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Assessment Of Deep Learning for Crop Type Mapping and Yield Prediction in Sub-Saharan Africa: A Systematic Review for Operational Agricultural Monitoring in Nigeria

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Abstract- The application of deep learning techniques in agriculture has gained significant attention due to their potential to improve crop monitoring, classification, and yield forecasting. However, evidence regarding their adoption, performance, and operational suitability within Sub-Saharan Africa remains fragmented. This study conducted a systematic literature review to synthesize existing evidence on deep learning architectures for crop type mapping and yield prediction in Sub-Saharan Africa. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework. Literature was retrieved from Scopus, Google Scholar, Frontiers, and MDPI databases using predefined search strings. An initial 4,777 records were identified, from which 27 studies met the inclusion criteria and were subjected to qualitative synthesis. The review examined deep learning architectures employed, remote sensing and geospatial datasets utilized, model performance, and emerging trends in agricultural monitoring. The findings revealed that Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Deep Neural Networks (DNNs), transfer learning frameworks, and hybrid models were the dominant architectures used for crop type mapping and yield prediction. Sentinel-2, Landsat, MODIS, UAV imagery, climatic datasets, and soil information constituted the primary data sources. The review further showed that deep learning models achieved high classification accuracies and strong predictive performance, particularly when multiple datasets were integrated through data fusion techniques. Emerging trends identified include transfer learning, explainable artificial intelligence, hybrid deep learning architectures, attention-based models, UAV-assisted monitoring, and IoT-enabled agricultural systems. The study concludes that deep learning technologies offer substantial potential for improving agricultural monitoring and yield forecasting across Sub-Saharan Africa. However, challenges relating to data scarcity, model transferability, and unequal geographical coverage remain. The study recommends increased investment in open agricultural datasets, multi-source data integration, and explainable artificial intelligence frameworks to enhance the scalability and operational deployment of deep learning systems in the region.

Keywords: Deep Learning, Crop Type Mapping, Yield Prediction, Remote Sensing, Agricultural Monitoring, Sub-Saharan Africa, Artificial Intelligence.

I. INTRODUCTION

Agriculture remains central to food security, rural livelihoods, employment generation, and economic stability in Sub-Saharan Africa, including Nigeria. However, crop production in the region is increasingly threatened by climate variability, drought, flooding, irregular rainfall, declining soil productivity, pests, diseases, and limited access to timely agricultural information.

These challenges are more pronounced in smallholder farming systems, where farms are often fragmented, irregularly shaped, rain-fed, and difficult to monitor using conventional survey methods (Rustowicz et al., 2019; Karst et al., 2020). As a result, timely and accurate information on crop type distribution, crop growth condition, and expected yield has become essential for food security planning, early warning, policy formulation, market forecasting, and operational agricultural monitoring.

Traditional agricultural monitoring systems in many African countries rely heavily on field surveys, farmer reports, and official crop statistics. Although these sources remain important, they are often expensive, labour-intensive, spatially limited, and slow to update during the growing season.

In data-scarce environments such as Nigeria and other parts of Sub-Saharan Africa, these limitations reduce the capacity of governments, researchers, and development agencies to respond quickly to emerging food production risks. Remote sensing and geospatial technologies have therefore become increasingly important because they provide repeated, large-area, and relatively low-cost observations of crop and environmental conditions (Lambert et al., 2018; Lee et al., 2022).

Recent advances in Earth Observation have expanded the range of datasets available for crop monitoring. Satellite products such as MODIS, Sentinel-2, Landsat, and climate datasets such as CHIRPS, TRMM, ERA5, and NASA POWER have been used to monitor vegetation condition, rainfall, temperature, phenology, water availability, and other crop growth indicators (Lee et al., 2022; Obahoundje et al., 2025).

In addition, unmanned aerial vehicle imagery has been applied for high-resolution crop yield estimation and phenotyping, especially where field-level variability is important (Alabi et al., 2022; de Villiers et al., 2024). These datasets are particularly relevant for smallholder farming systems because they can support crop type mapping, yield prediction, and early warning across large and heterogeneous agricultural landscapes.

Machine learning and deep learning methods have also gained attention in agricultural monitoring because of their ability to model complex and nonlinear relationships between spectral signals, weather conditions, soil properties, crop phenology, and yield outcomes. Earlier studies in Sub-Saharan Africa frequently applied conventional machine learning methods such as Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, Cubist, and K-nearest neighbour for crop mapping and yield estimation (Alabi et al., 2022; Lambert et al., 2018; Mupangwa et al., 2020).

More recently, deep learning approaches such as Convolutional Neural Networks, Artificial Neural Networks, Long Short-Term Memory networks, Deep Neural Networks, transfer learning, and attention-based models have been explored for crop type classification and yield prediction (Kaneko et al., 2019; Rustowicz et al., 2019; Bohra et al., 2025).

Evidence from existing studies shows that deep learning has significant potential for crop monitoring in Sub-Saharan Africa, but its performance varies across locations, crops, datasets, and modelling strategies. Rustowicz et al.

(2019) applied deep learning for crop type semantic segmentation in smallholder farms in Ghana and South Sudan and reported the challenges of cloud cover, small fields, irregular field shapes, and limited training data. Kaneko et al.

(2019) used MODIS data and an LSTM-based model to predict maize yields across six African countries, including Nigeria, but found that predictive performance differed substantially by country.

Similarly, Lee et al. (2022) demonstrated that Earth Observation and machine learning can support operational subnational maize yield forecasting in Sub-Saharan Africa, especially when sub-monthly and phenology-sensitive features are incorporated.

Despite these advances, the operational adoption of deep learning for agricultural monitoring in Nigeria remains limited. Many existing studies are experimental, crop-specific, or geographically restricted, and there is limited synthesis of how deep learning methods perform across the wider Sub-Saharan African context.

There are also persistent challenges related to insufficient ground-truth data, weak model transferability, limited explainability, inconsistent validation strategies, and inadequate representation of locally important crops beyond maize, soybean, and rice (Obahoundje et al., 2025; Olatinwo et al., 2026). For Nigeria, these gaps are important because an effective agricultural monitoring system must be scalable, reliable, interpretable, and adaptable to diverse agroecological zones and crop types.

A systematic review is therefore necessary to assess. This review assesses the state of deep learning for crop type mapping and yield prediction in Sub-Saharan Africa, with attention to its relevance for operational agricultural monitoring in Nigeria. The review is guided by the following research questions:

1. What deep learning architectures have been employed for crop type mapping and yield prediction in Sub-Saharan Africa?
2. What remote sensing and geospatial datasets are commonly utilized in deep learning-based crop monitoring studies within the region?
3. How do deep learning models perform in crop type classification and yield prediction applications?
4. What emerging trends and best practices can be identified from the existing literature on deep learning-driven crop monitoring and yield forecasting in Sub-Saharan Africa?

II. METHODOLOGY

2.1 Review Protocol

This systematic literature review (SLR) adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework, an evidence-based approach developed to improve the transparency, consistency, and reproducibility of systematic reviews (Page et al., 2021). The review process consisted of three major phases: (1) planning the review, (2) conducting the review, and (3) reporting the review, with each phase comprising a series of interconnected activities.

During the planning phase, the research questions were formulated based on the study objectives, and a review protocol was developed to guide the entire review process. The protocol specified the search strategy, databases to be searched, eligibility criteria, study selection procedures, data extraction framework, and synthesis approach. Predefined search strings and selection criteria were established to ensure consistency throughout the review.

The conducting phase involved systematic searches across selected databases using predefined search strings. Retrieved records were subjected to screening, eligibility assessment, and quality evaluation. Relevant information was subsequently extracted from eligible studies using a structured data extraction matrix.

The extracted data were synthesized according to the research questions focusing on deep learning architectures, remote sensing and geospatial datasets, model performance, and emerging trends in crop type mapping and yield prediction within Sub-Saharan Africa. The reporting phase involved the presentation of findings through descriptive statistics, thematic synthesis, summary tables, and narrative discussions. The review process was documented using a PRISMA flow diagram to ensure transparency and facilitate reproducibility of the study.

2.2 Search Strategies

The SLR included studies retrieved from four scientific databases, namely Scopus, Google Scholar, Frontiers, and MDPI. These databases were selected because of their extensive coverage of peer-reviewed literature in remote sensing, geospatial science, agriculture, artificial intelligence, and environmental studies.

The initial database search yielded 4,777 records comprising 657 records from Scopus, 4,100 records from Google Scholar, 7 records from Frontiers, and 13 records from MDPI. The search strategy involved the development of search queries using keywords and Boolean operators (“OR” and “AND”). Searches were conducted within the title, abstract, and keyword fields of the selected databases.

The search terms were derived from the major concepts underpinning the study, including deep learning, crop type mapping, crop classification, yield prediction, remote sensing, Earth observation, and Sub-Saharan Africa. Following several iterations and refinements to improve retrieval accuracy and relevance, the final search string adopted for the study was:

("deep learning" OR CNN OR LSTM OR Transformer) AND ("crop classification" OR "crop type mapping" OR "yield prediction") AND ("remote sensing" OR satellite OR "Earth observation") AND ("Sub-Saharan Africa" OR Africa)

Where necessary, minor modifications were made to accommodate the search requirements of individual databases while maintaining the conceptual integrity of the search strategy.

2.3 Eligibility Criteria

To ensure thematic relevance, methodological rigor, and geographical focus, a set of eligibility criteria was established and applied throughout the review process. The criteria consisted of inclusion criteria (IC) used to identify relevant studies and exclusion criteria (EC) used to eliminate irrelevant or unsuitable records. Table 1 presents the eligibility criteria adopted in this review.

Table 1: Inclusion and Exclusion Criteria for the Study

Inclusion Criteria (IC)	Exclusion Criteria (EC)
Studies focusing on crop type mapping, crop classification, agricultural monitoring, or crop yield prediction.	Studies unrelated to agriculture, crop monitoring, or yield prediction.
Studies employing deep learning techniques such as CNN, LSTM, Transformer, DNN, or hybrid deep learning models.	Studies relying solely on traditional statistical methods without machine learning or deep learning components.
Studies utilizing remote sensing, Earth observation, geospatial, UAV, climatic, or related datasets.	Studies without remote sensing, geospatial, or Earth observation data.
Studies conducted in Sub-Saharan Africa or containing Sub-Saharan African case studies.	Studies conducted exclusively outside Sub-Saharan Africa with no relevance to the region.
Studies published between 2015 and 2026.	Studies published before 2015.
Peer-reviewed journal articles, conference papers, and recognized technical reports.	Editorials, book reviews, commentaries, abstracts, and duplicate records.
Studies published in English and available in full text.	Studies not available in full text or published in languages other than English.

The eligibility criteria ensured that only studies directly relevant to the objectives and research questions of the review were included in the final synthesis.

2.4 Study Selection and Bias Assessment

The study selection process followed the PRISMA 2020 framework and consisted of four sequential stages: identification, screening, eligibility assessment, and inclusion. During the identification stage, all records retrieved from the selected databases were exported into a reference management system and merged into a single database. Duplicate records were subsequently identified and removed.

During the screening stage, the titles, abstracts, and keywords of the retrieved records were independently examined against the predefined inclusion and exclusion criteria. Studies that were clearly unrelated to deep learning applications in crop type mapping and yield prediction were excluded at this stage. The remaining articles were subjected to full-text assessment during the eligibility stage to determine their relevance to the study objectives and research questions.

To minimize selection bias and ensure methodological rigor, a structured quality assessment procedure was conducted on all eligible studies. The assessment focused on the clarity of research objectives, appropriateness of the deep learning methodology, adequacy of data sources, transparency of model development procedures, reporting of evaluation metrics, and validity of conclusions. Studies with insufficient methodological information or unclear results were excluded from the final synthesis.

The final set of studies included in the review formed the basis for data extraction and synthesis. The entire selection process was documented using a PRISMA flow diagram showing the number of records identified, screened, excluded, assessed for eligibility, and ultimately included in the review. This systematic procedure enhanced the transparency, reliability, and reproducibility of the review findings while minimizing the risk of publication and selection bias.

2.5 Data Extraction and Synthesis

Following the eligibility assessment and final selection of studies, a structured data extraction matrix was developed to systematically capture and synthesize relevant information from the selected publications. The matrix was designed to ensure consistency, transparency, and reproducibility during the extraction process. Prior to full-scale implementation, the extraction matrix was pilot-tested using approximately 20% of the selected studies to validate its structure and ensure that all relevant variables were adequately captured. Feedback obtained during the pilot phase informed subsequent refinements to the matrix.

The extraction matrix organized information into two major categories. The first category comprised general metadata, including bibliographic information such as author(s), publication year, article title, journal source, publisher, country of study, and document type.

The second category consisted of thematic and methodological information aligned with the research questions. These included crop type investigated, deep learning architecture employed, remote sensing and geospatial datasets used, data acquisition platforms, input variables, model development approaches, evaluation metrics, model performance indicators, key findings, and emerging trends.

Data synthesis was conducted using descriptive statistics and thematic analysis. Studies were grouped according to the research questions and analyzed comparatively. Deep learning architectures were categorized and their frequencies determined. Remote sensing and geospatial datasets were classified according to platform type and application. Model performance metrics such as Accuracy, F1-score, Precision, Recall, RMSE, MAE, and R^2 were extracted and compared across studies. Emerging trends and best practices were identified through thematic coding and synthesis of evidence across the selected studies. This systematic approach facilitated the integration of heterogeneous evidence and enabled the development of a comprehensive understanding of deep learning applications for crop type mapping and yield prediction in Sub-Saharan Africa.

III. RESULTS

3.1 Literature Search

The systematic literature search was conducted across four scientific databases: Scopus, Google Scholar, Frontiers, and MDPI. The initial search yielded a total of 4,777 records, comprising 657 records from Scopus, 4,100 records from Google Scholar, 7 records from Frontiers, and 13 records from MDPI. Following the removal of duplicate records and the application of the predefined inclusion and exclusion criteria, records were screened based on titles, abstracts, and keywords. Subsequently, full-text assessment was conducted to determine the eligibility of the remaining studies.

The screening and eligibility assessment process resulted in the inclusion of 27 studies that met all the predefined criteria and were considered suitable for qualitative synthesis. Of the selected studies, 12 were obtained through Google Scholar, 8 through Scopus, 4 through MDPI, and 3 through Frontiers (Figure 1).

Figure 1: Database Contribution to Selected Studies

The study selection process can further be summarized using a PRISMA flow diagram showing the stages of identification, screening, eligibility assessment, and final inclusion.

3.2 Literature Analysis

3.2.1 Dataset Overview

Analysis of the selected studies revealed extensive utilization of remote sensing, geospatial, climatic, and field-based datasets for crop type mapping and yield prediction. Satellite imagery constituted the most widely used data source, particularly Sentinel-2, Landsat, MODIS, and Planet imagery. These datasets were frequently combined with ancillary datasets such as climatic records, vegetation indices, soil information, and field observations to improve model performance.

UAV-based multispectral imagery was also commonly employed for high-resolution crop monitoring and yield estimation, particularly in soybean and maize studies. Recent studies demonstrated a growing trend toward integrating multiple data sources through data fusion approaches, combining satellite imagery with weather, soil, and IoT sensor data. Table 2 summarises the country/region, data sources, model architecture(s), and key reported performance outcome for each included study.

Table 2: Datasets Utilized in the Reviewed Studies

S/N	Author(s) & Year	Country/Region	Data Source(s)	Model(s)/ Algorithm(s)	Key Performance
1	Rustowicz et al. (2019)	Ghana; South Sudan	High-resolution, high-frequency satellite imagery	CNN – semantic segmentation	F1 57.3–69.7%; OA 60.9–85.3%
2	Kaneko et al. (2019)	Ethiopia, Kenya, Malawi, Nigeria, Tanzania, Zambia	MODIS (histogram features)	LSTM + Gaussian Process layer	R^2 0.50–0.56 (best countries); up to 0.63 (combined model)
3	Lee et al. (2022)	Kenya, Somalia, Malawi, Burkina Faso	Dekadal Earth Observation/climate data	EO-based machine-learning forecast system	NSE ≥ 0.6; MAPE ≤ 20% (skillful forecasts)
4	Alabi et al. (2022)	Nigeria	UAV multispectral imagery, GLCM texture	Cubist, XGBoost, GBM, SVM, Random Forest	R^2 up to 0.89 (Cubist/RF)
5	Obahoundje et al. (2025)	SSA, Asia, Americas (PRISMA review)	MODIS, TRMM, CHIRPS, ERA5	RF, SVM, ANN, ANFIS, XGBoost, LSTM, CNN (synthesis)	RF most-used algorithm (17–39% across tasks)
6	Lambert et al. (2018)	Mali	Sentinel-2 time series + ground survey	Random Forest classification	OA 80–85%; R^2 0.48–0.80 (yield)
7*	Lee, Jeong, Son & Lee (2019)	Not SSA-specific (comparator)	Weather data, farm sensors, crop images	CNN/R-CNN/YOLO (disease) + ANN (yield)	CNN 3.5–5.4% more accurate than R-CNN/YOLO
8	Karst et al. (2020)	Burkina Faso	Sentinel-2 + household field survey	Vegetation-index-based regression	R^2 0.40–0.54
9	Mupangwa et al. (2020)	Eastern & Southern Africa	Field/farmer survey data	LDA, LR, KNN, CART, Naive Bayes, SVM	Accuracy ≈61% (best: LDA)
10	Chew et al.	Rwanda	UAV RGB imagery	CNN (VGG16,	F1 0.86 overall

S/N	Author(s) & Year	Country/Region	Data Source(s)	Model(s)/ Algorithm(s)	Key Performance
	(2020)			transfer learning/ImageNet)	(0.49–0.96 by class)
11	Kerner et al. (2020)	Kenya	Sentinel-derived smallholder benchmark dataset	k-Nearest Neighbours	Accuracy 64% (maize); 70% (cassava)
12	Samasse et al. (2020)	Burkina Faso, Mauritania, Mali, Niger, Senegal	Landsat-8 + Google Earth Engine	Random Forest	OA 90.1%; cropland user's accuracy 79%
13*	Wang et al. (2020)	Southeast India (comparator)	Sentinel-2, DigitalGlobe, crowdsourced images	CNN	74% accuracy (3-class crop discrimination)
14	Ly et al. (2021)	Pan-African	NDVI, land surface temperature, rainfall, evapotranspiration	Artificial Neural Network	OOS RMSE ≈0.986–0.999 (normalised production)
15	Duke et al. (2022)	West Africa	UAV multispectral + Sentinel-1 SAR	SVM, Random Forest	OA 94.78% (UAV-SVM); 92.58% (SAR-RF)
16	Agboka et al. (2022)	East Africa	Climatic and edaphic variables	Fuzzy-logic–genetic algorithm; symbolic regression	$R^2 > 0.90$; RMSE < 0.09
17	Cedric et al. (2022)	West Africa	Climatic, weather, chemical/yield data	Decision Tree, multivariate logistic regression, KNN	R^2 95.3% (Decision Tree)
18	Jemo et al. (2023)	Nigeria	Mapped soil properties + weather variables	Conditional inference Random Forest	R^2 0.46–0.75
19	Talaat (2023)	General/IoT precision agriculture	IoT sensor + climate data	Decision Tree, Random Forest, ExtraTree Regressors	Model scores 0.9814–0.9933
20	Sisheber et al. (2023)	Ethiopia	Landsat–MODIS data fusion (ESTARFM)	SAFY crop model + EO data assimilation	rRMSE 16% (maize); 23% (rice)
21	de Villiers et al. (2024)	South Africa	UAV multispectral imagery	Random Forest, GradBoost, CatBoost, XGBoost	R^2 0.05–0.67 (GradBoost best)
22	Kuradusenge et al. (2024)	Rwanda	IoT weather/soil sensors	IoT-integrated machine learning regression	MAPE 0.177–0.339
23	Sitienei (2024)	Kenya	Farmer survey/questionnaire data (n=900)	Random Forest, KNN, XGBoost	RMSE 0.4563 (XGBoost best)

S/N	Author(s) & Year	Country/Region	Data Source(s)	Model(s)/ Algorithm(s)	Key Performance
24	Bohra et al. (2025)	Kenya & United States	Vegetation-index time series + meteorological data	Deep Neural Network (transfer learning/fine-tuning)	R^2 0.632 (fine-tuned model)
25	Olayinka et al. (2025)	Sub-Saharan Africa	Soil, atmospheric, and plant physical parameters	NB, SVM, KNN, DT, ANN, hybrid ANN–KNN	Accuracy 99.45% (hybrid ANN–KNN)
26	Olatinwo et al. (2026)	Sub-Saharan Africa	Multimodal soil, crop, and weather data	XGBoost, LGBM, CatBoost, SVM, RF, ANN–kNN + LIME	R^2 ≈76% (CatBoost); LIME-based interpretability
27	Fofanah (2026)	Sierra Leone	FAOSTAT + CHIRPS rainfall + NASA POWER	XGBoost, Gradient Boosting, Random Forest	RMSE 284 kg/ha (climate-augmented XGBoost) vs 428 (statistics-only)

Note: Entries marked with an asterisk (*) denote non-SSA comparator studies included for methodological relevance. OA = overall accuracy; R^2 = coefficient of determination; RMSE = root mean square error; rRMSE = relative RMSE; MAPE = mean absolute percentage error; NSE = Nash–Sutcliffe Efficiency; CRPS = continuous ranked probability score; PICP = prediction interval coverage probability.

3.2.2 Geographical Distribution of Case Studies

The reviewed studies were distributed across several countries within Sub-Saharan Africa as presented in Table 3. East Africa recorded the highest concentration of studies, particularly in Kenya, Ethiopia, Rwanda, Tanzania, and Uganda. West Africa was represented primarily by Nigeria, Ghana, and Sierra Leone, while Southern Africa included Zambia and Malawi. Several studies adopted multi-country approaches covering multiple regions simultaneously, reflecting increasing efforts to develop scalable deep learning models applicable across diverse agroecological zones.

Table 3: Geographical Distribution of Reviewed Studies

Region	Countries Represented	Frequency	Percentage (%)
East Africa	Kenya, Ethiopia, Rwanda, Tanzania, Uganda	11	40.74
West Africa	Nigeria, Ghana, Sierra Leone	7	25.93
Southern Africa	Zambia, Malawi	4	14.81
Multi-country SSA Studies	Multiple SSA Countries	5	18.52
Total		27	100.00

The results suggest that East Africa has attracted the greatest research attention due to the availability of agricultural monitoring programs, field datasets, and remote sensing initiatives. However, considerable research gaps remain in Central Africa and parts of West Africa.

3.2.3 Crop Type Analysis in the Studies Based on Region

The reviewed studies focused on a variety of crop types, with maize emerging as the most frequently investigated crop. The dominance of maize-related studies reflects its importance as a staple food crop and its contribution to food security across Sub-Saharan Africa (Table 4). Rice studies were mainly concentrated in West Africa, while soybean studies were distributed across selected countries where soybean production is economically important (Figure 2). Several studies adopted multi-crop classification approaches involving the identification and mapping of multiple crop types using satellite and UAV imagery.

Table 4: Distribution of Crop Types by Region

Crop Type	East Africa	West Africa	Southern Africa	Multi-country Studies
Maize	5	2	2	3
Rice	0	3	0	1
Soybean	1	1	0	1
Multiple Crops	5	1	2	0

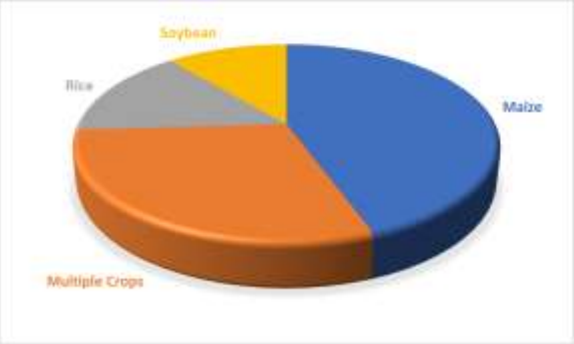

Figure 2: Relative Distribution of Crop Types

The analysis indicates that maize dominated the reviewed literature, accounting for approximately 44.44% of the studies. Multi-crop classification studies constituted 29.63% of the reviewed articles, demonstrating increasing interest in developing generalized crop mapping frameworks capable of supporting large-scale agricultural monitoring systems. Rice and soybean received comparatively less attention despite their growing importance to food security and agricultural development within the region.

3.2.4 Deep Learning Architectures Used for Crop Type Mapping and Yield Prediction

The analysis of the selected studies revealed a diverse application of deep learning and machine learning architectures for crop type mapping and yield prediction across Sub-Saharan Africa. The reviewed studies demonstrated a gradual transition from traditional machine learning approaches toward more sophisticated deep learning frameworks capable of handling large volumes of spatial and temporal data.

Distribution of Deep Learning Architectures

Based on the reviewed studies, Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Deep Neural Networks (DNNs), and hybrid deep learning models emerged as the dominant architectures employed for agricultural monitoring applications (Figure 3).

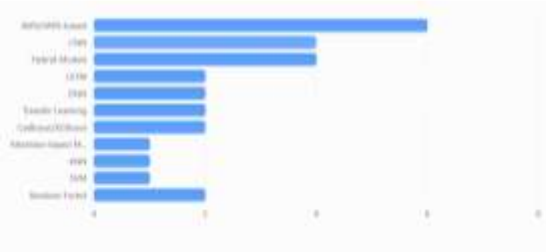

Figure 3: Distribution of Deep Learning Architectures in Reviewed Studies

The results indicate that ANN-based models were the most frequently utilized approaches, particularly for yield prediction studies. Their popularity can be attributed to their flexibility in handling nonlinear relationships between crop yields and environmental variables such as weather conditions, soil properties, and vegetation indices. Studies by Ly et al. (2021), Olayinka et al. (2025), and Olatinwo et al. (2026) demonstrated the effectiveness of ANN-based models for predicting maize yields under varying agroecological conditions (Table 2).

Deep Learning Architectures for Crop Type Mapping

Crop type mapping studies predominantly employed CNN-based architectures due to their superior ability to extract spatial features from remotely sensed imagery. CNN models were particularly effective when applied to Sentinel-2, Landsat, and UAV imagery, enabling accurate discrimination among crop classes. For example, Rustowicz et al. (2019) utilized deep CNN-based semantic segmentation techniques for crop classification, while chew et al. (2020) employed a transfer learning approach based on the VGG16 architecture, achieving high classification performance (Table 2). The effectiveness of CNNs stems from their capability to automatically learn hierarchical features from image data without requiring extensive manual feature engineering. This characteristic makes them particularly suitable for crop mapping applications involving high-dimensional satellite imagery.

Deep Learning Architectures for Yield Prediction

Unlike crop classification studies, yield prediction studies predominantly relied on ANN, LSTM, DNN, and hybrid models. Yield prediction is inherently a temporal problem requiring the modeling of crop growth dynamics over time. Consequently, recurrent architectures such as LSTM networks gained prominence because of their ability to capture temporal dependencies in vegetation and climatic datasets. Kaneko et al. (2019) demonstrated the utility of an LSTM-Gaussian Process framework for maize yield prediction across multiple African countries, while Zhu et al. (2026) employed temporal attention mechanisms to improve forecasting accuracy (Table 2). These findings suggest that temporal deep learning architectures are becoming increasingly important in operational agricultural forecasting systems.

Emergence of Hybrid and Transfer Learning Models

One notable trend identified in the reviewed studies is the increasing adoption of hybrid and transfer learning approaches. Hybrid models combine the strengths of multiple algorithms to improve prediction accuracy and model generalizability.

Examples include ANN-KNN models, CNN-LSTM combinations, and ensemble learning frameworks integrating CatBoost and XGBoost algorithms. Transfer learning approaches were particularly useful in addressing the limited availability of labeled agricultural datasets within Sub-Saharan Africa. Studies by Chew et al. (2020) and Bohra et al. (2025) demonstrated that pre-trained deep learning models could be effectively adapted to local agricultural contexts with relatively small training datasets (Table 2).

Emerging Trends in Deep Learning Architectures

Recent studies reveal a shift toward attention-based and probabilistic deep learning frameworks capable of handling uncertainty in agricultural systems. The Probabilistic Deep Network (PDN) proposed by Zhu et al. (2026) represents a significant advancement because it incorporates uncertainty estimation into crop yield forecasting. Similarly, explainable artificial intelligence (XAI) techniques are increasingly being integrated into agricultural prediction models to enhance model interpretability and support decision-making.

The findings indicate that deep learning architectures have evolved from conventional ANN and CNN models toward hybrid, transfer learning, and attention-based frameworks. This evolution reflects the increasing complexity of agricultural monitoring systems and the growing availability of multi-source geospatial datasets.

3.2.5 Remote Sensing and Geospatial Data Sources Used in Agricultural Monitoring

Remote sensing and geospatial datasets formed the foundation of the deep learning models reviewed in this study. The findings indicate that satellite imagery remains the most important source of information for crop type mapping and yield prediction, although recent studies increasingly incorporate complementary datasets such as UAV imagery, climatic records, soil information, and IoT sensor data.

Distribution of Data Sources

The reviewed studies utilized a wide range of data sources, reflecting the multidimensional nature of agricultural monitoring.

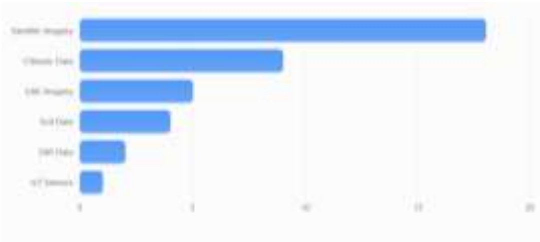

Figure 3: Major Data Sources Used in Agricultural Monitoring Studies

Satellite imagery accounted for approximately two-thirds of the reviewed studies, highlighting its central role in agricultural monitoring applications across Sub-Saharan Africa.

Satellite-Based Data Sources

Among the satellite platforms employed, Sentinel-2 emerged as the most frequently utilized data source. Its high spatial resolution, frequent revisit cycle, and free accessibility make it particularly suitable for crop monitoring applications. Landsat and MODIS datasets were also widely used, especially for regional-scale analyses and long-term yield prediction studies (Table 5).

Table 5: Major Satellite Platforms Used in Reviewed Studies

Satellite Platform	Major Application Areas
Sentinel-2	Crop classification, crop monitoring, yield estimation
Sentinel-1 SAR	Crop discrimination, all-weather monitoring
Landsat Series	Land cover mapping, crop monitoring
MODIS	Regional yield forecasting and vegetation monitoring
Planet Imagery	High-resolution crop mapping
CHIRPS	Rainfall monitoring and yield forecasting
NASA POWER	Climatic variable integration for yield prediction

The dominance of Sentinel-2 imagery can be attributed to its combination of high spatial resolution (10–20 m), multispectral capabilities, and open-access availability.

Integration of Climatic and Environmental Data

A significant proportion of studies incorporated climatic datasets such as rainfall, temperature, solar radiation, and evapotranspiration. Products such as CHIRPS and NASA POWER were frequently integrated with satellite-derived vegetation indices to improve yield prediction accuracy (Figure 3).

This integration reflects the recognition that crop productivity is influenced not only by vegetation conditions observable from satellite imagery but also by climatic and environmental factors that affect crop growth throughout the growing season.

Increasing Adoption of UAV-Based Monitoring

The reviewed literature demonstrates growing adoption of UAV platforms for agricultural monitoring. UAVs provide ultra-high-resolution imagery that enables detailed assessment of crop health, canopy structure, and yield variability at field scale. Studies by Alabi et al. (2022), Duke et al. (2022), and de Villiers et al. (2024) demonstrated that UAV-based systems can significantly improve yield estimation accuracy when combined with machine learning and deep learning algorithms (Tables 2 & 5). Although UAVs remain less frequently used than satellite platforms due to operational costs and limited spatial coverage, they offer substantial advantages for precision agriculture applications.

Emergence of Multi-Source Data Fusion

One of the most important trends identified in the reviewed studies is the movement toward multi-source data integration. Rather than relying on a single data source, recent studies increasingly combine satellite imagery, climatic variables, soil properties, UAV observations, and field measurements (Table 6).

Table 6: Common Data Fusion Approaches Identified in the Reviewed Studies

Data Combination	Purpose
Satellite + Climate Data	Yield prediction
Satellite + Soil Data	Crop productivity assessment
Satellite + UAV Data	High-accuracy crop mapping
Satellite + SAR Data	Improved crop discrimination
Satellite + IoT Sensors	Real-time monitoring
Climate + Soil + Satellite Data	Precision yield forecasting

This trend reflects the growing recognition that agricultural systems are complex and multidimensional. Multi-source data fusion enables deep learning models to capture a broader range of environmental factors, thereby improving predictive performance and model robustness.

Implications for Operational Agricultural Monitoring
The findings suggest that operational agricultural monitoring systems in Sub-Saharan Africa should prioritize open-access satellite datasets such as Sentinel-2, Landsat, and MODIS while integrating climatic and environmental information wherever possible.

Furthermore, the increasing use of UAVs, SAR data, and IoT technologies indicates a transition toward more comprehensive and data-rich agricultural monitoring frameworks. Such developments are expected to enhance the accuracy, scalability, and reliability of crop type mapping and yield prediction systems across the region.

3.2.6 Performance Evaluation of Deep Learning Models

The performance of deep learning and machine learning models varied considerably across studies. For crop type mapping, Rustowicz et al. (2019) achieved an average F1 score and overall accuracy of 57.3% and 60.9% in Ghana, and 69.7% and 85.3% in South Sudan. These results show that deep learning can classify crop types in smallholder systems, but performance is affected by local data quality, cloud cover, field size, and crop heterogeneity.

Chew et al. (2020) reported an overall test F1 score of 0.86 for UAV-based crop identification in Rwanda, although performance differed by crop, with legumes proving more difficult to classify than bananas and maize (Table 7). Conventional machine learning models also performed strongly in some classification studies. Lambert et al. (2018) reported 80% overall accuracy for Sentinel-2-based crop type mapping in Mali, increasing to 85% when parcel boundaries from very high-resolution imagery were incorporated.

Duke et al. (2022) reported strong classification performance using UAV and SAR datasets, with SVM achieving 94.78% accuracy using UAV data and Random Forest achieving 92.58% accuracy using SAR data. Samasse et al. (2020) produced a 30-m cropland map for the West African Sahel with 90.1% overall accuracy, demonstrating the value of high-density training data and locally optimized modelling.
For yield prediction, performance was more variable. Kaneko et al. (2019) found that LSTM-based maize yield prediction performed better in Kenya, Tanzania, and Zambia, with average R^2 values from 0.50 to 0.56, but weaker results in Ethiopia, Malawi, and Nigeria, with average R^2 values from -0.60 to 0.13. This country-level variation highlights a major challenge for operational monitoring: models may not transfer well across regions without local calibration. Lee et al. (2022) showed that sub-monthly and serial Earth Observation features improved forecast skill, with skillful forecasts emerging during the growing season before harvest. Alabi et al. (2022) reported strong soybean yield prediction in Nigeria, with Cubist and Random Forest models reaching R^2 values up to 0.89. Karst et al.

(2020) achieved R^2 values between 0.40 and 0.54 for household-level yield estimation in Burkina Faso, indicating moderate but operationally useful prediction skill (Table 7). Recent studies emphasize advanced modelling strategies. Bohra et al. (2025) showed that transfer learning can improve corn yield mapping in Kenya, with a fine-tuned DNN achieving an overall R^2 of 0.632. Olatinwo et al. (2026) highlighted the importance of explainability, reporting that CatBoost performed best among several models and using LIME to interpret plot-level yield drivers.

Zhu et al. (2026) demonstrated that probabilistic deep networks can improve regional production forecasting while also providing calibrated uncertainty bounds. These studies suggest that future operational systems should not only maximize accuracy but also quantify uncertainty and explain predictions to users.

Table 7: Performance of Deep Learning Models for Crop Type Classification and Yield Prediction

Author(s) & Year	Model	Task	Performance
Rustowicz et al. (2019)	CNN Segmentation	Crop type mapping	F1 = 57.3–69.7%; OA = 60.9–85.3%
Kaneko et al. (2019)	LSTM-GP	Yield prediction	R^2 = 0.50–0.63
Lambert et al. (2018)	RF + Sentinel-2	Crop mapping	OA = 80–85%; Yield R^2 = 0.48–0.80
Karst et al. (2020)	VI-based models	Yield prediction	R^2 = 0.40–0.54
Chew et al. (2020)	VGG16 CNN	Crop classification	F1 = 0.86
Kerner et al. (2020)	KNN	Crop classification	Accuracy = 64–70%
Samasse et al. (2020)	Random Forest	Cropland mapping	OA = 90.1%
Duke et al. (2022)	SVM	Crop classification	OA = 94.78% (UAV)
Duke et al. (2022)	RF	Crop classification	OA = 93.84%
Alabi et al. (2022)	RF/Cubist	Yield prediction	R^2 up to 0.89
Agboka et al. (2022)	Symbolic Regression	Yield prediction	$R^2 > 0.90$
Cedric et al. (2022)	Decision Tree	Yield prediction	R^2 = 0.953
Jemo et al. (2023)	Random Forest	Yield prediction	R^2 = 0.46–0.75
Sisheber et al. (2023)	Data Fusion Model	Yield estimation	rRMSE = 16–23%
de Villiers et al. (2024)	Gradient Boosting	Yield prediction	R^2 = 0.05–0.67
Kuradusenge et al. (2024)	ML-IoT System	Yield prediction	MAPE = 0.177–0.339
Bohra et al. (2025)	Transfer Learning DNN	Yield mapping	R^2 = 0.632
Olayinka et al. (2025)	ANN-KNN	Yield prediction	Accuracy = 99.45%
Olatinwo et al. (2026)	CatBoost	Yield prediction	$R^2 \approx 0.76$
Zhu et al. (2026)	PDN	Yield prediction	RMSE = 0.31 t/ha
Fofanah (2026)	XGBoost	Yield prediction	RMSE reduced by ~33%

3.2.7 Emerging Trends and Best Practices in Deep Learning-Based Agricultural Monitoring

The synthesis of the reviewed studies revealed several emerging trends and best practices that are shaping the future of deep learning-driven agricultural monitoring in Sub-Saharan Africa. These developments reflect ongoing efforts to improve prediction accuracy, enhance model scalability, address data limitations, and support operational decision-making in agricultural systems.

Transition from Conventional Machine Learning to Deep Learning

One of the most prominent trends identified in the reviewed studies is the gradual transition from conventional machine learning algorithms toward advanced deep learning architectures. Earlier studies frequently relied on algorithms such as Random Forest, Decision Trees, Support Vector Machines, and K-Nearest Neighbors. However, recent studies increasingly employ CNNs, LSTMs, DNNs, Transformers, and hybrid deep learning frameworks. This transition reflects the superior capability of deep learning models to automatically extract complex spatial and temporal patterns from large volumes of remote sensing data. As satellite imagery archives continue to expand, deep learning techniques are becoming increasingly attractive for large-scale agricultural monitoring applications.

Growth of Transfer Learning Approaches

Transfer learning emerged as one of the most important methodological developments identified in the reviewed literature. The scarcity of labeled agricultural datasets remains a major challenge across many Sub-Saharan African countries. Transfer learning addresses this limitation by adapting pre-trained models developed using large datasets to specific local agricultural applications.

Studies by Chew et al. (2020) and Bohra et al. (2025) demonstrated that transfer learning significantly improves classification and prediction performance while reducing training data requirements. This approach is particularly valuable in data-scarce environments where extensive field observations may be unavailable.

Increasing Adoption of Multi-Source Data Fusion

Another major trend is the integration of multiple data sources within a single modeling framework. Rather than relying solely on satellite imagery, recent studies increasingly combine remote sensing data with weather information, soil characteristics, UAV observations, and field measurements.

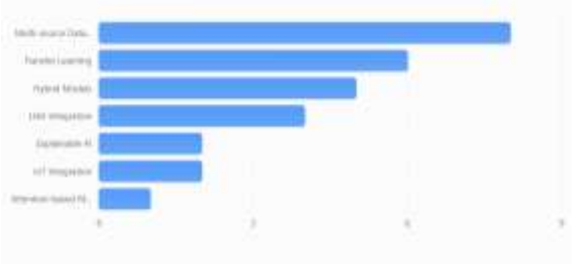

Figure 4: Emerging Trends Identified in the Reviewed Studies

The widespread adoption of data fusion techniques reflects the recognition that agricultural productivity is influenced by multiple interacting factors. Integrating diverse datasets allows deep learning models to capture these interactions more effectively, thereby improving predictive performance.

Expansion of UAV-Based Agricultural Monitoring

The reviewed studies also revealed increasing use of Unmanned Aerial Vehicles (UAVs) for agricultural monitoring. UAVs provide ultra-high-resolution imagery capable of detecting subtle variations in crop health, nutrient status, and yield potential. Studies by Alabi et al. (2022), Duke et al. (2022), and de Villiers et al. (2024) demonstrated the effectiveness of UAV-based systems in supporting precision agriculture applications.

Although UAVs are currently less scalable than satellite platforms, their integration with deep learning algorithms offers significant potential for field-level crop management and yield estimation.

Emergence of Explainable Artificial Intelligence

As deep learning models become increasingly complex, concerns regarding model interpretability have also grown. Consequently, explainable artificial intelligence (XAI) is emerging as an important area of research. Studies such as Olatinwo et al. (2026) emphasize the need for transparent and interpretable models capable of providing understandable explanations for their predictions.

The adoption of XAI techniques is expected to enhance stakeholder confidence and facilitate the operational deployment of deep learning systems in agricultural decision-making processes.

Development of Attention-Based and Probabilistic Models

Recent studies indicate a movement toward attention-based and probabilistic deep learning architectures capable of addressing uncertainty in agricultural systems. The temporal attention mechanisms employed by Zhu et al. (2026) improved the ability of models to identify critical periods influencing crop growth and yield formation.

Similarly, probabilistic deep learning models offer the advantage of generating uncertainty estimates alongside predictions, thereby providing more reliable information for risk assessment and decision support.

Best Practices Identified from the Reviewed Studies

Based on the synthesis of evidence, several best practices emerged for implementing deep learning-based agricultural monitoring systems:

1. Utilize open-access satellite datasets such as Sentinel-2, Landsat, and MODIS for large-scale monitoring applications.
2. Integrate multiple data sources, including climatic, soil, and field datasets, to improve model performance.
3. Employ transfer learning approaches where labeled datasets are limited.
4. Incorporate UAV imagery for detailed field-scale analysis and precision agriculture applications.
5. Apply robust model evaluation procedures using multiple performance metrics.
6. Promote explainable AI techniques to improve transparency and user trust.
7. Adopt hybrid and attention-based architectures for complex crop monitoring and yield forecasting tasks.

The reviewed studies demonstrate that agricultural monitoring in Sub-Saharan Africa is undergoing rapid transformation driven by advances in deep learning, remote sensing, cloud computing, and data integration technologies. These innovations are expected to play a critical role in improving agricultural productivity, food security, and climate resilience across the region.

IV. DISCUSSION

4.1 Synthesis of Findings Across the Studies

The findings paint a picture of a field that is methodologically active but unevenly mature. Deep learning architectures like CNNs, LSTMs, and ANN/DNN variants have shown clear value for image- and time-series-based crop type mapping, where they can learn directly from spectral, textural, or temporal patterns without extensive manual feature engineering.

For yield prediction, however, classical and ensemble machine learning methods remain the de facto standard across most of the reviewed literature, not because deep learning is unsuitable in principle, but plausibly because the tabular, moderately sized, and feature-engineered datasets typical of SSA yield studies do not yet provide the volume of labelled examples that deep architectures generally require to outperform well-tuned ensemble methods. This pattern echoes the explicit observation by Obahoundje et al. (2025) that infrastructure and data limitations push African applications toward simpler, more interpretable models relative to the more advanced techniques seen in Asian regions.

The datasets underpinning this literature reveal a pragmatic reliance on freely available global satellite and climate products (Sentinel-1/2, Landsat, MODIS, CHIRPS, ERA5, NASA POWER) supplemented, where resources allow, by UAV imagery and ground survey or IoT sensor data. This pattern is encouraging from an operational standpoint: it suggests that meaningful crop monitoring capability does not strictly require expensive proprietary imagery or dedicated national satellite infrastructure, provided that ground-truth labelling and validation are adequately resourced. The performance evidence however, makes clear that data quality and quantity, rather than algorithmic sophistication alone, remain the binding constraint on model performance: the same or similar architectures perform markedly better in data-rich contexts (e.g., Germany, in Rustowicz et al., 2019) than in data-scarce SSA smallholder settings, and performance for under-represented countries such as Nigeria has, in at least one multi-country study, lagged behind that achieved for better-instrumented countries such as Kenya (Kaneko et al., 2019).

The emerging trends (transfer learning, multimodal fusion, explainable AI, uncertainty quantification, and IoT integration) collectively point toward a maturing field that is beginning to grapple with the practical requirements of operational deployment, rather than focusing solely on maximising benchmark accuracy. The relative novelty of these practices, however, and their concentration in only a handful of the most recent studies, indicates that they have not yet become standard practice across the field as a whole.

4.2 Implications for Operational Agricultural Monitoring in Nigeria

Several implications for Nigeria follow directly from this synthesis. First, the comparative absence of Nigeria-specific deep learning applications and the lack of a dedicated, openly available Nigerian smallholder benchmark dataset represent a foundational gap: the Kenya smallholder dataset released through Radiant MLHub (Kerner et al., 2020) illustrates the catalytic effect that a single, well-curated, openly available national dataset can have on subsequent research activity, and a comparable Nigerian effort would likely have similar value. Second, given that fine-tuning-based transfer learning has shown demonstrable benefit in adapting models from data-rich to data-scarce contexts (Bohra et al., 2025; Chew et al., 2020), Nigerian researchers and agencies may be able to accelerate model development by fine-tuning architectures pre-trained on better-resourced countries within the region (e.g., Kenya, Rwanda) or on global benchmarks, rather than starting model development entirely from scratch.

Third, the demonstrated value of combining national crop statistics with free satellite climate data in a similarly data-constrained country, Sierra Leone (Fofanah, 2026), suggests a low-cost, near-term pathway for Nigeria: combining existing National Bureau of Statistics and Federal Ministry of Agriculture and Food Security crop production records with open CHIRPS, ERA5, or NASA POWER climate data could plausibly yield meaningful forecasting improvements without requiring new satellite infrastructure. Fourth, the existing Nigeria-focused work on multimodal soil-and-weather-based yield prediction (Jemo et al., 2023) provides a credible domestic methodological foundation that could be extended with UAV or Sentinel-derived vegetation indices, following the multimodal fusion approaches demonstrated elsewhere in the region (de Villiers et al., 2024; Olatinwo et al., 2026).

Fifth, given that any operational system intended to inform government decision-making, input subsidy targeting, or early-warning bulletins will require the trust of non-specialist stakeholders, the explainability practices demonstrated by Olatinwo et al. (2026) merit early adoption in any Nigerian deployment, rather than being treated as an optional refinement to be added after a system is already in use.

4.3 Methodological Gaps in the Existing Literature

The review identifies several methodological gaps that cut across the broader literature. Validation practices are frequently insufficiently conservative: many studies report performance based on a single growing season or a randomly assigned train/test split, which can overstate the model's likely performance on a genuinely unseen future season, particularly an atypical one. Studies employing temporally or spatially held-out validation such as the leave-one-year-out approach used by Bohra et al. (2025) or the expanding-window walk-forward evaluation used by Fofanah (2026) are comparatively rare but provide a more credible indication of real-world forecasting skill, and their wider adoption would strengthen the evidentiary basis for operational deployment decisions. In addition, the heterogeneity of reported performance metrics across studies (F1, overall accuracy, R^2, RMSE, rRMSE, MAPE, NSE, and others) makes direct cross-study comparison difficult and precluded a quantitative meta-analysis in this review; greater standardisation of reporting, or at minimum the consistent reporting of a small common set of metrics, would materially improve the cumulative value of future studies in this domain.

4.4 Limitations of This Review

Despite the contributions of this review, the following limitations are acknowledged:

i. The review was restricted to studies published in English and indexed within the selected databases. Consequently, relevant studies published in other languages or contained in regional repositories may not have been captured.
ii. The review relied on published literature, which may introduce publication bias because studies reporting positive or significant results are more likely to be published than studies reporting negative or inconclusive findings.
iii. Geographical distribution of the reviewed studies was uneven, with a higher concentration of studies conducted in East Africa and relatively limited representation from Central Africa and some parts of West Africa. This imbalance may affect the generalizability of the findings across the entire Sub-Saharan African region.
iv. The reviewed studies employed diverse datasets, model architectures, performance metrics, and evaluation procedures. Such methodological heterogeneity limited the possibility of conducting a formal meta-analysis and necessitated the use of qualitative synthesis approaches.
v. Rapid evolution of deep learning technologies means that new architectures, datasets, and methodologies continue to emerge. Consequently, some recent developments may not have been captured within the temporal scope of this review.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This systematic literature review synthesized evidence from 27 studies on the application of deep learning techniques for crop type mapping and yield prediction in Sub-Saharan Africa. The review demonstrated that deep learning is an increasingly important tool for agricultural monitoring, enabling the extraction of meaningful information from large volumes of remote sensing and geospatial data. The findings showed that CNNs, ANNs, LSTMs, DNNs, transfer learning models, and hybrid architectures are the most commonly employed techniques in the region. Among these, CNN-based models were particularly effective for crop classification tasks, while LSTM and hybrid models were widely applied to yield prediction due to their ability to capture temporal relationships in agricultural datasets. The study also established that satellite imagery, particularly Sentinel-2, Landsat, and MODIS, are the dominant source of information for agricultural monitoring, although recent studies increasingly integrate climatic, soil, UAV, and IoT datasets to improve model performance.

The review further revealed that deep learning models generally achieve high levels of classification accuracy and yield prediction performance, especially when multiple data sources are combined. Emerging trends such as transfer learning, explainable artificial intelligence, attention mechanisms, and multi-source data fusion are shaping the next generation of agricultural monitoring systems. These developments indicate a gradual transition from conventional machine learning approaches toward more intelligent, scalable, and operationally relevant agricultural analytics frameworks.

The study concludes that deep learning-based agricultural monitoring systems possess significant potential for supporting food security, precision agriculture, and climate-resilient farming in Sub-Saharan Africa. Nevertheless, sustained efforts are required to address data limitations, improve model generalizability, and expand research coverage across underrepresented regions of the continent.

5.2 Recommendations

5.3 Recommendations

Based on the findings of this systematic literature review, the following recommendations are made:

1. Governments, agricultural research institutions, and development agencies in Sub-Saharan Africa should invest in the development of open-access agricultural datasets containing crop, soil, weather, and field observation data to support the training and validation of deep learning models.
2. Researchers should promote the integration of multi-source datasets, including satellite imagery, climatic records, soil information, UAV observations, and IoT-generated data, to improve the accuracy, robustness, and generalizability of crop type mapping and yield prediction models.
3. Greater attention should be given to the adoption of transfer learning approaches, particularly in countries where labeled agricultural datasets are limited. Transfer learning can reduce data requirements and facilitate the adaptation of existing models to local agricultural conditions.
4. Agricultural monitoring projects should increasingly utilize freely available Earth observation datasets such as Sentinel-1, Sentinel-2, Landsat, MODIS, CHIRPS, and NASA POWER to support cost-effective and scalable monitoring systems.
5. The integration of UAV technologies with deep learning models should be encouraged for field-level crop monitoring, precision agriculture, and early detection of crop stress, particularly in high-value agricultural production systems.
6. Future research should explore advanced deep learning architectures such as Transformers, attention-based networks, probabilistic deep learning models, and foundation models to improve crop classification and yield forecasting under varying climatic conditions.
7. Agricultural extension agencies and policymakers should collaborate with geospatial scientists, data scientists, and artificial intelligence experts to facilitate the operational deployment of deep learning-based agricultural monitoring systems for food security planning and climate resilience initiatives.
8. Regional and international organizations should support the establishment of shared geospatial data infrastructures and cloud-based agricultural monitoring platforms that enable real-time access to agricultural information across Sub-Saharan Africa.

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