies. AI tools play a crucial role in this context, providing support through automated data analysis and sophisticated algorithms, facilitating improvements in agricultural practices and sustainability efforts. The rise in annual scientific production related to ML and AI applications in agricultural science over the past two decades is depicted in Figure 3. Analysis of publication trends and tendencies concerning AI and ML in agriculture reveals a consistent increase in reported research case studies from 2016 to the present. This trend highlights the

analysis. Thus, physically based agriculture models consider detailed data on soil settings (texture, structure, porosity, permeability) (Liao et al., 2025; Lindh and Lemenkova, 2023c) and significant computational resources. In contrast, statistical ML-based algorithms and soft computing approaches offer more direct applications with varying accuracy and precision (MacNish et al., 2025; Lemenkova, 2024a; Guo and Li, 2023), which depend on various soil conditioning factors necessary for optimal plant growth: neutralization of soil pH, the improvement in soil structure and optimized nutrient availability at neutral pH. Accurate crop mapping and environmental risk assessment strongly depend on digital elevation models (DEMs), which enable to determine water availability through morphometric analysis of slopes and terrain (Wang et al., 2025; Nhu et al., 2022). With this regard, the availability of high-resolution DEM datasets has significantly improved crop mapping by providing valuable information on topographic setting, land cover, and hydrological network (Khosravi, 2025; Rehman et al., 2021; Vashisht et al., 2022). Besides topographic data, accurate crop mapping also relies on precise precipitation datasets and climate analysis (Sahoo et al., 2025).

Among the analyzed papers, most were published in the journal Environmental Monitoring and Assessment, comprising 21 manuscripts. This was followed by The Science of the Total Environment with 19 case studies, and Environmental Science and Pollution Research International, which published 14 papers from the analyzed pool. The selection of journals was influenced by factors such as the scope of the publisher regarding the topic of AI in agriculture, the availability of open access, and the target audience, as illustrated in Table 3.

Table 3. Most Relevant Sources

No	Journal name	Papers
1	Environmental Monitoring and Assessment	21
2	The Science of the Total Environment	19
3	Environmental Science and Pollution Research International	14
4	Journal of Environmental Management	12
5	Scientific Reports	11
6	Sensors (Basel Switzerland)	9
7	International Journal of Environmental Research and Public Health	7
8	Scientific Data	4
9	Environmental Research	3
10	Heliyon	3

Table 4 reports the statistics on the corresponding author's countries which reflects the activities of the main authors ad their distributions globally.

Table 4. Corresponding author's countries

No	Country	Papers	Freq.	SCP	MCP	Ratio
1	China	24	0.2124	15	9	0.375
2	India	16	0.1416	11	5	0.312
3	Iran	12	0.1062	5	7	0.583
4	Italy	8	0.0708	4	4	0.500
5	Malaysia	5	0.0442	1	4	0.800
6	Usa	5	0.0442	3	2	0.400
7	Korea	4	0.0354	2	2	0.500
8	Vietnam	4	0.0354	0	4	1.000
9	Germany	3	0.0265	1	2	0.667
10	Australia	2	0.0177	0	2	1.000

Figure 5 presents a co-word analysis visualized through clusters of keywords derived from both a full database and a reduced database representing 50% of the original data. These keyword clusters are interpreted as themes, with their density and position (either central or peripheral) aiding in theme identification and mapping on a 2D diagram. The thematic map strategically categorizes research areas based on their quadrant placement: the upper-right quadrant denotes motor-themes, the lower-right quadrant illustrates basic themes characterized by general concepts found in case studies, while the lower-left quadrant indicates either emerging or disappearing themes that may shift based on the relevance of ongoing research. Finally, the upper-left quadrant visualizes a very specialized, i.e., niche themes with high level of individual studies and particular research.

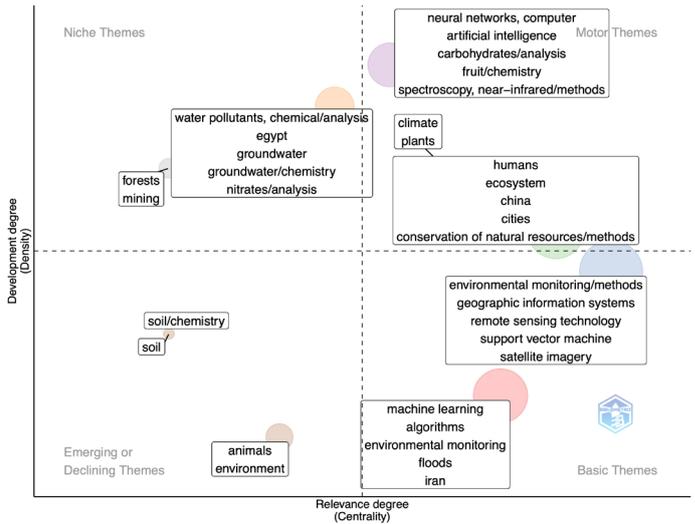


Fig. 5. The R-based analysis of the keywords clusters grouped as themes based on the full database

Figure 6 presents a diagram that demonstrates the collaborative links between countries, highlighting the relationships among co-authors and their respective universities. The diagram illustrates the geographical distribution of research clusters, showcasing over 140 publications generated through these collaborations. This analysis specifically examines the connectivity between co-authors from various countries, as indicated in the diagram. The thickness of the lines in the figure reflects the frequency of interactions among the authors. Notably, there are prominent connections between researchers based in China and those in Australia, Vietnam, and France. Additionally, the diagram reveals clusters connecting countries such as Sweden and Malaysia, as well as Finland with Australia and France, and the United States with Austria. This visual representation illustrates the complex network of academic collaboration among various nations. The selection method for studies is influenced by several factors: the geographic context of the study area, which includes soil composition and crop types; the specific questions and objectives of the study; and the availability of datasets pertaining to the seasonal growth periods of crops, which are crucial for effective differentiation and data analysis (Singh et al., 2024; Sosa-Herrera et al., 2019). Despite this effectiveness of many ML methods, there is no commonly accepted agreement on the best algorithm, although the studies comparing several approaches do exist (Vafadar et al, 2023; Lemenkova, 2025b, 2025c; Pugh et al., 2024). Each method has its strengths and limitations, making the selection highly context-dependent. Therefore, the comparative analysis comparing case studies is important in agriculture practices.

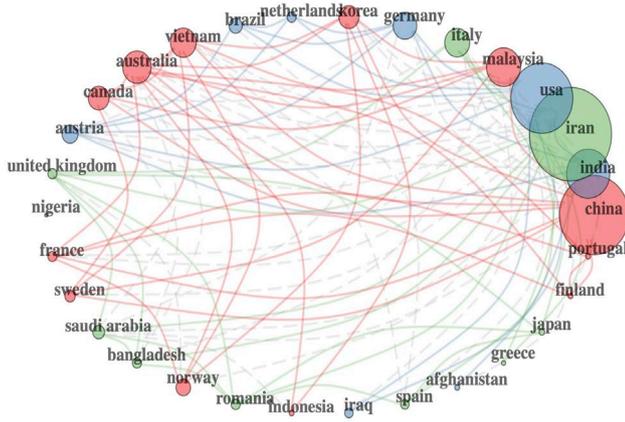


Fig. 6. Country collaboration analysis through links between the co-authors

Figure 7 shows the overall analysis of over 140 documents using the keyword cloud which illustrates the most important words highlighted through size and font: "machine learning" and "artificial intelligence". The systematic analysis of the research papers using the generated keyword cloud reveals the significant application of AI and ML methods in the agriculture, as shown by the second-level keywords: "crop", "algorithms", "GIS", "spatial analysis". The size of the font represent the most frequently used words that appearing in largest letters. Other important concepts used by the authors include the following terms which can be divided into two large groups: 1) technical concepts and 2) environmental concepts. For instance, the first group include the "R-CNN", "Optimization", "Bayesian networks", "Decision trees", while the second group include "Resource management", "Sustainability", "Environmental pollution", "Crop", etc. The swarm of the concepts is represented in Figure 7.

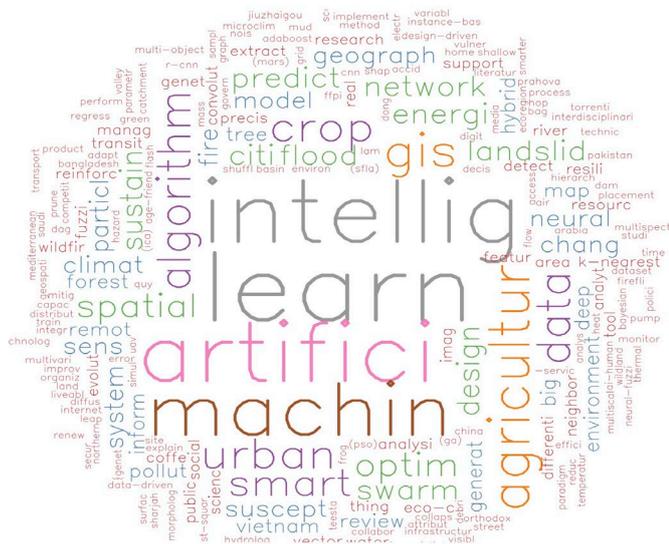


Fig. 7. Wordcloud visualizing authors' keywords. Source: Author. Software: R library 'wordcloud'.

Figure 8 presents a treemap diagram that visually illustrates the hierarchical structure of the publication dataset through a series of nested rectangles, each representing distinct concepts. The diagram features three primary information clusters: "Artificial Intelligence," "Agriculture," and "GIS & remote sensing," each of which is further subdivided into logical subsets. The first cluster, "Artificial Intelligence," encompasses advanced methods

including machine learning (ML), convolutional neural networks (CNN), artificial neural networks (ANN), deep learning (DL), and predictive analysis specifically applied to the spatial planning of crop distribution, as referenced in studies by Choi et al. (2025), Lemenkova (2024b), and Morales et al. (2023). The second cluster, "GIS and remote sensing," pertains to cartographic techniques and data visualization, incorporating elements like mapping and digital elevation models (DEM), which are essential for topographic assessments and provide vital information for geographical analyses. These data are necessary for proper planning of the agriculture fields and selecting sites designing field layouts and can be processed using multi-criteria selection (Deepa and Krishnaveni, 2012). For instance, the elements of the analysis include crop rotation, drainage, storage, and selecting location for constructing of buildings, as indicated in various papers. Third cluster, the "Agriculture" includes important concepts used by the authors in their reports: soil structure (Deng et al., 2015; Nguyen et al., 2022; Parvizi and Fatehi, 2025), farming, crop growth (Drees et al., 2024), harvest and yield (Cheng et al., 2022), precision agriculture (Rani et al., 2023), and others. Together, these three clusters represent the integration of interdisciplinary approaches employed by the authors for optimal workflow in the AI-enhanced agriculture management in seasonally dynamic rural landscapes (Chen et al., 2025; Medina Medina et al., 2024; Pande, 2022).

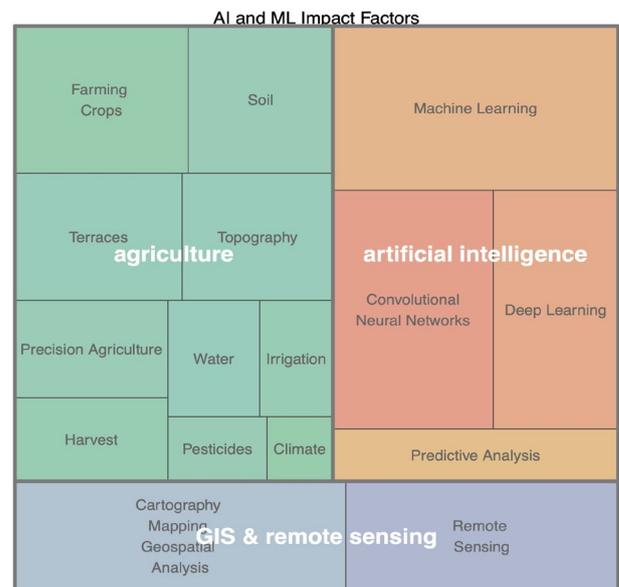


Fig. 8. The frequently employed concepts in three categories: AI, agriculture and GIS. Software: R library 'treemap'. Source: author.

This scoping analysis identified several major interdisciplinary challenges faced in agricultural implementation. First, there is significant variability among the AI algorithms suitable for image analysis, compounded by the diversity of tools available for image processing, including popular frameworks and libraries such as TensorFlow, Keras, and PyTorch. Second, the increased availability of spatial data, often referred to as big Earth data, presents a requirement for advanced processing tools, particularly AI-based approaches, that can handle such extensive datasets. Lastly, the complexity of agricultural approaches mandates the integration of multiple data sources along with advanced machine learning (ML) and deep learning (DL) solutions. These solutions are essential for capturing the diverse mechanisms governing soil-plant interactions and for identifying the various factors influencing crop productivity, all while simultaneously monitoring yield.

This analysis is based on using the R libraries designed for bibliometric analysis of large datasets generated through search of bibliographic repositories which ensured rapid and accurate data processing. Besides bibliometric reporting, this work study can also be used serves as a complimentary resource for land planning and agricultural management, policy making, assisting soil ecosystems services, susceptibility mapping and crop resilience through AI-enhanced decision-making.

CONCLUSION

This study presents a detailed R-based review of the applicability of AI tools, specifically within the subsets of ML and DL, for processing RS data in the context of precision agriculture. It highlights AI's effectiveness as a strategic approach to RS, particularly in agriculture monitoring, where satellite imagery enables the detection of crop fields. The review encompasses a comprehensive bibliometric analysis of scholarly manuscripts focusing on agriculture monitoring and soil-plant research, investigating various ML and DL methodologies. The paper analyzes the efficacy, advantages, and limitations of these AI techniques, emphasizing their potential in enhancing data-driven analyses pertinent to agriculture. The methodology utilized the R programming language, applying libraries including 'bibliometrix', 'wordcloud', and 'treemap', alongside auxiliary tools to scrutinize a collection of scientific publications related to AI applications in agriculture. The bibliometric search was conducted using well-regarded databases such as Scopus, PubMed, and Elsevier, leading to significant findings regarding the current trends and future directions of AI in natural and life sciences, particularly in agricultural contexts. This systematic review not only showcases the growing role of AI in precision agriculture but also fosters a deeper understanding of its methodologies and implications for future research.

The work presented focuses on the diversity of AI approaches utilized in agricultural monitoring, specifically through the identification of parameters visible in images processed using ML and DL techniques. A comprehensive review, conducted via bibliometric analysis with R software, assessed various case studies demonstrating the integration of multidisciplinary methods between agriculture monitoring and AI. The findings indicate that AI enhances the accuracy and precision of soil mapping through automated workflows, which is essential for the advancement of precision agriculture.

Key insights from the study suggest several directions for enhancing future research in agricultural engineering. These include (1) the selection of optimized tools and techniques for data analysis tailored to specific local conditions—such as soil characteristics, plant life, topography, and climate; (2) a review of existing open access repository platforms suitable for literature analysis; and (3) the development of frameworks for bibliometric statistical analysis, encompassing citations, H-index, and keywords, which will facilitate quick assessments of extensive literature databases. These methodological advancements aim to assist specialists in agricultural monitoring by providing a deeper understanding of current trends and identifying the most effective AI-based techniques for soil monitoring. Ultimately, this analysis is expected to contribute to better soil protection and planting strategies, with the overarching goal of increasing resilience and productivity in diverse landscapes and climate conditions.

Future research should build upon this analysis by utilizing R libraries and delving deeper into AI and ML methodologies. These approaches should incorporate regional environmental variables to enhance the precision and dependability of soil and crop monitoring systems. Furthermore, the combination of ML

techniques with RS datasets presents substantial opportunities for improving local and regional land management strategies, as well as ecosystem practices. In this context, it is crucial to understand the current SOTA applications of AI, including their benefits and the limitations that have been documented in existing literature. The integration of multi-source geospatial data from local and regional agricultural communities, such as RS data and real-time seasonal observations can support mapping characteristics of crop growth in various phenological stages and improve the precision and accuracy of agricultural mapping. Moreover, future research might also analyse the available pool of literature that reports climate issues in agriculture through analysis of parameters (evapotranspiration, temperature, precipitation, humidity) and scenarios of land use for resilient land planning strategies and mitigating potential yield losses caused by environmental factors: weather, pests, and crop diseases (Zhu *et al.*, 2024).

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