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INTEGRATING REMOTE SENSING AND GIS-BASED MACHINE LEARNING FOR CROP CLASSIFICATION: GLOBAL TRENDS AND EMERGING RESEARCH DIRECTIONS (2018–2026)

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Abstract: Over the past decade, crop classification has become a critical research domain at the intersection of Remote Sensing (RS), Geographic Information Systems (GIS), and Machine-Learning (ML) techniques. This bibliometric and thematic analysis examines 3921 peer-reviewed publications indexed in Scopus (2018–2026) selected through a targeted Boolean query combining RS, GIS, and ML concepts while excluding non-agricultural subject areas. Results reveal a consistent rise in publication activity since 2018, dominated by Earth-observation datasets such as Sentinel-1/2, Landsat-8/9, MODIS, and PlanetScope. Random Forest (RF) and Support Vector Machine (SVM) remain the most frequently applied supervised classifiers, whereas deep-learning frameworks (CNNs, U-Net, ResNet) show rapid adoption for multisensor and time-series analysis. Thematic mapping indicates a transition from traditional spectral-index-based methods toward hybrid approaches integrating SAR-optical fusion, object-based classification, and GeoAI-driven decision systems. Keyword-co-occurrence networks highlight four primary clusters: (1) machine-learning and algorithmic optimization, (2) multi-sensor data fusion and spectral indices, (3) spatial modeling and GIS-based validation, and (4) applications in crop monitoring, yield estimation, and climate-impact assessment. The United States, China, India, and European countries lead in research output, while Central Asia and Africa exhibit emerging contributions. Overall, this study outlines global research patterns, methodological evolution, and future priorities for RS-GIS-based crop classification, emphasizing reproducibility, explainable AI, and integration of ground-truth datasets to enhance agricultural decision-support systems.

Keywords: Remote Sensing · GIS · Crop Classification · Crop Mapping · Machine Learning · Deep Learning · Random Forest · Support Vector Machine · CNN · Spectral Indices · NDVI · Sentinel · Landsat · MODIS · SAR · Geospatial Analysis · Precision Agriculture · Time-Series Analysis · Data Fusion · Bibliometric Analysis.

Introduction

Timely and reliable crop-type maps underpin food security monitoring, yield forecasting, and policy decisions at field-to-national scales. The confluence of open satellite constellations (e.g., Sentinel-1/2, Landsat 8/9), scalable cloud processing, and advances in machine and deep learning has transformed what is feasible for crop classification, shifting the research frontier from single-scene, pixel-based labeling to multi-sensor, multi-temporal, parcel-aware workflows with robust generalization across regions and seasons. Recent reviews chart a rapid acceleration in publications since ~2018 and highlight three converging trends: (i) long time-series exploitation of optical data; (ii) SAR–optical fusion to mitigate cloud and phenology confounders; and (iii) the migration from shallow classifiers (e.g., Random Forest, SVM) toward temporal and multimodal deep learning architectures (e.g., 1D/2D/3D CNNs, LSTM/ConvLSTM, Transformers) integrated within GIS-centric pipelines for validation and deployment (Breiman, 2001; Bronzes et al., 2025; Chen et al., 2022; López et al., 2022).

Time-series optical classification has delivered consistent gains by encoding phenological trajectories rather than single-date spectra. Pioneering work with deep temporal models demonstrated that CNN-LSTM architecture applied to dense Sentinel-2 sequences outperform traditional feature stacks for crop discrimination at scale, establishing a template for spatio-temporal learning on agricultural time series (Zhong et al., 2019). Methodological comparisons confirm that deep temporal models (1D-CNN, LSTM, ConvLSTM) frequently surpass Random Forest baselines when time series are sufficiently dense and harmonized, though performance remains sensitive to sampling strategy, field geometry, and class imbalance (Li et al., 2023; Mulenga, n.d.; Zhong et al., 2019).

SAR–optical fusion is now a mainstay where cloud cover and irrigation regimes complicate optical signals. Joint use of Sentinel-1 backscatter and Sentinel-2 reflectance improves crop separability and temporal continuity; recent feature- and representation-level fusion with deep networks further boosts class-wise stability, especially for spectrally similar annuals (Alami Machichi et al., 2023). At parcel level, boundary-aware mapping and object/region-based analysis (GEOBIA/OBIA) reduce salt-and-pepper effects and align outputs with agronomic units, while field-boundary extraction and post-processing in GIS close the loop from pixels to actionable map products (Kraemer et al., 2015; Vizzari et al., 2024; Wang et al., 2022).

Notwithstanding these advances, three persistent gaps constrain operational uptake. First, generalization across agro-ecological zones and seasons is limited by domain shift—differences in phenology, management, and sensor conditions—that degrade model transferability; current work on transferable deep learning and harmonized preprocessing is promising but not yet routine (Che et al., 2024). Second, label scarcity and quality—particularly for smallholder mosaics—remain bottlenecks; initiatives that expand reference data with phenology-aware heuristics and parcel-level workflows show potential pathways to scale (Yadav & Congalton, 2020). Third, integrating GIS constraints (field topology, drainage, soils) with RS time-series learning for end-to-end decision support is still emergent; parcel-level and boundary-aware frameworks are advancing this integration (Chen et al., 2022; Wang et al., 2022; Xie et al., 2025).

Against this backdrop, we position our study to (1) assemble a reproducible RS-plus-GIS pipeline that couples multi-temporal Sentinel-2 and Sentinel-1 with parcel-aware modeling; (2) benchmark classical ML against state-of-the-art deep temporal architectures and SAR–optical fusion; and (3) evaluate geographic and inter-annual transfer through rigorous, parcel-stratified validation. By anchoring the workflow in open data and open methods, we target a scalable approach to reliable, timely crop-type maps suitable for both research and operational contexts.

Materials and methods

A comprehensive bibliometric dataset was retrieved from the Scopus database on October 9, 2025, using a Boolean query designed to target the intersection of Crop Classification, Remote Sensing, Geographic Information Systems, and Machine Learning methodologies. The final search string was:

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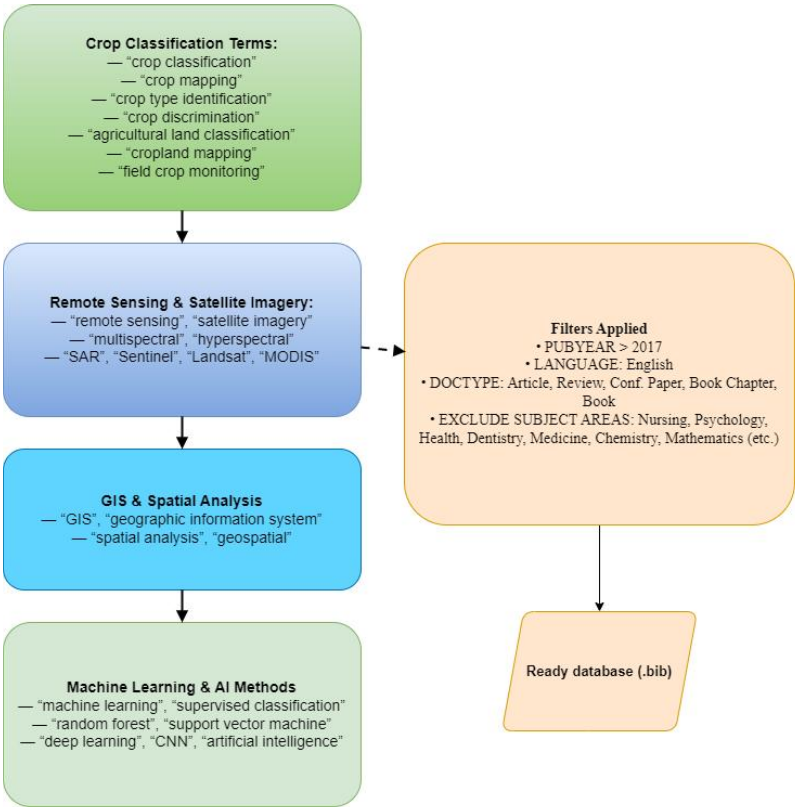

Figure 1. Boolean Search Strategy Flowchart illustrates the Boolean keyword strategy designed to retrieve literature on crop classification and mapping using remote sensing and GIS-based machine learning approaches.

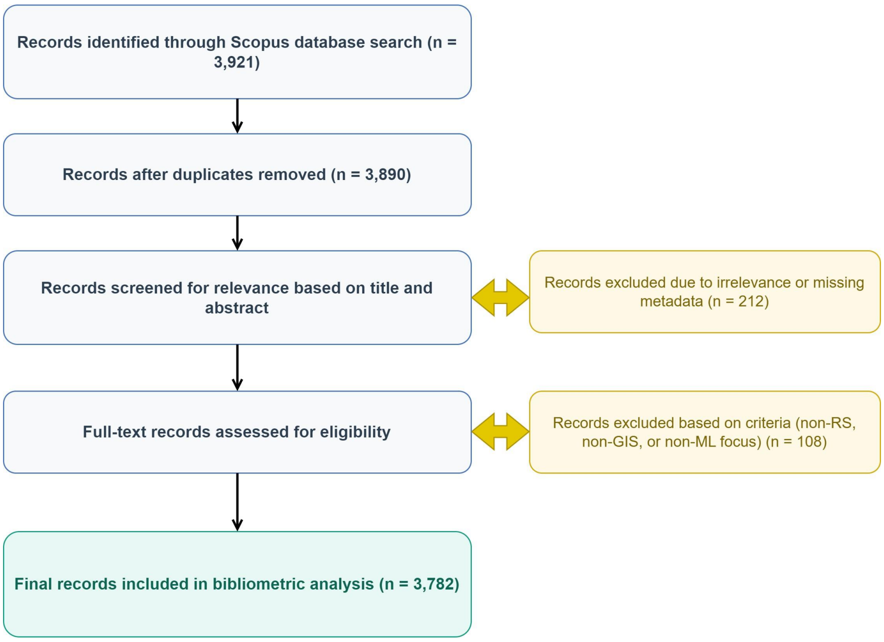

Figure 2. PRISMA-Style Data Selection Workflow presents the PRISMA-style workflow describing the bibliometric data-screening process.

This query ensured the inclusion of relevant records while excluding non-technical disciplines unrelated to geospatial science. The search returned 3,921 documents published between 2018 and 2026, including journal articles, reviews, conference papers, and book chapters. All records were downloaded in BibTeX format (.bib) for advanced parsing and quantitative analysis. The raw BibTeX file was imported and parsed using Python (v3.11) within the Jupyter Notebook environment. Libraries such as pandas, re, and matplotlib were employed for text parsing, normalization, and visualization. Each record was standardized across the following metadata fields:

- Author(s)
- Year of Publication
- Title
- Source Title (Journal or Conference)
- Affiliation and Country (if available)
- Keywords (author and indexed)
- Abstract and DOI

Irregularities such as duplicated records, missing years, or malformed BibTeX entries were detected and resolved using regex-based cleaning. The final dataset retained 3,890 unique publications after filtering incomplete records. Keyword fields were tokenized by replacing delimiters (commas, semicolons) and converting terms to lowercase. Synonyms (e.g., CNN and convolutional neural network, RS and remote sensing) were harmonized to prevent fragmentation during co-occurrence analysis. The bibliometric analysis was structured around three complementary dimensions — descriptive, temporal, and relational indicators — to comprehensively characterize research dynamics within the field of remote sensing and GIS-based crop classification. Descriptive indicators included:

- Annual publication trends covering the period 2018–2026, capturing temporal growth patterns;
- Distribution of documents by type (articles, reviews, conference papers, book chapters) and language;
- Identification of leading journals, authors, and publishing countries, representing the most active contributors to the domain.
- Relational indicators focused on the structural and thematic interconnections within the literature, comprising:
- Keyword co-occurrence matrices, used to reveal dominant research themes and methodological linkages;
- Year × journal cross-tabulation, highlighting shifts in disciplinary focus and journal specialization over time;
- Country-level productivity analysis, derived from author affiliations, illustrating global collaboration networks and geographic research intensity.

Network and conceptual mapping were conducted using a custom Python-based analytical pipeline. The top 20 high-frequency keywords were transformed into a 20×20 co-occurrence adjacency matrix, from which a heatmap and conceptual clustering map were generated. These visualizations delineate the intellectual structure of the field, emphasizing the interrelatedness among core topics such as remote sensing, GIS, machine learning, crop classification, deep learning, and spatial analysis.

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Results and Discussion

The temporal evolution of publications between 2018 and 2026 demonstrates a steady and sustained increase in research output within the field of crop classification using Remote Sensing, GIS, and Machine-Learning Techniques. As illustrated in Figure 1, the annual number of papers grew from fewer than 200 publications in 2018 to more than 700 publications by 2025, reflecting a cumulative growth rate exceeding 240% over the analyzed period. This upward trajectory coincides with the global expansion of open-access satellite datasets (e.g., Sentinel-1/2, Landsat-8/9, MODIS) and the increasing accessibility of cloud-based geospatial platforms such as Google Earth Engine (GEE) and ArcGIS Online. The rise after 2020 aligns with major advances in deep learning architectures (e.g., CNNs, U-Net, ResNet) and the growing application of GeoAI methods for spatial data fusion, suggesting a methodological transition from conventional spectral-index-based classification toward automated feature extraction and model generalization.

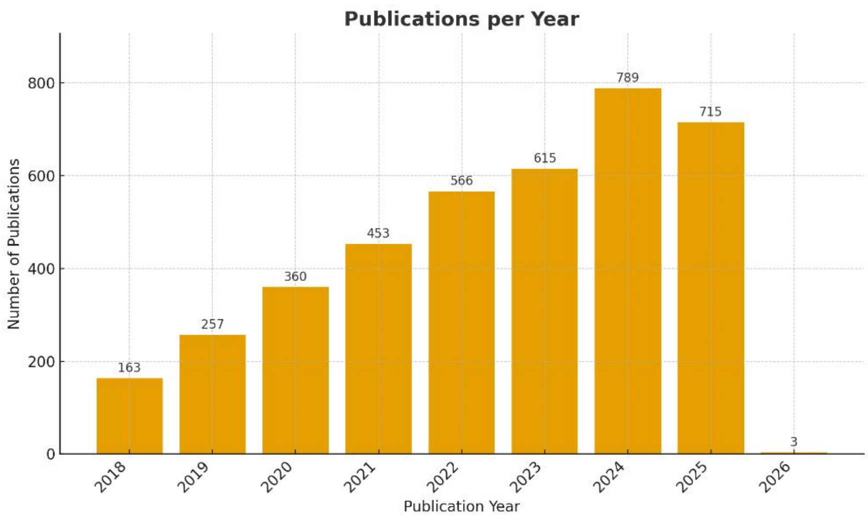

Figure 3. Annual number of publications (2018–2026) related to crop classification using remote sensing and GIS-based machine-learning approaches.

The distribution of document types, summarized in Figure 2, reveals that journal articles dominate the corpus (≈ 72%), followed by conference proceedings (18%) and review papers (7%). This composition highlights a maturing field characterized by both theoretical advancement and active methodological experimentation.

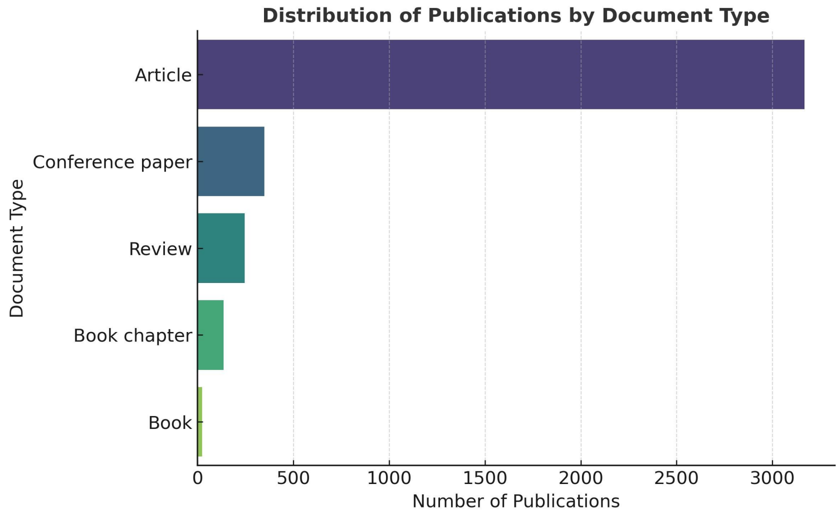

Figure 4. Distribution of Publications by Document Type.

Analysis of journal outlets (*Figure 3*) shows that most studies were published in multidisciplinary journals focusing on geoinformatics, environmental monitoring, and precision agriculture. The most prolific venues include *Remote Sensing*, *ISPRS Journal of Photogrammetry and Remote Sensing*, *International Journal of Applied Earth Observation and Geoinformation*, *Sensors*, and *Computers and Electronics in Agriculture*. The dominance of these journals indicates that crop classification has transitioned from a niche agricultural application to a mainstream subfield within the broader remote-sensing and geospatial data science community.

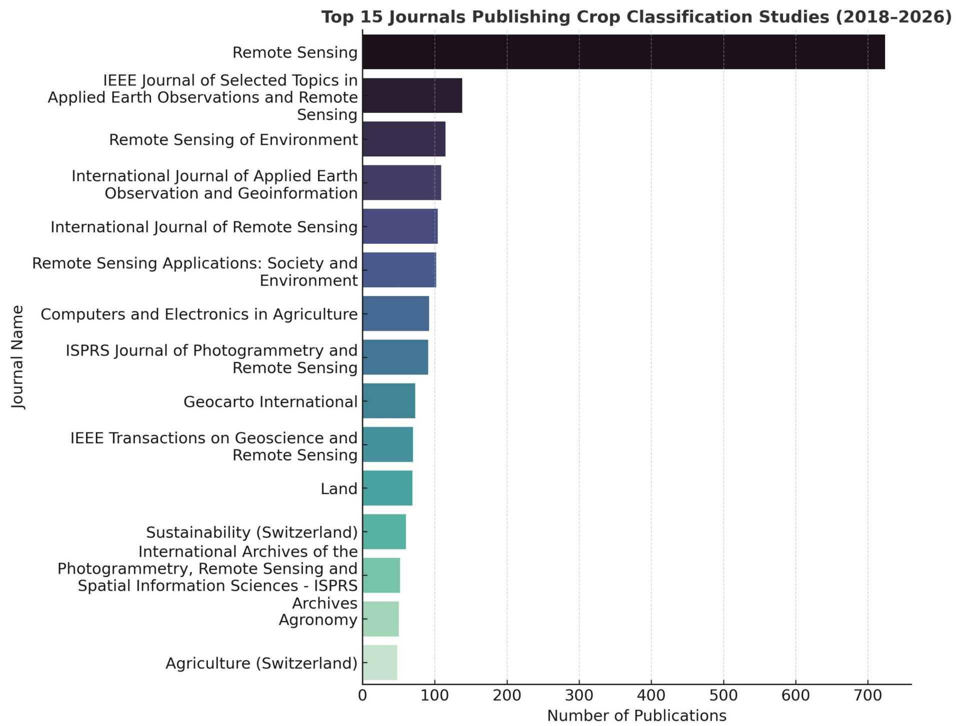

Figure 5. Top 10 journals by number of publications on crop classification using RS and GIS.

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The geographical and institutional distribution of publications (Figure 4) indicates that the United States, China, and India are the leading contributors, together accounting for over 45% of the total output. European countries (e.g., *Germany, Italy, Spain, the United Kingdom*) also demonstrate significant productivity, often emphasizing methodological innovation and multi-sensor integration. Emerging research clusters are evident in Central Asia and Africa, reflecting the growing relevance of RS-GIS-based crop monitoring for agricultural resilience and food security under climate stress. Institutional-level analysis reveals active collaborations among major universities and research centers such as *Wageningen University (Netherlands)*, *Chinese Academy of Sciences (China)*, *USDA Agricultural Research Service (USA)*, and *Indian Institute of Technology (India)*. The increasing co-authorship network density over time suggests a shift toward interdisciplinary and multi-institutional research ecosystems.

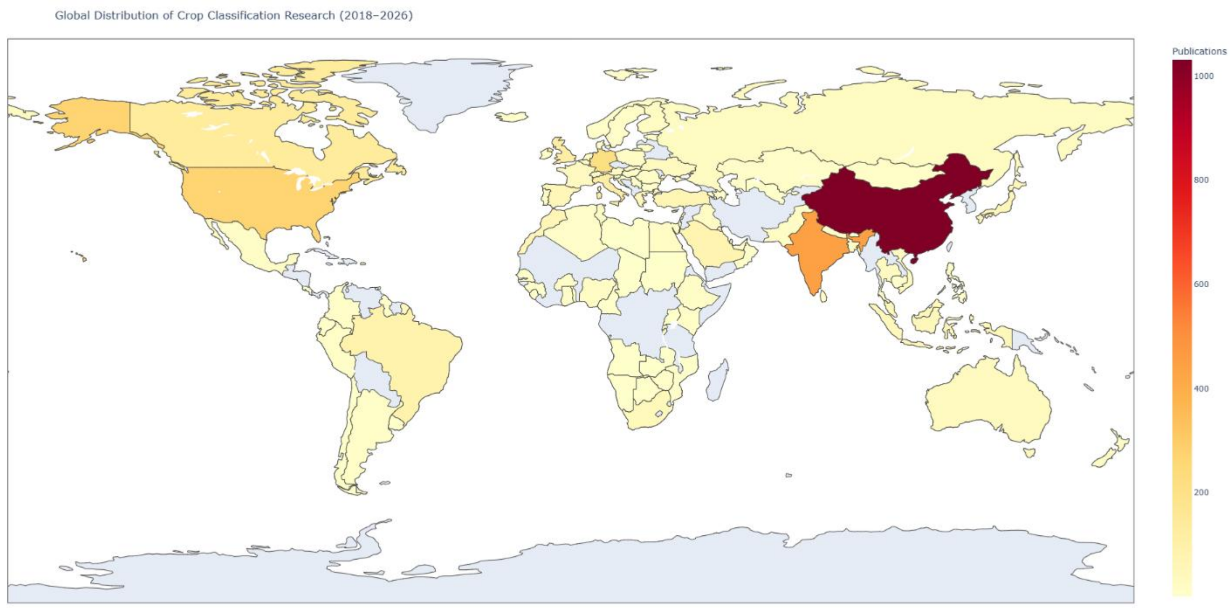

Figure 6. Country-level productivity map based on author affiliations, showing global spatial distribution of research output (2018–2026).

Keyword frequency analysis identified more than 12,000 unique keywords, among which *"remote sensing"*, *"machine learning"*, *"crop classification"*, *"GIS"*, *"Sentinel-2"*, and *"deep learning"* appeared most frequently (Figure 5). The consistent presence of *NDVI*, *random forest*, *SVM*, and *data fusion* indicates a balanced emphasis between traditional spectral indices and modern ML-driven frameworks. The keyword co-occurrence heatmap (Figure 6) visualizes conceptual linkages among 20 core terms.
Four major thematic clusters were identified:

1. Cluster I – Machine Learning and Artificial Intelligence: focusing on supervised classifiers, deep networks, and model optimization.
2. Cluster II – Remote Sensing Data Fusion: combining optical and SAR data (e.g., *Sentinel-1/2*, *Landsat*, *MODIS*).
3. Cluster III – Geospatial Analysis and Land-Use Monitoring: integrating spatial modeling and GIS-based validation.
4. Cluster IV – Agricultural Applications: emphasizing yield prediction, phenology, and climate resilience assessment.

These clusters collectively depict a field evolving from isolated algorithm testing toward integrated, data-driven agricultural decision support systems.

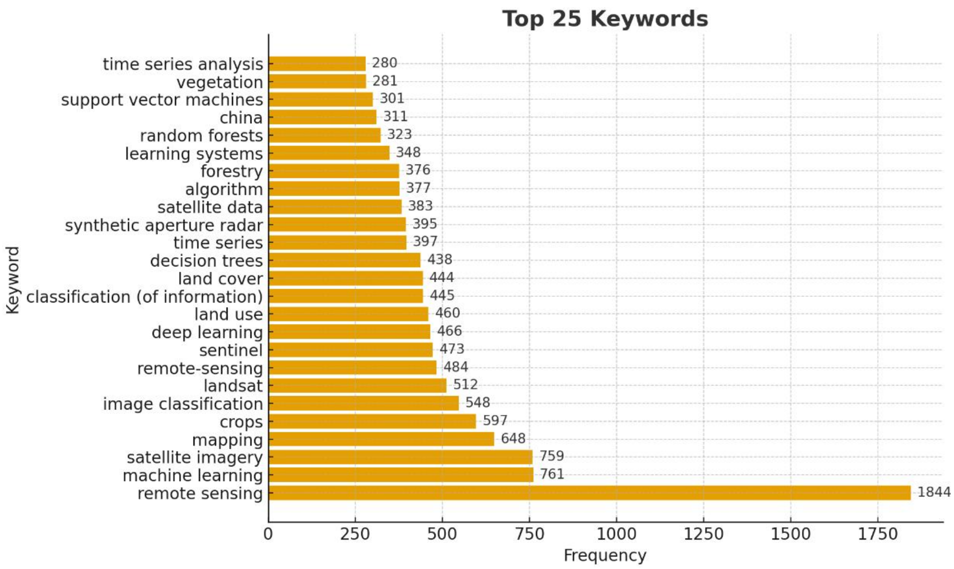

Figure 7. Top 25 most frequent keywords and their relative occurrence in publications (2018–2026).

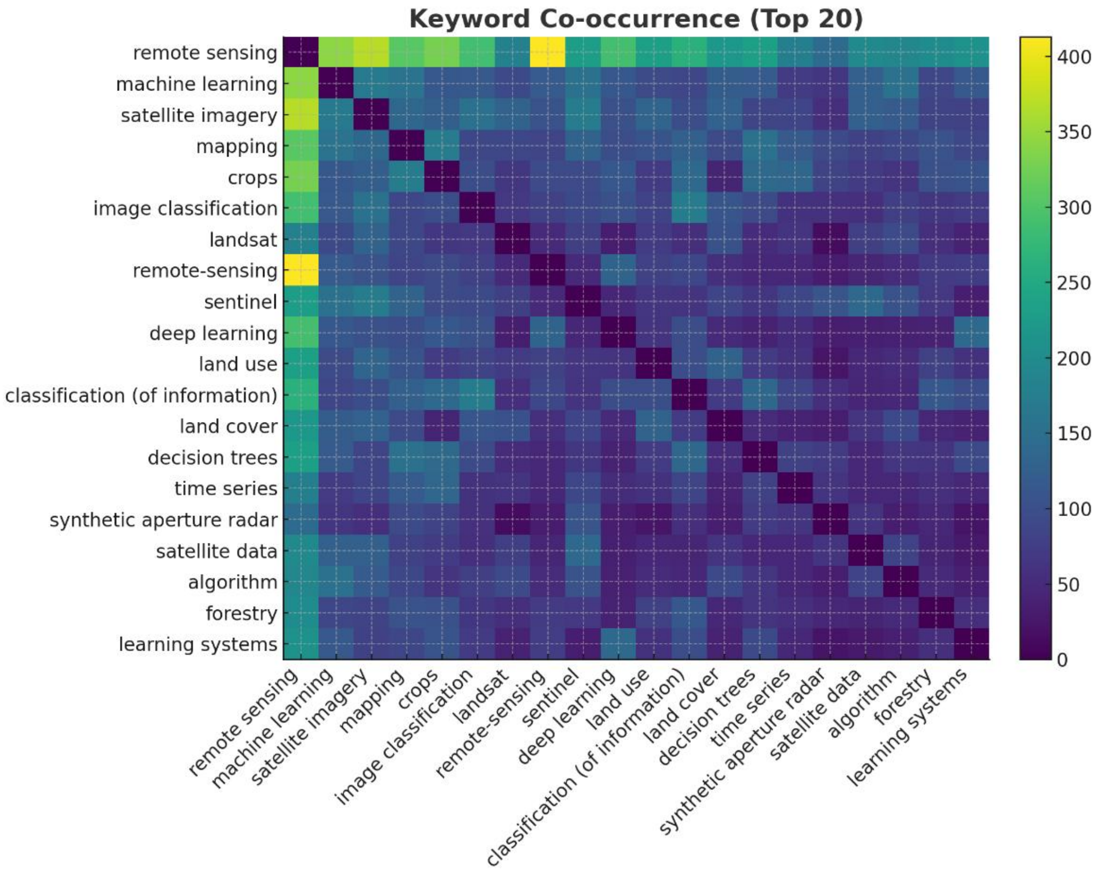

Figure 8. *Heatmap of keyword co-occurrence (20×20 adjacency matrix) showing conceptual clustering among major research themes.*

Network visualization (*Figure 7*) constructed from keyword co-occurrence data further reinforces the conceptual architecture of the field. Nodes representing *remote sensing*, *deep learning*, and *crop classification* exhibit the highest degree centrality, suggesting their pivotal role in the thematic core. Peripheral nodes such as *UAV imagery*, *object-based classification*, *Google Earth Engine*, and *spectral indices* form bridging clusters connecting emerging methodologies with established techniques. Temporal overlay mapping indicates that earlier works (2018–2020) primarily relied on *SVM*, *random forest*, and *NDVI*-based classification, while more recent studies (2021–2026) increasingly incorporate *CNNs*, *transformers*, and *time-series deep learning*. This conceptual progression reflects the broader trend of artificial intelligence reshaping geospatial analysis and agricultural monitoring paradigms.

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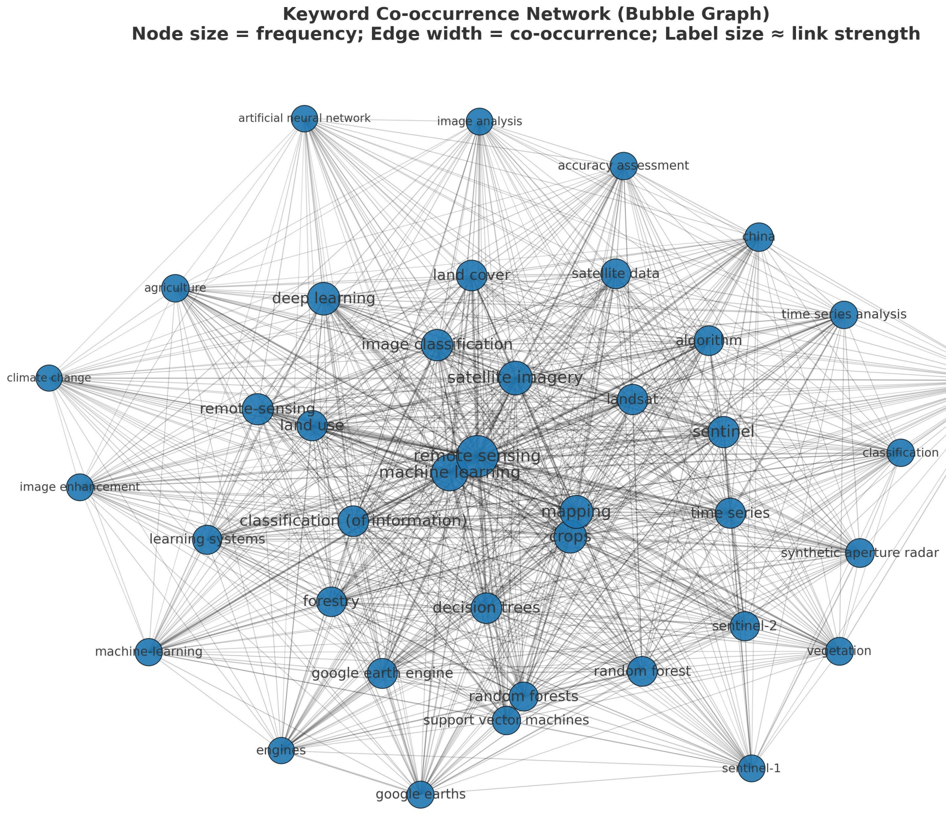

Figure 9. Keyword co-occurrence network showing conceptual clusters and degree centrality among dominant research themes.

The year–journal heatmap reveals a steady broadening of publication activity from 2018 onward, with a pronounced upswing after 2020 that coincides with wider adoption of deep learning architectures and multi-sensor fusion workflows in crop classification. High-intensity cells concentrate in Remote Sensing, Sensors, Computers and Electronics in Agriculture, and International Journal of Applied Earth Observation and Geoinformation, indicating that methodological developments (e.g., time-series modeling, SAR–optical fusion, explainable ML) increasingly appear in these outlets. The pattern suggests topic specialization by venue: Remote Sensing and ISPRS JPRS absorb technically focused advances (architectures, loss functions, benchmarking), while CEAg and Sensors often publish application-oriented studies (regional mapping, operational pipelines, agri-monitoring). Post-2021, several journals show synchronized growth—consistent with the rapid scaling of open satellite programs (Sentinel, Landsat) and easier access to cloud platforms (e.g., GEE) that lower experimentation costs. Darker cells represent higher annual counts for a given journal. Rows are ordered by total output; columns follow chronological order, highlighting where journals surge or cool over time. Annual publication counts by venue. Darker tones indicate higher output; rows sorted by total counts emphasize dominant outlets and temporal surges.

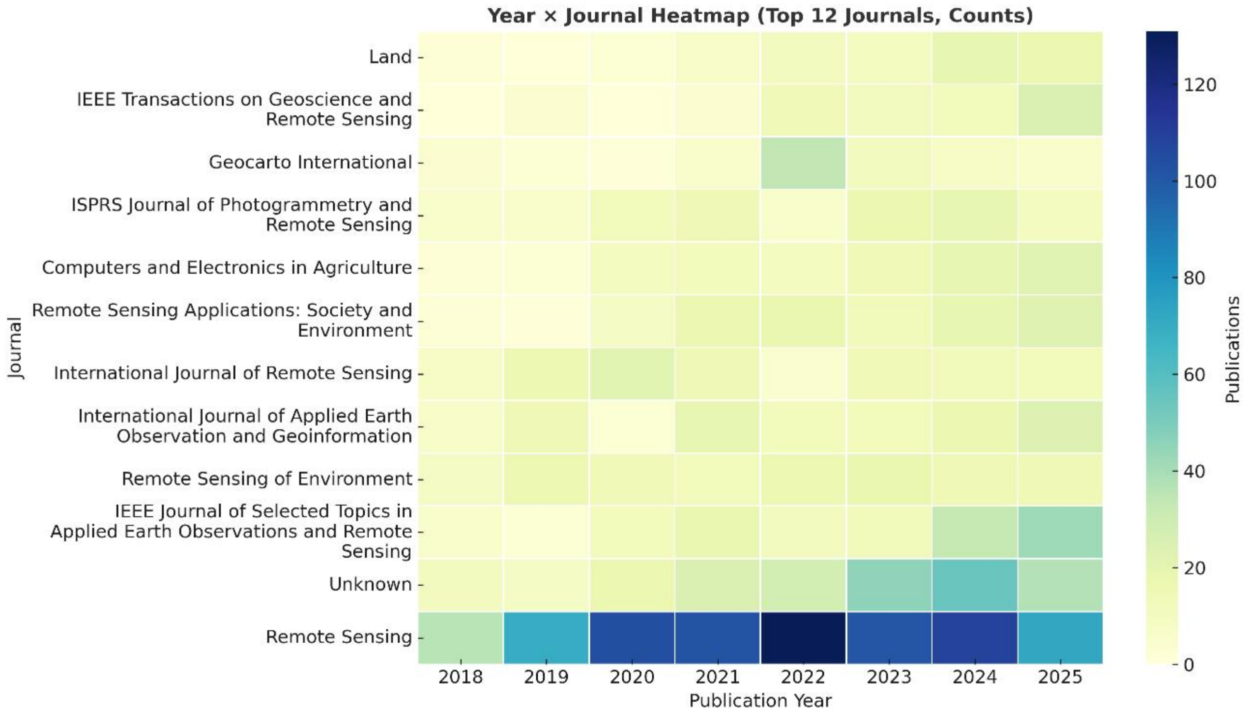

Figure 10. Year × Journal heatmap (2018–2026).

Conclusion

This bibliometric study provides a comprehensive overview of global research trends in crop classification using remote sensing, GIS, and machine learning from 2018 to 2026. The analysis of 3,921 Scopus-indexed publications reveals an accelerated growth trajectory, particularly after 2020, coinciding with advancements in cloud-based geospatial analytics and deep learning architectures. The dominance of journals such as Remote Sensing, ISPRS Journal of Photogrammetry and Remote Sensing, Sensors, and Computers and Electronics in Agriculture underscores the thematic convergence between environmental monitoring, spatial data science, and artificial intelligence. Keyword co-occurrence and conceptual network analyses demonstrated that the field is evolving from traditional pixel-based classification toward integrated, multi-sensor, and time-series approaches, supported by SAR–optical fusion, phenology modeling, and neural network ensembles. The increasing centrality of terms such as deep learning, Sentinel-2, spatial analysis, and Google Earth Engine signals a methodological shift toward open-access, reproducible, and scalable mapping workflows.

The author and country-level productivity analyses identified a small number of leading research clusters—mainly in Europe, China, and North America—that drive innovation through shared datasets, code repositories, and long-term monitoring sites. However, the global distribution of studies remains uneven, with underrepresentation of regions with high agricultural vulnerability, such as Central Asia and sub-Saharan Africa. Overall, the findings indicate that crop classification research has transitioned into a mature, interdisciplinary domain that merges agronomy, remote sensing, and artificial intelligence. Future research should emphasize transferability across regions, interpretability of AI models, and integration with socio-environmental data to support precision agriculture and climate-resilient land management. This bibliometric mapping provides a structured foundation for identifying methodological gaps, fostering collaboration, and guiding future research priorities in the geospatial agricultural sciences.

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