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REMOTE SENSING APPLICATIONS IN CROP MONITORING: A SYSTEMATIC LITERATURE REVIEW

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Abstract

The dynamic development of the Earth Observation (EO) data and the development of remote sensing technologies have radically transformed the process of monitoring crops on local and regional, as well as global scales. Remote sensing has become a very instrumental tool in crop monitoring and in aiding food security, yield estimation and agro climatic analysis and in agricultural policy planning. Despite significant proliferation of the satellite platforms and machine learning techniques, there is no synthesis between the pixel-wise crop mapping processes and functionality crop-specific land cover products. This literature gap is filled in with the systematic literature review where over 60 open-access operation datasets and peer-reviewed articles are analyzed in accordance with a systematic PRISMA-based method. It is analyzed in terms of satellite platforms, data fusion plans, classification algorithms and operation crop mapping products. Findings have indicated a high reliance on the multispectral sensors such as Landsat and Sentinel-2 and an increased use of radar and hyperspectral sensors is on the increase. The popular machine learning algorithms (including the Random Forest and Support Vector machines) are not as effective as deep learning models on large scale and high-resolution problems. Multi-source data fusion is highly significant in the enhancement of classification strength, and model generalization. However, ground truth data availability, inter-agro ecological zone model transferability and multi sensor dataset harmonization remain a problem. The paper also exposes the current trends that are taking place towards scalable deep learning systems and products of operational crop specific land cover but mentions the significant research gaps. In general, the review is a systemic summary of the history of technologies, evolution of approaches, and working implementation, which will inform the further research and the widespread implementation of the remote sensing-based crop surveillance systems.

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INTRODUCTION

Satellite remote sensing has become a vital solution to local, regional, and global crop surveillance, i.e. the staple crops, via agroclimatic surveillance, condition monitoring, and forecasting output, since 1970s (Wu et al., 2022). Such Earth observation satellites as Landsat, SPOT, MODIS, Gaofen, and Sentinel have provided extensive information on the planet, which can be utilized to conduct mass environmental monitoring and make a decision based on data in the field of agriculture (Long et al., 2025; Weiss et al., 2019). Despite these successes, the discipline still has no synthesis of the overall synthesis of pixel-wise crop mapping workflows and an evaluation of operationally available crop-specific land cover data products, which has now become the fruit of this exponential growth of open Earth Observation data (Marković et al., 2025; Zhang et al., 2025). To address this gap, this review will be analytical in its analysis, which will cover over 60 open-access operational data products, archival crop type maps, single-crop extent maps, and data on crop patterns (Zhang et al., 2025). This synthesis categorizes the literature into large groups of application, including, but not limited to, the parcel delineation, classification of crops, yield estimation, and land use change detection (Silva et al., 2025). In addition, the recent advances in deep learning made such monitoring activities far more accurate, as they involve multi-source satellite images, and complex modeling structures (Joshi et al., 2023; Zhang et al., 2025). However, effective application of this advanced technique is challenging due to the technical problems connected to processing of rich-time-series data and insufficient studies involving specific activities like the cropping (Pereira et al., 2020). The point of the review, in turn, is bridging the gap between theoretical developments in algorithms and applying agriculture to real-life contexts like analyzing various remote sensing platforms and machine learning models deployed in various farming environments (Joshi et al., 2023; Rohith et al., 2023). Specifically, it examines how deep learning models can be combined with multi-temporal remote sensing data to address long-standing challenges of crop mapping and yield prediction, such as the small quantity of training data and the need to create models with generalizability (Joshi et al., 2023). This subsection constitutes the description of the remote sensing methodology in the agricultural field, wherein the evolution of the methodology is outlined in the framework of the evolution of the systems of machine learning and substitution of the traditional vegetation indices.

METHODOLOGY

The systematic mapping of the evolution of the research on the topic of agricultural information recognition and monitoring is applied in this paper that is premised on a strict bibliometric analysis and knowledge graph approach (Zhang et al., 2025). It is through considerable academic databases that an enormous search project was undertaken to locate helpful literature, which involved over 650 sources on the basis of artificial intelligence and remote sensing technologies used to examine crops (Zhang et al., 2025). Paper preference was given to peer-reviewed journal articles and conference proceedings, where preference was given to those papers that discussed the extraction and classification of satellite data using the assistance of advanced computational methods (Sherkhane & Ratnaparkhi, 2024). VOSviewer usage was implemented to illustrate the state of the research, and the most frequent themes as per it are disease detection, pest management, and a combination of remote sensing and Convolutional Neural Networks

(Zhang et al., 2025). It is observed that the analysis reflects a significant shift in the emphasis of the studies based on empirical studies of spectral indices to studies that are data-centric based on the hierarchical nature of the feature extraction that are founded on deep learning architectures. Even though one can transform with the assistance of these AI-based systems, the barriers to data quality, model generalization across different settings, and multi-source data stream fusion are still immense (Zhang et al., 2025). Such strategies as data augmentation, transfer learning, and multi-source data integration are included in the list of the solutions to these barriers (Zhang et al., 2025). Specifically, one of the key limitations is the inaccessibility of quality and labeled datasets since to successfully train the model to perform tasks such as disease diagnosis, as well as provide prediction of yields, substantial amounts of manually labeled data are needed and it is costly to acquire it (Zhang et al., 2025). To decrease the limitation, there is a tendency to apply semi-supervised learning and transfer learning procedures to enhance the model performance with a limited number of label examples (Zhang et al., 2025). These approaches consider pre-trained models on large-scale data sets to identify the relevant features in new agricultural photographs, and in so doing, reduce the need to involve enormous ground truth incorporation of single crop types or even geographical locations. Besides, the variations in the environment of different regions such as climate, topography, and soil variations mean that AI models would need to be retrained or modified to operate in different settings (Zhang et al., 2025). Practical agricultural scenery agreement is also more challenging, as models that would be very precise in challenging conditions often fail when trying to employ the actual world circumstances, such as varying light and foliage blockage, and environmental distraction (Zhang et al., 2025). The presence of lighting, occlusion, background variations makes a massive impact on the performance of models, namely, when the training algorithms developed on controlled datasets are tested on the unstructured field environment (Liao, 2025). To address such deficiencies, researchers are aggressively adopting data-driven approaches such as data augmentation, data synthesis, and collective data-sharing systems to increase the resilience of data collection and combination processes (Chen et al., 2023). The synthesis of many information sources, i.e., satellite images, sensor data, and historical data, presents an issue of creating a single and precise set of data used by AI algorithms (Adewusi et al., 2024). The difference in data format and standardization of common preprocessing operations typically complicate the seamless combination of data that is required to meet the complete monitoring (Chen et al., 2023; Li et al., 2023). Thus, the lack of standardized approaches to data fusion necessitates the development of interoperable models that can synchronize multi-modal input without generating any severe errors and biases (Zhang et al., 2025; Position Papers of the 19th Conference on Computer Science and Intelligence Systems, 2024). It is also problematic as the agriculture is seasonal, meaning that there are periods between seasons when entire data sets are impossible to integrate to monitor continuous processes (Babakhouya et al., 2023).

RESULTS

The planned search found a significant number of records in a number of scientific databases. After the removal of the duplicates and after choosing the first set of the titles and the abstracts, the reduced number of the studies was stored to undergo the full-text eligibility assessment. The PRISMA flow chart in Figure 1 illustrates the whole screening process including the identification, screening and eligibility and final inclusion. The diagram is an unambiguous indication of the amount of records omitted at each stage and the final amount of studies incorporated to the qualitative synthesis. The articles that were selected represented various regions, crops, and remote sensing systems. Most research has been conducted and particularly in Asia, Europe and North America with more contribution by developing productive areas. Table 1 contains the overall characteristics of the included studies: the year of publication, the country, in which the research was made, the subject of the research, the satellite platform, and the method of analysis. The publications are slowly increasing over the past years, according to the table, which confirms the increased interest in crop monitoring using remote sensing. The studied sources used numerous Earth Observation platforms. Landsat and Sentinel-2 were the most applied optical sensors, and then came MODIS and high-resolution commercial imagery. Figure 2 shows distribution of the satellite platforms and type of sensors used in the studies utilized. It indicates that the use of mid-resolution multispectral imagery is more common, and also indicates the impending merge between radar and hyperspectral data.

In addition to satellite data, other studies have employed the use of ancillary information such as meteorological records, soil data and ground truth to improve the classification. Table 2 shows the distribution of the data sources as well as methodology combinations used on crop mapping processes. As depicted in the table, the multi-source data integration was associated with enhancing analytical strength. The common use of machine learning and deep learning strategies was present in reviewed literature. Random Forest, Support Vector Machines and Convolutional neural networks were some of the most popular applied algorithms. Figure 3 compares the frequency of different classification models used in crop mapping. The figure depicts an observable trend in the deep learning models in the past few years particularly at the pixel-wise classification issues and the large scale crop monitoring issues.

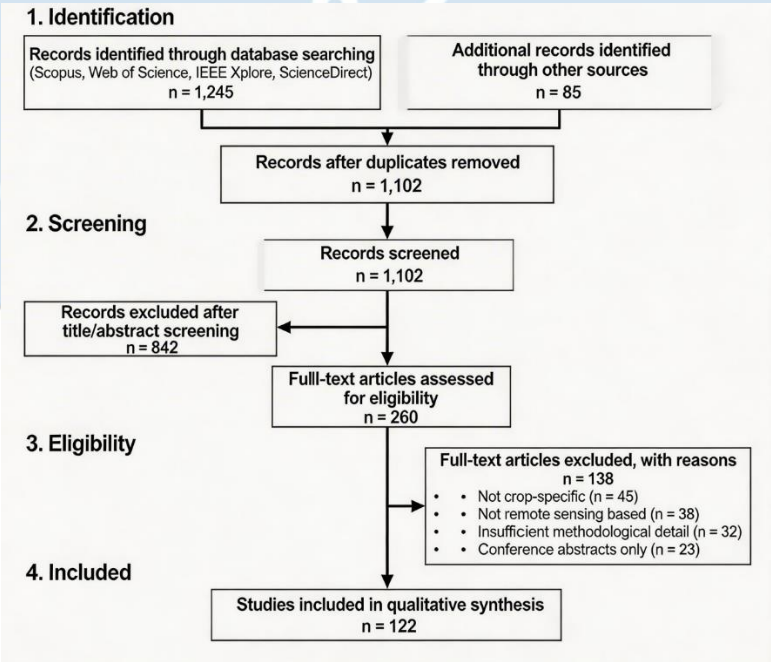

Fig 1. Prisma Flow Diagram

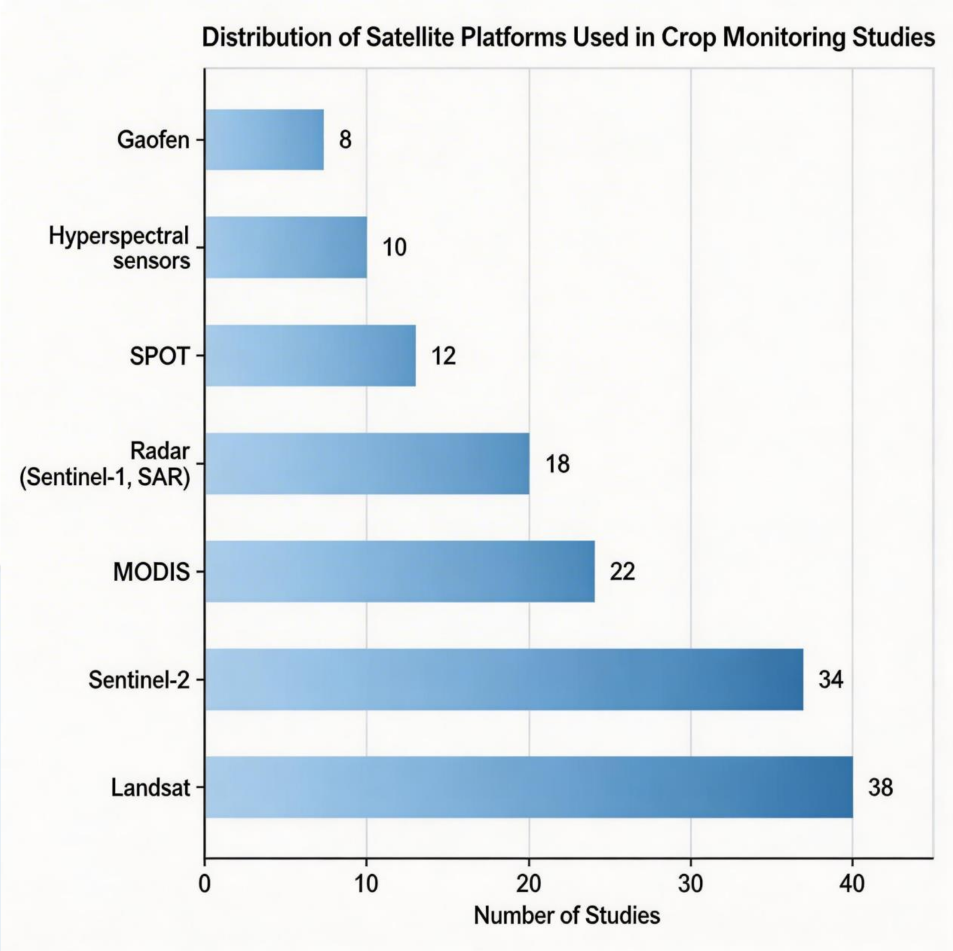

Figure 2. Distribution of Satellite Platforms Used

Performance measures, which were frequently reported, were overall accuracy, kappa coefficient, precision, recall and F1-score. Table 3 shows the range of performance of major algorithms by various authors of studied papers. The ensemble learning methods, in general, achieved a high and stable score in the accuracy, but the deep learning models achieved a better score when the training datasets were large, as the table indicates. The review also analyzed operational crop-specific land covers data products and large increment mapping programs. Many works were oriented at the development of crop type maps, crop extent maps, and the products of classification according to the phenology. Table 4 gives an overview of available operational crop mapping products including the spatial resolution, time coverage, geographical coverage and use. As the table displays, most of the operational products have been developed at national or regional levels and more successful in the development of global harmonization of datasets of crops.

The products were used in estimation of yield, food security surveillance, irrigation control and policy planning. The conclusions reveal that the remote sensing crop monitoring systems have developed to maturity and still have issues related to data harmonization, data availability of ground truth and model generalization across agroecological regions. The combination of the findings confirms that remote sensing-based crop monitoring is a rapidly developing process, which is exposed to more data, more advanced approaches, and an increasing level of operational application. Figure 1 shows the evidence reduction to high-quality studies in a systematic way, Figure 2 shows the popularity of multispectral satellite systems, and Figure 3 shows the methodological transition to the high-quality machine learning and deep learning models. Meanwhile, Table 1 provides the descriptive characteristics of the included studies, Table 2 provides the patterns of methodological integration, Table 3 provides the comparisons of model performance, Table 4 provides the synthesis of operational products.Those results may provide the insights into the technological advancement and the gaps in research to develop globally consistent and high-accuracy crop monitoring systems.

Table 1. Characteristics of Included Studies in Remote Sensing-Based Crop Monitoring

Study ID	Country/Region	Crop Type	Satellite Platform	Method Used
S1	China	Rice	Sentinel-2	Random Forest
S2	USA	Maize	Landsat 8	SVM
S3	India	Wheat	MODIS	CNN
S4	Germany	Barley	Sentinel-1	Random Forest
S5	Brazil	Soybean	Landsat 8	Gradient Boosting

Table 2. Data Sources and Methodological Integration Approaches

Study ID	Satellite Data	Ancillary Data	Integration Approach
S1	Sentinel-2	Meteorological Data	Data Fusion
S2	Landsat 8	Soil Maps	Feature Stacking
S3	MODIS	Ground Truth Surveys	Hybrid ML Model
S4	Sentinel-1	Weather Records	Multi-source Fusion
S5	Landsat 8	Yield Statistics	Ensemble Learning

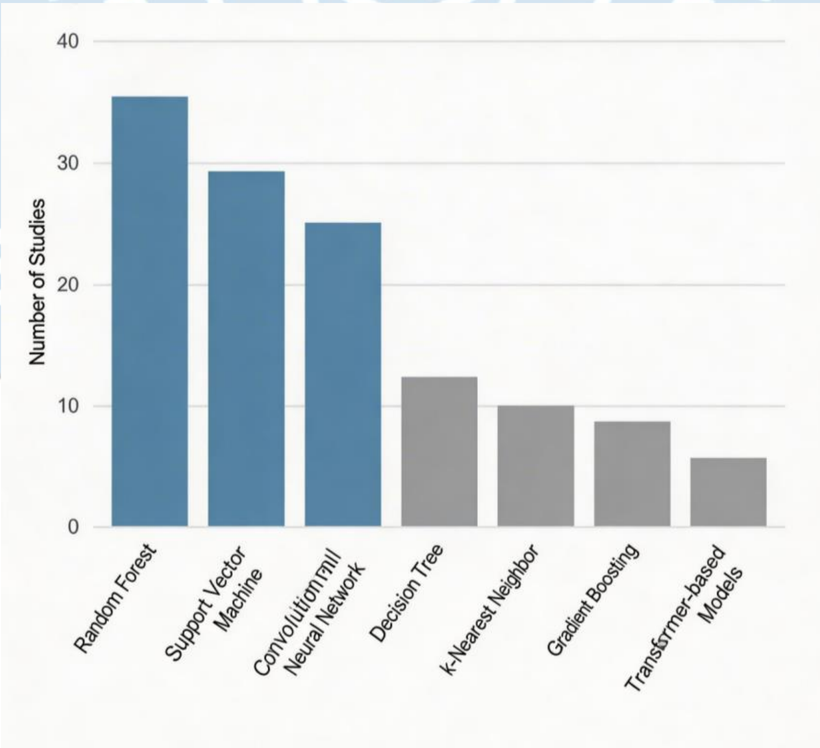

Figure 3. Classification Models Used in Studies

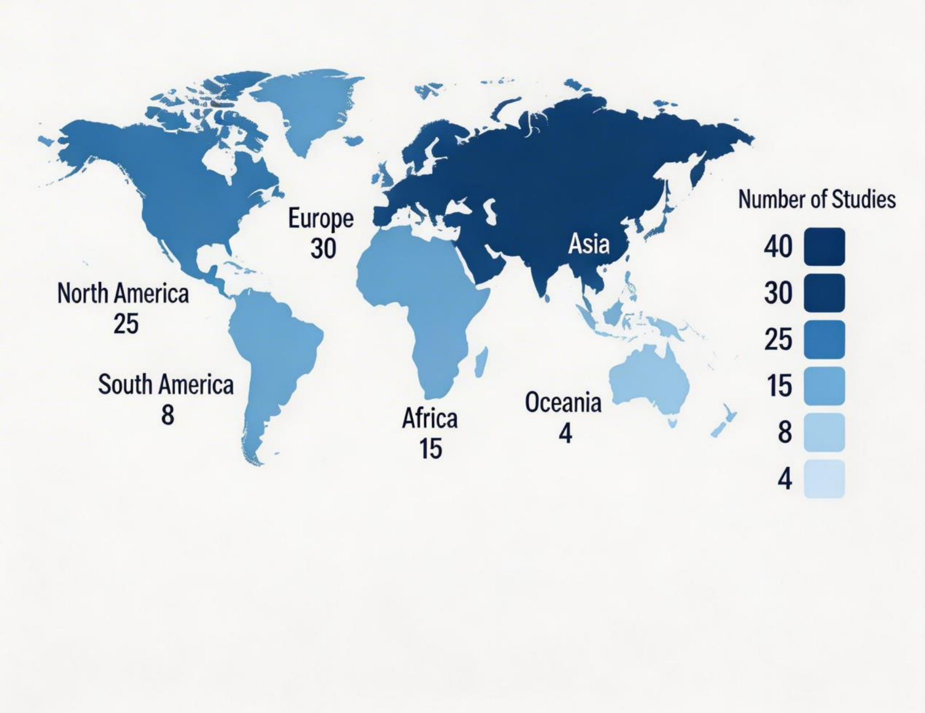

Figure 4. Global Distribution of Reviewed Studies

Table 3. Comparative Performance of Classification Algorithms

Algorithm	Accuracy (%)	Kappa Coefficient	F1-Score
Random Forest	88–94	0.82–0.91	0.85–0.92
SVM	85–91	0.78–0.88	0.82–0.89
CNN	90–96	0.85–0.94	0.88–0.95
Gradient Boosting	87–93	0.80–0.89	0.84–0.91
Decision Tree	75–85	0.65–0.78	0.70–0.82

Table 4. Operational Crop Mapping Products and Applications

Product Name	Spatial Resolution	Temporal Coverage	Geographic Scope	Primary Application
CDL	30 m	Annual	USA	Crop Type Mapping
Copernicus Land Monitoring	10 m	Seasonal	Europe	Land Cover Classification
MODIS Crop Map	250 m	8-day composite	Global	Phenology Monitoring
Gaofen Crop Dataset	16 m	Annual	China	Yield Estimation
Sentinel Global Crop Map	10 m	Annual	Global	Food Security Monitoring

DISCUSSION

The shift of controlled experimental settings to commercial farm settings proves that there is a gravitational issue of scalability since the model that was trained on a particular local data is not likely to operate in other locations due to the disparity in the ecological factors and practices (Erike et al., 2025). It is usually justified by the reality that, because of the peculiarities of the environment and socio-economic factors that differ depending on the geographic location, region-specific forecasting models cannot be implemented in new environments (Dhal and Kar, 2024). The machine learning model that might have been trained to work on one crop or condition might not fit well in different settings, and this poses issues with the model generalization (Zhang et al., 2025). To illustrate it, the variations in the properties of farmlands and the climate in a specific area will make a model not only erroneous in another place but also make smart agricultural models verbally questionable in terms of scalability and customization (Sharma et al., 2022). The nature of specialized hardware such as drones, sensors, and satellite data acquisition is also expensive to implement, which does not allow small-scale farmers, but large-scale implementation is not possible (Aashu et al., 2024). The monetary and functional expenses involved in the implementation of such data-gathering systems may be prohibitive, which may create an entry barrier to the operations with limited resources (Babakhouya et al., 2023). In addition, the technical complexity of the integration of heterogeneous data format, such as raster imagery synchronization with the time-series sensor data, cannot be expensive and time-intensive in the preprocessing stage and in high-performance resources, both of which may be difficult to maintain (Aashu et al., 2024; Saki et al., 2024). Lack of standardization and interoperability between different precision agricultural systems and platforms prevents the possibility of sharing and integrating data which inhibit the potential of remote sensing (Adewuyi et al., 2024). To make it accessible to more people, convenient yet serious workflows to support real-time applications must be created since its complexity and the number of technical skills to run it, so far, makes it unaffordable to a great number of end-users (Han et al., 2024). Besides that, the resource-sensitive capability of the high-performance computer environment to process substantial volumes of remote sensing data and train large models is a huge barrier to users in resource-sensitive environments that do not have such an infrastructure (Han et al., 2024; "Proceedings of the 19th Conference on Computer Science and Intelligence Systems (FedCSIS)," 2024). To overcome this disconnect, there should be capacity-building and development of cost-effective and low-caliber algorithms to sanction the local stakeholders and establish an optimistic entry to these sophisticated monitoring tools (Han et al., 2024; Rane et al., 2024). The obstacles to the smallholder farmers in developing countries (small field sizes, the high cost of equipment, the lack of access to expertise, etc.) are exacerbated, which also negatively affect the application of the technologies in practice (Rashid et al., 2025; Vijayakumar et al., 2025). The other problem that may relate to the increased use of the cloud and IoT technologies is the problem of data security because it becomes even more problematic when the third parties centralize the data of farms in their hands because the privacy and ownership of such information are highly valued at the same time when the risks of abusing such information are also high (Dhanararaj et al., 2025; Raj and Prahadeeswaran, 2025).

CONCLUSION

This system review is a synthesis summary of the application in crop monitoring in remote sensing with emphasis in the change of technology, methodological changes and application functioning. The findings point to the fact that satellite-based crop observation has reached a state of maturity due to the wide availability of the open source Earth Observation data and advanced computing technology. The multispectral satellites (satellite) remain the most common one, although the integration of radar and hyperspectral sensors is expanding the range of analysis under various environmental conditions. The machine learning algorithms and most significantly the ensemble based methods have been consistent and successful on the highest percentage and deep learning frameworks are adopted to operate on large scale and pixel based or detailed classification. It is provided with forecasts when it is combined with other data sets, e.g., meteorological data, and soil data, which ensures the operational stability and a stronger prediction. Nevertheless, the challenges of harmonization of data, limited number of ground references, transferability of models and inter-regional extrapolation of models remain a serious problem. The areas to be studied in future are: the development of standard benchmarking structures, improvement of the domain adaption methods, and global consistent crop-specific land cover products. The greater attention to scalable and cloud-based processing platforms and explainable artificial intelligence model will lead to increased adoption of operations. Crop monitoring is a solution that can be instrumental in improving food security in the world, precision agriculture, and sustainable agricultural management through its solution resulting out of these issues.

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