Artificial Intelligence for Management Zone Delineation: A Bibliometric Review (2008-2025)

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Abstract.

This bibliometric review aims to map research trends, key terms, and leading institutions in the use of artificial intelligence (AI) methods, with emphasis on Machine Learning (ML), Deep Learning (DL), and Neural Networks, applied to the delineation of management zones (MZs) in Precision Agriculture (PA). The analysis was conducted using the Scopus database, applying a structured search string to titles, abstracts, and keywords. Metadata were collected on September 26, 2025. The initial search retrieved 101 documents; after applying filters by document type (articles) and publication period (2008 to August 2025), 73 documents remained. Subsequently, the language filter (English) resulted in a final set of 69 publications analysed. The bibliometric analysis was carried out using the bibliometrix package and the Biblioshiny interface in the RStudio environment. The methodological workflow included descriptive and network-based analyses, covering annual scientific production, identification of core journals according to Bradford's Law, the most relevant authors and affiliations, thematic evolution, keyword co-occurrence networks, and international collaboration networks among countries. To ensure greater terminological consistency and analytical robustness, customized thesauri were developed, including stopword removal and term aggregation, to normalize recurring conceptual variations in the AI and PA literature. The adopted methodological protocol, as well as reproducible R scripts for importing Scopus data, applying thesauri, and generating the main figures and tables. The results indicate that scientific production related to the application of AI in management zone delineation showed gradual growth from 2010 onward, with marked intensification after 2018. This advance is associated with the consolidation of Machine Learning techniques and the increased availability of remote sensing (RS) data and proximal soil sensors (PSS). According to Bradford's Law, the main core journals in this research field are Computers and Electronics in Agriculture and Remote Sensing, both with seven publications, followed by Precision Agriculture (4), Agriculture (3), and Agronomy (3). An analysis of institutional affiliations per paper reveals a clear dominance of Chinese institutions. Nanjing Agricultural University (China) leads with 21 publications, followed by Embrapa (Brazil) with 15 publications, and China Agricultural University (China) with nine publications. Five institutions present similar contributions, each with eight publications: Heilongjiang Bayi Agricultural University and Jilin

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Agricultural University (China), Massey University (New Zealand), Ghent University (Belgium), and the University of Patras (Greece). At the national level, China, the United States, Brazil, Canada, and Greece emerge as the most influential countries. The thematic analysis revealed well-defined clusters and emerging topics, highlighting conceptual differences between general Neural Network approaches and specific Deep Learning applications. The main themes identified include climate change and sustainability, geostatistics, RS, crop yield, soil properties, and nitrogen management. Motor themes focus on the integration of ML, RS, and PA, while emerging themes point to the growth of the Internet of Things and big data. This review provides a reproducible overview of the evolution, collaboration patterns, key actors, and research gaps associated with AI-driven MZs delineation and reinforces the need for robust validation frameworks capable of translating data-driven models into effective field-scale management strategies.

Keywords: Machine Learning, Deep Learning, Internet of Things, Big Data Analytics, Remote Sensing, Spatial Variability

Introduction

Precision agriculture (PA) is defined as a management strategy that gathers, processes, and analyses temporal, spatial, and individual plant and animal data, combining it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability, and sustainability of agricultural production (ISPA, 2024). Within this framework, management zones (MZs) are areas delineated within fields that present relatively homogeneous characteristics and therefore require differentiated input management. In practical terms, each zone represents a portion of land with similar patterns and constraints, allowing uniform management within the zone but not necessarily across the whole field (Molin and Castro, 2008; Sterle and Molin, 2025).

The concept is straightforward, but the implementation is not. MZs delineation depends on which data layers are used, how they are integrated, and how the resulting zones are validated. This remains one of the main bottlenecks in PA research. Sterle and Molin (2025) emphasized that MZs are useful precisely because they reduce the complexity of within-field variability, but also pointed out that robust validation is still lacking in many studies. In other words, the field has become more capable of mapping variability than of demonstrating that the resulting zones improve agronomic decisions.

The global expansion of PA provides the broader context for this challenge. The global PA market reached USD 9.86 billion in 2024 and is projected to reach USD 22.49 billion by 2034, growing at a compound annual growth rate of 8.59%, driven by the increasing adoption of technologies such as Internet of Things (IoT), Artificial Intelligence (AI), and data analytics in farming practices (BISResearch, 2024). This growth reflects a structural transition in agricultural management, from experience-based, uniform practices toward data-intensive, spatially differentiated strategies. Within this transition, MZs delineation occupies a critical position: it is the operational step that translates spatial data into actionable management units, and its quality determines whether the broader investment in sensing, modelling, and variable-rate technology generates agronomic returns.

At the same time, agriculture has become increasingly data-rich. RS, proximal sensing, yield monitors, and georeferenced soil sampling now generate large volumes of spatial information. This shift is reinforced by the spread of the IoT and cloud-based systems, which are key elements of the broader digital agriculture and big data landscape (Wolfert et al., 2017). The volume, variety, and velocity of agricultural data have grown to the point where classical statistical methods are insufficient to extract actionable patterns from heterogeneous, high-dimensional spatial datasets. Machine learning (ML) methods have become more accessible and more powerful, making it possible to detect patterns in heterogeneous datasets that would be difficult to interpret with classical statistics alone (Liakos et al., 2018). Deep learning (DL) and neural networks, especially convolutional neural networks, have further expanded the possibilities for image-based agricultural analysis (Coulibaly et al., 2022).

The convergence of the trend of expanding data availability, increasing computational power, and the maturation of machine learning frameworks, has produced a new generation of approaches to MZs delineation that departs substantially from the classical paradigm. Earlier studies relied primarily on fuzzy clustering of soil electrical conductivity, terrain derivatives, and yield maps to define zones. Contemporary approaches increasingly integrate multi-temporal satellite imagery, UAV-based sensing, DL architectures, and IoT-enabled sensor networks to generate more dynamic, data-dense representations of within-field variability. The compound annual growth rate of ML publications in agriculture from 2000 to 2024 is approximately 16.37%, with significant increases in 2023 and 2024 reflecting the growing role of ML in sustainable and efficient agricultural practices (Hossain et al., 2025). This acceleration in scientific output makes it increasingly difficult for researchers and practitioners to maintain an updated, structured understanding of the field, precisely the gap that bibliometric reviews are designed to address.

Despite the rapid growth of the literature at the intersection of AI and PA, systematic mappings of the specific subfield concerned with AI-driven MZ delineation remain scarce. Most existing reviews focus either on AI applications in agriculture broadly (Liakos et al., 2018; Coulibaly et al., 2022) or on MZs delineation methods without an explicit AI focus. The absence of a structured bibliometric analysis of this intersection leaves researchers without a clear picture of which institutions are driving the field, which journals concentrate the core literature, which AI methods are most applied, and which thematic gaps remain underexplored. Understanding these structural dimensions is a prerequisite for identifying productive directions for future research and for avoiding redundancy in a rapidly expanding literature.

In this context, the objective of this review was to map the evolution of scientific production, leading institutions, thematic trends, and collaboration patterns in the application of AI methods, with emphasis on ML, DL, and neural networks, to MZ delineation in PA. The review is structured to provide not only a descriptive account of publication patterns but also a thematic interpretation of the conceptual clusters, motor themes, and emerging directions that characterize the current state of the field.

Material and Methods

A structured bibliographic search was carried out in Scopus using a search string built around terms related to "management zone," "precision agriculture," "machine learning," "deep learning," and "neural networks," among others. The search targeted titles, abstracts, and keywords. Metadata were collected on September 26, 2025.The initial query returned 101 documents. After restricting the results to articles and the publication period from 2008 to August 2025, 73 records remained. A final language filter limited the dataset to English-language publications, yielding 69 articles for analysis.

The bibliometric analysis was conducted using the bibliometrix package in R and the Biblioshiny web interface (Aria and Cuccurullo, 2017). These tools are widely used for reproducible science mapping and bibliometric workflows. The analysis included annual scientific production, Bradford's Law to identify core journals, author and institutional productivity, thematic evolution through keyword clustering, keyword co-occurrence networks, and international collaboration networks.

To improve terminological consistency, custom thesauri were developed to merge equivalent terms and remove irrelevant variants. For instance, expressions such as "deep learning" and "DL" were standardized. Stopwords and low-information terms were removed to reduce noise in the thematic maps and co-occurrence networks. All scripts used for data import, thesaurus application, and figure generation were documented to ensure reproducibility.

Results and Discussion

Scientific Production Over Time

The annual publication trend shows slow growth until around 2010, followed by a steady increase and a sharper expansion after 2018 (Figure 1). The rise is strongly associated with the consolidation of ML methods and the increasing availability of RS and proximal sensing data. This is not merely a publication trend; it reflects a methodological shift. Earlier studies on MZs relied heavily on empirical soil and yield interpretation; more recent work increasingly depends on data-driven models capable of handling spatial complexity and multimodal datasets.
The dataset of 69 articles spans from 2008 to August 2025, with an annual growth rate of 16.79%, well above the average observed for PA. The document average age of 3.2 years confirms that the corpus is predominantly recent, reflecting a field that consolidated rapidly rather than accumulating gradually. Publication counts were low until around 2010, increased steadily through the mid-2010s, and accelerated markedly after 2018. This inflection point coincides with the broader maturation of ML frameworks and the expanded availability of multisource sensing data, including satellite imagery and PSS.

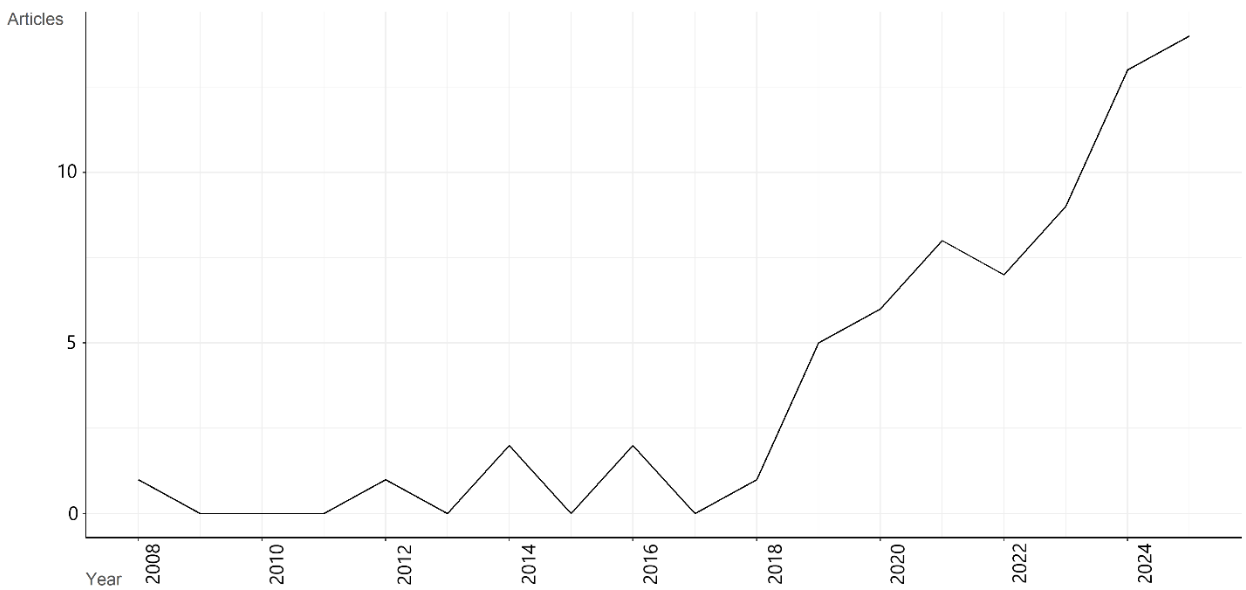

Fig 1 Annual Scientific Production.

Core Journals

Applying Bradford's Law, the field appears concentrated in a small group of journals. Computers and Electronics in Agriculture and Remote Sensing are the leading core journals, with seven publications each. They are followed by Precision Agriculture (four), Agriculture (three), and Agronomy (three). This distribution is not surprising, as the topic sits at the intersection of agronomy, RS, and computational methods (Figure 2).

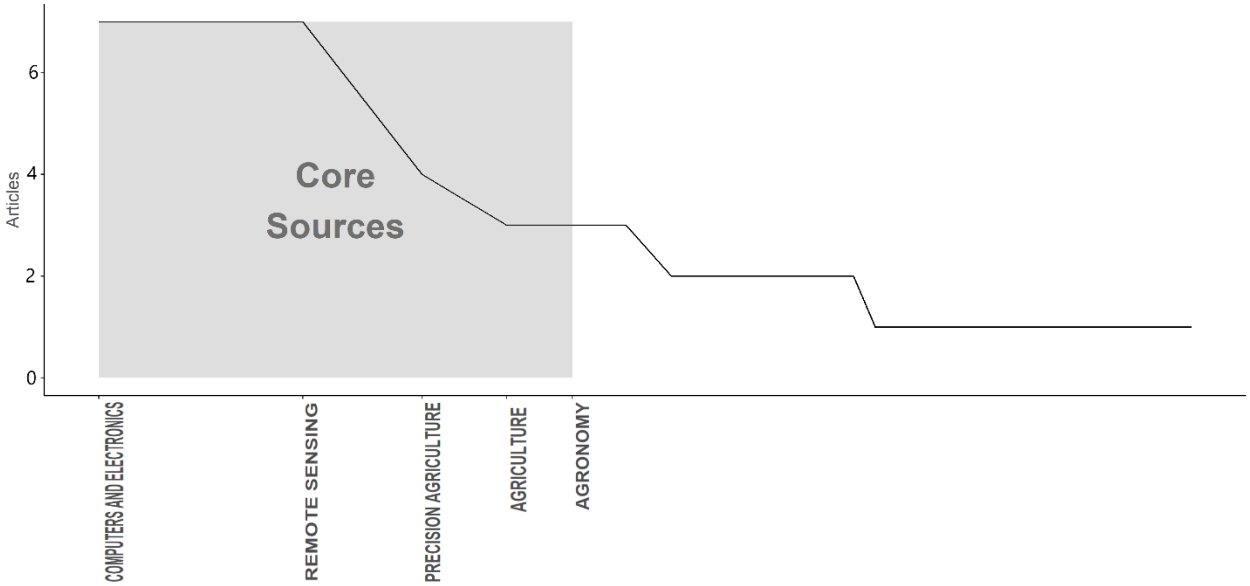

Fig 2 Core sources by Bradford's law.

Authors, Institutions, and Countries

The institutional and geographic distribution of scientific output reveals a field shaped by a small number of highly productive actors. At the author level, four researchers tied at the top with four documents each: Liu Xiaojun, Tian Yongchao, and Zhu Yan, all affiliated with Chinese institutions, and Mouazen, A.M. (Ghent University, Belgium), the only non-Chinese author in the top tier, suggesting meaningful European engagement despite the overall dominance of Chinese output. A second group of three authors (Cao Qiang, Cao Weixing, and Li Yue) contributed three documents each, while Barouchas, P.E., Bretherton, M.R., and Chen, H. each appeared in two publications. The low absolute counts reflect both the recent nature of the field and the small size of the corpus (69 articles), in which even four documents represent a meaningful concentration of output by a single researcher (Figure 3).

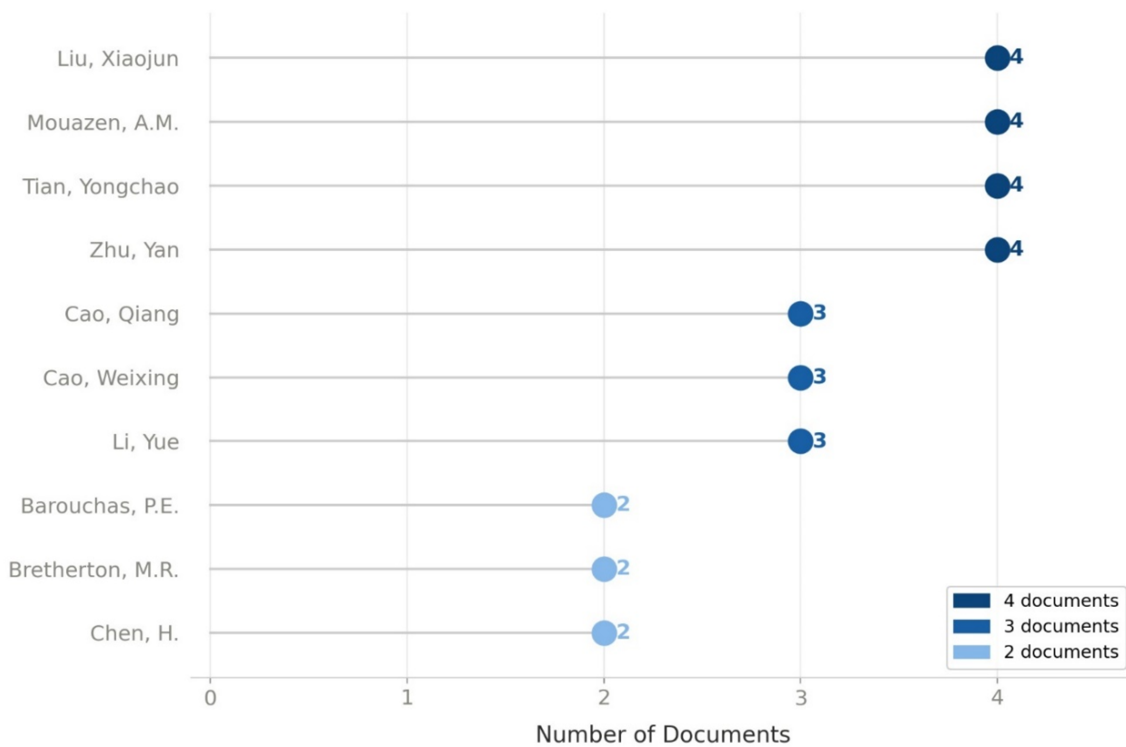

Fig 3 Most relevant authors and their number of documents.

This concentration at the author level is mirrored at the institutional level. Nanjing Agricultural University leads with 21 publications, followed by Embrapa with 15 and China Agricultural University with nine. Five institutions contributed eight publications each: Heilongjiang Bayi Agricultural University, Jilin Agricultural University, Massey University, Ghent University, and the University of Patras. The dominance of Chinese universities reflects a broader national investment in digital agriculture research, while Embrapa's prominent position confirms its role as the central actor in applied agricultural innovation in Brazil, a pattern consistent with the country's second place ranking in total output (Figure 4).

At the country level, as shown in Figure 5, China leads by a wide margin with 92 articles, followed by Brazil with 54 and the United States with 47. These three countries alone account for most of the global output in this field. Greece ranks fourth with 24 articles, Canada fifth with 21, and Belgium sixth with 16. South Korea (14), Italy (13), and New Zealand (13) also contribute meaningfully and should be considered part of the core productive countries in this domain. Despite this geographic concentration, the field shows a clear capacity for international collaboration: the overall rate of international co-authorship reached 40.58%, meaning that more than four in ten articles involved authors from at least two different countries. The collaboration network shows that the United States functions as the main hub of international exchange, with the strongest ties directed toward China and Brazil. Secondary connections are observed between the USA and Europe, between China and Europe, and between Brazil and Europe, while direct China–Brazil collaboration appears less prominent.

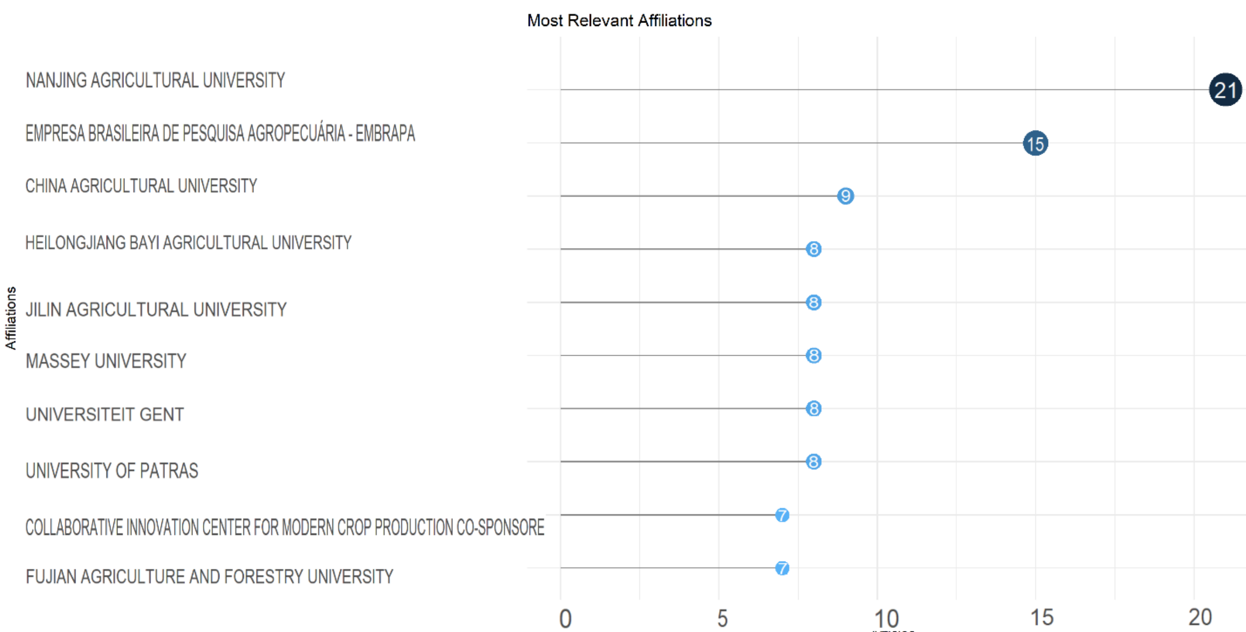

Fig 4 Most relevant affiliation and their number of documents.

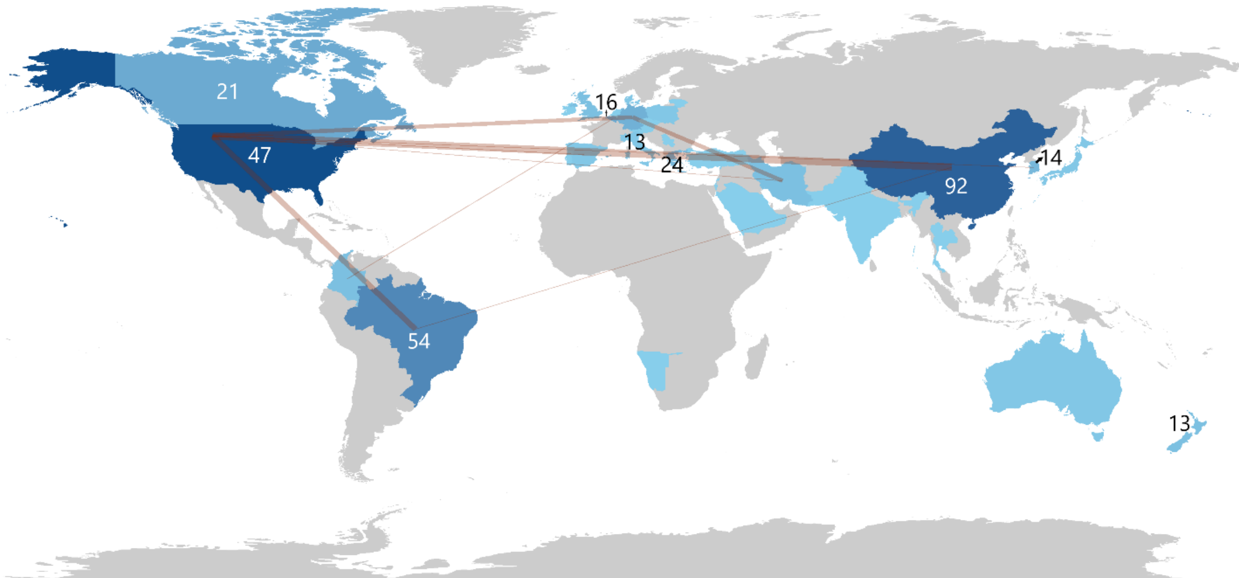

Fig 5 Map of international collaboration network.

The influence of this research, however, is not evenly distributed across time. The most globally cited document in the dataset is Abbas et al. (2020), published in Agronomy, which accumulated 204 citations at a rate of 34 per year, the highest annual accumulation rate in the corpus by a substantial margin. This paper, focused on crop yield prediction through proximal sensing and ML, functions as a structural reference point for the field and helps explain the concentration of the thematic cluster linking ML to yield and soil data. The second most cited work is Thorp et al. (2008), published in Computers and Electronics in Agriculture, with 122 citations. Its presence near the top of the ranking despite being the earliest paper in the dataset indicates that foundational methodological contributions retain influence even as the field accelerates. Three papers from 2019 appear in the top six, all with more than 75 citations and annual rates between 11 and 12 citations per year, further confirming that the post-2018 period produced the most structurally influential work. No article published after 2020 reached the top ten, a pattern that reflects the natural lag in citation accumulation rather than a decline in research quality, and one that should be considered when interpreting citation-based rankings in fast-growing fields.

Keyword Co-occurrence and Thematic Structure

The keyword analysis revealed a strong concentration around ML, RS, crop yield, MZs, and climate change and sustainability, as shown by the word cloud (Figure 6). These terms represent the central conceptual structure of the field and reflect the increasing integration of AI techniques with PA applications.

Fig 6 Keywords word cloud.

The thematic map further identified well-defined thematic clusters (Figure 7). Motor themes were primarily associated with ML, RS, and PA, indicating a mature and highly connected research area. Themes related to climate change, sustainability, and agricultural modeling also showed strong centrality, reinforcing the role of digital agriculture in supporting resilient production systems. A second cluster focused on geostatistics, sensors, and soil variability, representing the more classical approach to MZ delineation based on spatially explicit soil and yield information (Sterle and Molin, 2025). Emerging themes included IoT and big data, which are increasingly associated with real-time monitoring, data integration, and decision-support systems (Wolfert et al., 2017). DL and object detection appeared as highly central themes, reflecting the rapid expansion of image-based applications such as crop classification, disease detection, and spatial prediction (Coulibaly et al., 2022).

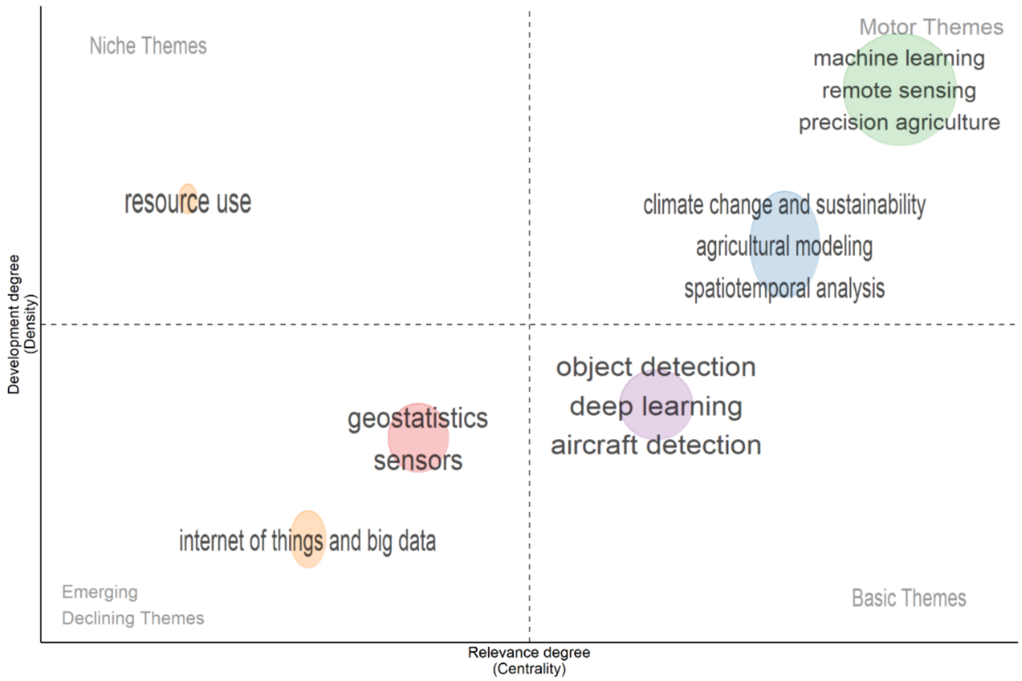

Fig 7 Thematic clusters.

The Validation Problem

One issue remains stubbornly present across the literature: validation. Delineating MZs is considerably easier than demonstrating that they consistently improve agronomic management or economic return under real production conditions. Many studies generate statistically coherent maps, but far fewer evaluate whether these zones support superior decision-making in the field. As discussed by Sterle and Molin (2025), validation remains one of the major unresolved gaps in MZ research.

This limitation reflects a broader transition within PA, where the focus is gradually shifting from descriptive spatial analysis toward operational and farmer-centered frameworks. Bramley (2009) emphasized that the value of spatial management depends on measurable agronomic and economic responses rather than solely on the identification of variability patterns, a perspective that anticipated much of the discussion that followed over the next decade. This shift became more explicit with the emergence of data-intensive, on-farm experimentation approaches. Bullock et al. (2019) argued that large-scale on-farm precision experimentation represents one of the main pathways for transforming spatial data into operational management strategies under commercial farming conditions, providing field-specific yield response functions that uniform management cannot generate. Colaço and Bramley (2023) reinforced this point by demonstrating that, even with advanced sensing and analytics, the precision of site-specific nitrogen recommendations remains limited unless validated against field-observed optimal rates, an irony they noted explicitly in a system explicitly designed for precision. More recently, Lacoste et al. (2022) argued that digital agriculture should increasingly adopt farmer-centered and system-oriented approaches capable of generating actionable insights under real production environments. Together, these studies suggest that the future of MZ delineation depends not only on advances in sensing, ML, or spatial modelling, but also on robust validation frameworks integrating agronomic, operational, spatial, and economic performance.

Conclusion

This bibliometric review shows that research on AI-based MZs delineation has grown substantially since 2010, with a pronounced acceleration after 2018. The expansion is linked to the consolidation of ML methods and the increased availability of RS and proximal sensing data.
The field is concentrated in a small set of journals, led by Computers and Electronics in Agriculture and Remote Sensing. Chinese institutions dominate the publication landscape, although Embrapa and several European and Oceanian institutions also play relevant roles.
Thematic analysis indicates that the field is shaped by the convergence of ML, RS, soil variability analysis, and crop yield modelling. At the same time, IoT and big data are emerging as new directions. The main limitation remains validation: there is still a gap between producing technically elegant MZs and proving that they improve real-world decisions. Future research should focus less on generating new models and more on testing whether those models work under field conditions.
This review provides a replicable basis for understanding the evolution, key actors, and research gaps in the application of AI to management zone delineation, contributing to the direction of future studies and the strengthening of scientific collaboration in PA and sustainable production systems.

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