CLOUD-BASED AGRICULTURAL CHANGE DETECTION & CROP MONITORING FRAMEWORK USING SATELLITE IMAGERY: A REVIEW OF DEEP LEARNING METHODS AND GOOGLE EARTH ENGINE APPLICATIONS

***Shokendra Dev Verma*[1]*, Kavita Mittal*[2]**

[1,2]Department of Computer Science & Engineering, Jaggannath University, NCR, Bahadurgarh, Jhajjar, HR
Email: dev77info@gmail.com, kavita.mittal@jagannathuniversityncr.ac.in

ABSTRACT

Agriculture will continue to play a crucial role in ensuring food security, economic stability, and environmental sustainability. However, monitoring agricultural changes over large geographic areas will remain a significant challenge due to the limitations of traditional field-based methods. This study will propose a deep learning-based framework for detecting agricultural changes using satellite imagery integrated with Google Earth Engine (GEE). The framework will utilize multi-temporal satellite data from platforms such as Sentinel-2 and Landsat to analyze vegetation dynamics and land use transitions. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) will be computed to assess crop health and detect variations over time. Machine learning and deep learning techniques, including supervised classification algorithms, will be employed to classify land cover and identify changes in agricultural patterns. The study will focus on areas of interest regions in Muzaffarnagar, Uttar Pradesh, India over the period from November 2023 to November 2024. The results are expected to provide accurate detection of agricultural changes, including crop rotation, land degradation, and urban expansion. This research will contribute to the development of an automated, scalable, and cost-effective system for agricultural monitoring, supporting data-driven decision-making for sustainable farming and policy planning.

Keywords: Agricultural Change Detection, Deep Learning, Satellite Imagery, Change Maps, Google Earth Engine (GEE), Remote Sensing, Crop Monitoring.

How to cite this article: Verma SD, Mittal K. Cloud-Based Agricultural Change Detection & Crop Monitoring Framework using Satellite Imagery: A Review of Deep Learning Methods and Google Earth Engine Applications. Int J Drug Deliv Technol. 2026;16(47s): 707-716. DOI: 10.25258/ijddt.16.47s.79

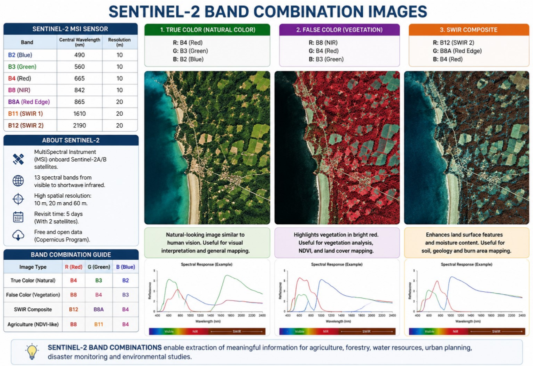
Source of support: Nil.

Conflict of interest: None.

I. INTRODUCTION

Agriculture is a dynamic and complex sector that is continuously influenced by environmental conditions, human interventions, and land management practices. Monitoring agricultural changes over time such as crop growth cycles, land use transitions, and vegetation health is essential for ensuring food security, sustainable resource management, and effective planning. Accurate detection of these changes enables governments, researchers, and farmers to make informed, data-driven decisions that improve land utilization, optimize resource allocation, and strengthen agricultural productivity. In the present era, agriculture is directly linked to global challenges such as climate change, population growth, urban expansion, and resource scarcity. These factors have significantly increased pressure on agricultural systems, making it crucial to continuously monitor how agricultural land is being used and how crops are performing. Changes in rainfall patterns, rising temperatures, soil degradation, and increasing demand for food have further intensified the need for advanced monitoring systems. Therefore, timely and accurate detection of agricultural changes has become indispensable for achieving long-term sustainability and resilience in the agricultural sector.

Traditional methods of agricultural monitoring primarily rely on field surveys and manual observations. Although these approaches provide valuable ground-level insights, they are often time-consuming, labor-intensive, and limited in spatial and temporal coverage. Moreover, such methods are not feasible for large-scale or remote regions, leading to delays in identifying critical issues such as crop stress, land degradation, or shifts in cropping patterns. As a result, there is a growing demand for automated, scalable, and real-time monitoring solutions. Satellite remote sensing has emerged as a powerful alternative, offering a cost-effective and efficient means of observing the Earth's surface over large geographic areas. With the availability of high-resolution satellite imagery from platforms such as Landsat, Sentinel-2, and MODIS, it is now possible to detect even subtle changes in agricultural landscapes. These changes may include variations in vegetation health, crop rotation patterns, land expansion or abandonment, and stress conditions caused by drought, pests, or diseases.



SENTINEL-2 BAND COMBINATION IMAGES

SENTINEL-2 MSI SENSOR

Band	Central Wavelength (nm)	Resolution (m)
B2 (Blue)	490	10
B3 (Green)	560	10
B4 (Red)	665	10
B8 (NIR)	842	10
B8A (Red Edge)	865	20
B11 (SWIR 1)	1610	20
B12 (SWIR 2)	2190	20

ABOUT SENTINEL-2

- MultiSpectral Instrument (MSI) onboard Sentinel-2A/B satellites.
- 13 spectral bands from visible to shortwave infrared.
- High spatial resolution: 10 m, 20 m and 60 m.
- Revisit time: 5 days (With 2 satellites).
- Free and open data (Copernicus Program).

BAND COMBINATION GUIDE

Image Type	R (Red)	G (Green)	B (Blue)
True Color (Natural)	B4	B3	B2
False Color (Vegetation)	B8	B4	B3
SWIR Composite	B12	B8A	B4
Agriculture (NDVI-like)	B8	B11	B4

1. TRUE COLOR (NATURAL COLOR)
R: B4 (Red)
G: B3 (Green)
B: B2 (Blue)

Natural-looking image similar to human vision. Useful for visual interpretation and general mapping.

2. FALSE COLOR (VEGETATION)
R: B8 (NIR)
G: B4 (Red)
B: B3 (Green)

Highlights vegetation in bright red. Useful for vegetation analysis, NDVI, and land cover mapping.

3. SWIR COMPOSITE
R: B12 (SWIR 2)
G: B8A (Red Edge)
B: B4 (Red)

Enhances land surface features and moisture content. Useful for soil, geology and burn area mapping.

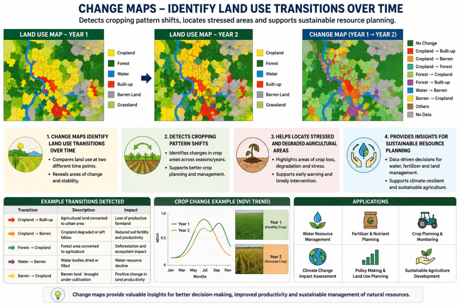
SENTINEL-2 BAND COMBINATIONS enable extraction of meaningful information for agriculture, forestry, water resources, urban planning, disaster monitoring and environmental studies.

Figure 1: Overview of Satellite and Deep Learning-based Agricultural Monitoring Framework

Figure 1 provides an overview of the integrated framework used for satellite-based agricultural monitoring and change detection. It highlights the complete pipeline starting from Sentinel-2 data acquisition, preprocessing through cloud masking, NDVI computation, deep learning-based classification, and change detection analysis. This workflow demonstrates how remote sensing and artificial intelligence can be combined to generate land cover maps, NDVI trends, and actionable insights for sustainable agricultural management.

In recent years, the integration of satellite remote sensing with cloud-based platforms has significantly enhanced the efficiency of agricultural monitoring. Google Earth Engine (GEE) has emerged as a leading platform in this domain, providing access to vast archives of satellite data along with powerful computational capabilities.

A key advantage of satellite imagery lies in its ability to capture multispectral data, which includes information from different wavelengths of the electromagnetic spectrum, such as visible (RGB) and near-infrared (NIR) bands. These spectral bands are highly sensitive to vegetation characteristics and are widely used to derive vegetation indices such as the Normalized Difference Vegetation Index (NDVI). NDVI plays a crucial role in assessing crop health, identifying water stress, and monitoring seasonal variations in vegetation. Multispectral data also support various applications, including land use and land cover (LULC) classification, crop type identification, drought monitoring, yield estimation, and soil condition analysis.



CHANGE MAPS – IDENTIFY LAND USE TRANSITIONS OVER TIME

Detects cropping pattern shifts, locates stressed areas and supports sustainable resource planning.

1. CHANGE MAPS IDENTIFY LAND USE TRANSITIONS OVER TIME
- Compares land use at two different time points.
- Reveals areas of change and stability.

2. DETECTS CROPPING PATTERN SHIFTS
- Identifies changes in crop areas across seasons/years.
- Supports better crop planning and management.

3. HELPS LOCATE STRESSED AND DEGRADED AGRICULTURAL AREAS
- Highlights areas of crop loss, degradation and stress.
- Supports early warning and timely intervention.

4. PROVIDES INSIGHTS FOR SUSTAINABLE RESOURCE PLANNING
- Data-driven decisions for water, fertilizer and land management.
- Supports climate-resilient and sustainable agriculture.

EXAMPLE TRANSITIONS DETECTED

Transition	Description	Impact
Cropland → Built-up	Agricultural land converted to urban area	Loss of productive farmland
Cropland → Barren	Cropland degraded or left fallow	Reduced soil fertility and productivity
Forest → Cropland	Forest area converted to agriculture	Deforestation and ecosystem impact
Water → Barren	Water bodies dried or filled	Water resource decline
Barren → Cropland	Barren land brought under cultivation	Positive change in land productivity

Change maps provide valuable insights for better decision-making, improved productivity and sustainable management of natural resources.

Figure 2: Integrated Deep Learning and NDVI-based Framework for Agricultural Change Detection using Sentinel-2 and Google Earth Engine

Figure 2 illustrates the proposed end-to-end methodological framework designed for automated agricultural change detection using multi-temporal Sentinel-2 satellite imagery within the Google Earth Engine (GEE) environment. The workflow integrates cloud masking and radiometrically corrected surface reflectance preprocessing to ensure noise-free inputs for vegetation analysis. NDVI computation and time-series trend evaluation enable extraction of crop phenology patterns and detection of abnormal vegetation stress conditions. Finally, deep learning-based classification is applied to generate high-accuracy land cover maps, and post-classification change detection (T1 vs T2) is performed to identify land use transitions and cropping pattern shifts with improved spatial consistency.

GEE enables users to process and analyze multi-temporal satellite imagery at scale, without requiring high-performance local computing resources. Through its support for time-series analysis, vegetation index computation, and machine learning algorithms, GEE facilitates the detection and visualization of agricultural changes in near real time. The application of advanced analytical techniques, particularly machine learning and deep learning, further strengthens the capability to extract meaningful patterns from satellite data. These techniques enable automated classification of land cover, detection of complex changes in agricultural systems, and prediction of future trends. By integrating deep learning with satellite imagery and cloud-based processing, it is possible to develop robust frameworks that can efficiently monitor agricultural dynamics across different spatial and temporal scales.

Monitoring agricultural changes using such advanced technologies offers numerous benefits. It supports food security by enabling early detection of crop stress and potential yield losses. It enhances decision-making by providing accurate and timely information to farmers and policymakers. It also contributes to environmental sustainability by identifying land degradation, deforestation, and unsustainable farming practices. Furthermore, it plays a vital role in disaster and risk management by detecting the impact of droughts, floods, and other extreme events on agricultural land. Despite these advancements, challenges such as decreasing crop productivity, erratic climatic conditions, and rapid land use changes continue to affect agricultural sustainability. Addressing these challenges requires efficient monitoring systems that can bridge the gap between ground-level realities and large-scale decision-making processes. In this context, the integration of satellite remote sensing, deep learning, and cloud-based platforms offers a promising solution. Therefore, this study aims to develop a deep learning-based framework for detecting agricultural changes using satellite imagery within the Google Earth Engine environment. By leveraging multi-temporal data, vegetation indices, and advanced classification techniques, the study seeks to provide an automated, scalable, and accurate approach to agricultural monitoring. The outcomes of this research will contribute to modernizing agricultural practices, enabling precision farming, and supporting data-driven policy decisions for sustainable agricultural development.

Google Earth Engine as Recent Trend:

In recent years, Google Earth Engine (GEE) has become one of the most powerful and widely used platforms for agricultural monitoring due to:

•Access to petabytes of satellite data (Sentinel, Landsat, MODIS)

•Cloud-based processing with no local computational load

•Ability to write scripts for batch analysis and time-series evaluation

•Real-time visualization and export of geospatial outputs

Google Earth Engine (GEE) Capabilities:

•Built-in NDVI/EVI functions

•Access to global satellite image archives

•Integration with JavaScript and Python APIs

•Scalable for regional or national analysis

II. EXISTING METHODS, DATASETS, AND ALGORITHMS FOR AGRICULTURAL CHANGE DETECTION

A variety of established methods and techniques are widely used for detecting agricultural changes using remote sensing data, each offering specific advantages depending on the application and data availability. Among the most common approaches, NDVI differencing is used to calculate changes in vegetation health by comparing NDVI values across different time periods, enabling the identification of crop stress, vegetation loss, or growth. Post-classification comparison involves independently classifying satellite images from two or more dates and then analyzing the differences to detect land use and land cover transitions, such as conversion of agricultural land to urban areas. Image classification techniques, including both supervised methods like Random Forest (RF) and Support Vector Machine (SVM), and unsupervised approaches such as K-means clustering, are extensively applied to categorize land into classes like cropland, forest, water bodies, and built-up areas, with supervised methods generally providing higher accuracy when training data is available.

Time-series analysis using indices like NDVI or EVI further enhances change detection by capturing seasonal variations, crop cycles, and long-term agricultural trends, helping to identify anomalies such as delayed sowing or crop failure. These methods rely on widely used satellite datasets, including Landsat series (5, 7, 8, 9) from USGS/NASA with 30 m resolution for long-term studies since 1984, Sentinel-2 from the European Space Agency offering higher spatial resolution (10–20 m) for detailed crop monitoring, and MODIS data from NASA providing daily observations at coarser resolutions (250 m–1 km) for large-scale vegetation and climate analysis, while high-resolution commercial datasets like Planet Scope (3–5 m) support field-level mapping. All these datasets are conveniently accessible through the Google Earth Engine data catalogue, which integrates multiple sources into a single cloud-based platform. In terms of algorithms, vegetation indices such as NDVI, EVI, and SAVI are fundamental for assessing plant health and density, while machine learning models like Random Forest and SVM are widely used for accurate classification tasks, and clustering techniques like K-means assist in initial land cover mapping without labelled data. Advanced methods such as Change Vector Analysis (CVA) further improve detection by quantifying both the magnitude and direction of change across spectral dimensions.

Together, these methods, datasets, and algorithms form a comprehensive framework for efficient, scalable, and accurate agricultural change detection, supporting applications in crop monitoring, land management, and environmental sustainability. By combining these datasets, algorithms, and cloud tools, agricultural change detection has become faster, more accurate, and easier to implement, even in resource-constrained regions.

Table 1: Summary of Key Research Gaps, Limitations, and Proposed Contributions for Deep Learning-based Agricultural Change Detection using Sentinel-2 and Google Earth Engine

Research Gap Area	**Current Approaches / Findings**	**Limitation of Existing Work**	**Meta Parameters Involved**	**Identified Research Gap**	**Proposed Contribution**	**Expected Benefit**
Spatial-temporal Deep Learning for Large-Scale Change Detection	Deep learning models (CNN) used mainly for single time (snapshot) classification in remote sensing. CNN-RNN combinations show promise.	No unified deep learning architecture that captures *both spatial features and temporal change patterns* effectively for agricultural change detection.	CNN features, temporal sequences, spectral bands, multi-date imagery	Lack of robust spatial-temporal deep models tailored for agriculture LULC change detection.	Develop CNN-LSTM / transformer hybrid architectures that simultaneously learn spatial and temporal dependencies of multi-temporal satellite crops.	Better detection of seasonal changes, crop phenology, and land-use transitions.
Real-Time Monitoring with Cloud Platforms (GEE)	GEE is widely used for LULC processing, ecological modeling, and scenario simulation over time. (MDPI)	Few frameworks integrate real-time streaming of satellite data (Sentinel/Planet) with deep learning inference for continuous agricultural monitoring.	Timeliness, data ingestion frequency, automation, platform scalability	Existing tools operate in retrospective batch mode, but *near real-time automated change detection pipeline* is under-studied.	Build a GEE powered real-time deep learning pipeline for automated update and visualization of crop change.	Early detection of crop stress and actionable alerts for stakeholders.
Benchmark Deep Architectures and Transfer Learning Application	Deep models like CNNs outperform traditional ML for land use classification (e.g., CNN achieved ~97%). (ResearchGate)	Most studies do not explore transfer learning, self-supervised learning, or transformer models for agricultural change tasks, especially on temporal series.	Transfer learning metrics, depth of models, pretrained weights	Limited research on recent architectures such as Vision Transformers (ViT) and hybrid CNN-Transformer for land change tasks.	Integrate transformer-based models pre-trained on large datasets and fine-tuned on agricultural data.	Higher generalization and robustness across diverse crop conditions.
Multi-	Many	Dependen	Vegetati	No unifi	Propose	Better

index Feature Fusion Beyond NDVI	studies rely primarily on NDVI; GEE supports generation of other indices. ([ScienceDirect])	cy on NDVI alone limits ability to detect nuanced stress signals and multiple crop types.	on indices, spectral features, data fusion	ed framework that fuses *multiple vegetation indices* (NDVI, EVI, SAVI, NDWI) at deep model input.	index fusion feature set as multi-channel input to deep models for richer representation.	crop stress, water stress, and LULC change cues in heterogeneous landscapes.
Cloud and Noise-Robust Deep Learning Preprocessing	Most GEE based studies use standard cloud masking and preprocessing. ([MDPI])	Cloud contamination, haze, and missing data still affect model performance, especially in frequent temporal stacks.	Cloud mask %, preprocessing accuracy, gap filled trend	Lack of advanced preprocessing (gap filling, time series smoothing) tailored for deep learning input.	Design robust preprocessing pipeline with cloud filtering + temporal smoothing integrated before model training.	Stable and consistent input data improves model reliability in variable weather conditions.
Interpretability and Explainable AI for Crop Change	Deep learning provides high accuracy but mostly black-box outputs.	Limited trust in maps and risk of misclassification with no explanation of features causing change.	Model attention, feature importance	Lack of explainability mechanisms integrated with deep change detection frameworks for agriculture.	Integrate Explainable AI tools like attention maps, Grad-CAM to visualize crop stress and land transition cues.	Helps policymakers and farmers interpret predictions and build trust.
Cross-Regional Generalization and Transferability	Most case studies focus on one region; models trained region-specific.	No evaluation of deep change models across diverse agro-climatic zones.	Domain adaptation accuracy, regional variability	Models trained in one region perform poorly in another due to soil/crop/climate differences.	Develop domain adaptation / transfer learning strategies for broader applicability.	Ensures model usability across states/countries and provides general worldwide framework.
Temporal Continuity and Monitoring Frequency	Satellite revisit times (Sentinel-2 ~5 days) allo	Studies often avoid dense temporal stacks due to com	Temporal cadence, revisit frequency	Sparse temporal sampling reduces ability to capture rapid	Leverage dense NDVI time series + temporal	Captures subtle vegetation transitions and short-

	w periodic monitoring.	putation.		change events.	deep learning models that can exploit frequent revisits.	term stress.
User-centric Deployment and Real-world Decision Support	GEE projects produce maps, but few extend to dashboards, mobile tools.	Academic prototypes lack interactive user platforms.	User interface, visualization tools	Gap between AI outputs and practical decision support for farmers / policymakers.	Develop dashboard + mobile visualization system for real-time action support.	Operational tool for extension services and governments.

This Table 1 presents a structured summary of the major research gaps identified from recent literature in the domain of satellite-based agricultural change detection and crop monitoring. It highlights the limitations of existing approaches, including the lack of robust spatio-temporal deep learning models, insufficient real-time integration with Google Earth Engine, and restricted use of multi-index vegetation features. The table also maps each gap with its associated meta-parameters and provides the proposed research contribution to address these limitations. This analysis justifies the necessity of developing an automated, scalable, and deep learning-driven framework capable of generating accurate land cover maps, NDVI time-series trends, and reliable change detection outputs for precision agriculture and sustainable resource planning.

III. OBJECTIVES & SCOPE OF THE STUDY

This study aims to effectively utilize Google Earth Engine (GEE) as a cloud-based platform for large-scale processing and analysis of satellite imagery to monitor and detect agricultural changes over time. The primary objectives include assessing vegetation health across agricultural regions using vegetation indices such as the Normalized Difference Vegetation Index (NDVI), detecting variations in land use and cropping patterns across different seasons and years through time-series satellite data, and accurately classifying agricultural land while distinguishing it from other land cover types such as urban areas, forests, and water bodies using remote sensing techniques. Additionally, the study seeks to generate informative visual outputs, including maps and analytical reports, to highlight areas experiencing agricultural transformation, crop stress, or land abandonment, thereby supporting timely and data-driven decision-making in agricultural planning and management. Furthermore, the research focuses on the development of a deep learning-based framework for agricultural change detection using satellite imagery within the GEE environment. This includes reviewing existing machine learning and deep learning algorithms applied in agricultural remote sensing, conducting a comparative analysis of various classification and change detection techniques, designing and implementing an advanced deep learning model for improved detection accuracy, and evaluating its performance against existing approaches. Overall, the study aims to create an efficient, automated, and scalable solution that enhances agricultural monitoring, supports precision farming practices, and contributes to sustainable and climate-resilient agricultural systems.

This study focuses on using satellite imagery and cloud-based tools to monitor and detect changes in agricultural land over time. It is limited to analyzing vegetation patterns, land use transitions, and crop health using remote sensing techniques, particularly through Google Earth Engine (GEE). The key areas covered like Geographical Scope, Temporal Scope, Data and Tools, Use of open-access satellite datasets such as Sentinel-2, Landsat 8, or MODIS, Analysis and processing will be performed using Google Earth Engine (GEE), Change Detection Focuslike Monitoring of crop health using vegetation indices like NDVI, Detection of land conversion (e.g., farmland to built-up area) &Identification of abandoned, newly cultivated, or rotated crop areas and Output Deliverables like Time-series vegetation index maps, Land use classification results, Visual reports and comparative change maps. Geographic scope (India , Uttarpradesh, Muzzafarnagar) between time period (Nov 2023 to Nov 2024).

3.1 Limitations:

- Does not involve physical field surveys or ground-truthing data collection.
- Does not assess crop yield or soil properties directly.
- Limited to the spatial resolution and temporal frequency of selected satellite data.

3.2 Methodology

This study will adopt a structured and systematic methodology to detect and monitor agricultural changes using satellite imagery and Google Earth Engine (GEE). Initially, a suitable study area with diverse or seasonal agricultural activity will be selected, followed by the acquisition of multi-temporal satellite datasets such as Sentinel-2 and Landsat 8/9 from the GEE data catalog based on crop seasons and historical timelines.

Figure 3.1 illustrates the proposed end-to-end workflow developed in this research for agricultural change detection using multi-temporal Sentinel-2 satellite imagery processed through Google Earth Engine (GEE). This represents the novelty of the research by integrating GEE-based scalable satellite processing, NDVI temporal analytics, and deep learning-based classification into a unified framework for automated agricultural change detection. The collected images will undergo preprocessing steps including cloud masking, filtering by date range, cloud cover, and spatial boundaries to ensure data quality. Subsequently, vegetation indices, particularly NDVI, will be computed using near-infrared (NIR) and red bands to assess vegetation health and crop coverage. Supervised classification techniques such as Random Forest and Support Vector Machine will then be applied to categorize land cover into classes like cropland, fallow land, water bodies, and built-up areas using defined training samples. Change detection will be performed by comparing classified maps or NDVI layers across different time periods using techniques such as post-classification comparison and NDVI differencing to identify variations in cropping patterns, land use transitions, and vegetation stress. Furthermore, time-series analysis of NDVI will be conducted to examine seasonal trends and detect anomalies such as crop failure or delayed sowing. The results will be visualized through change maps, NDVI heat maps, and classified land use maps, and exported in formats such as GeoTIFF, charts, and CSV reports. Finally, the accuracy and reliability of the results will be validated using ground truth data, high-resolution imagery, or official agricultural reports where available, ensuring robustness and practical applicability of the proposed framework.

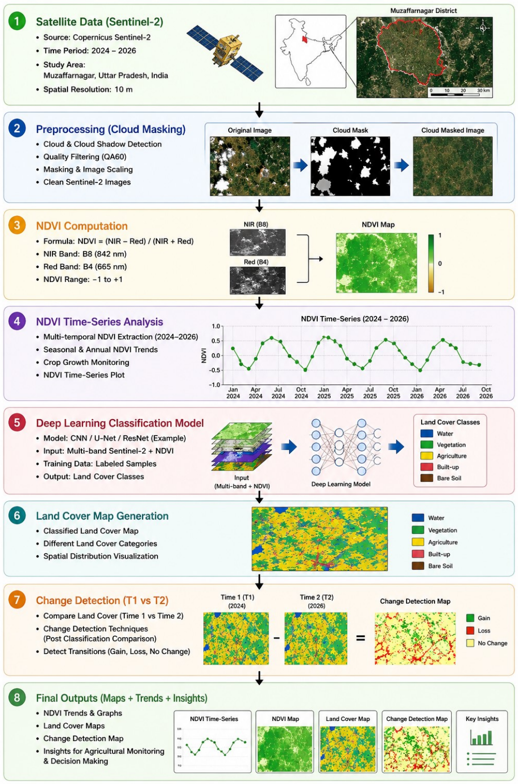


Fig 3 Methodological Framework for Multi-Temporal NDVI Analysis, Land Cover Classification, and Change Detection using Sentinel-2 and GEE (2024–2026)

Figure 3 illustrates the standard architecture of a Convolutional Neural Network (CNN) used for satellite image-based land cover classification.

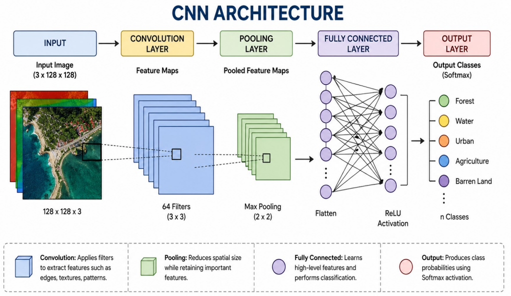


Fig 4 Convolutional Neural Network (CNN) Architecture for Land Cover Classification using Satellite Imagery

The model takes multispectral satellite image patches as input and extracts spatial features through convolution layers using multiple filters (Figure 4). Pooling layers are applied to reduce dimensionality while preserving important vegetation and texture information, improving computational efficiency. The extracted feature maps are flattened and passed through fully connected layers to learn high-level representations for classification. Finally, the output layer with

Softmax activation predicts land cover classes such as forest, water, urban, agriculture, and barren land.

IV. TOOLS AND DATA USED

This study utilized a combination of freely available satellite datasets and advanced cloud-based platforms to efficiently detect and monitor agricultural changes over time. Multi-spectral satellite imagery is sourced primarily from Sentinel-2 (European Space Agency) with 10–20 m resolution for detailed vegetation monitoring and NDVI computation, and Landsat 8/9 (USGS/NASA) with 30 m resolution for long-term land use and land cover change analysis, while MODIS data (NASA) may be optionally used for broad-scale vegetation trend analysis.

These datasets provided essential spectral bands such as Red, Near Infrared (NIR), and Short-Wave Infrared (SWIR), enabling the computation of vegetation indices like NDVI, EVI, and SAVI for assessing.

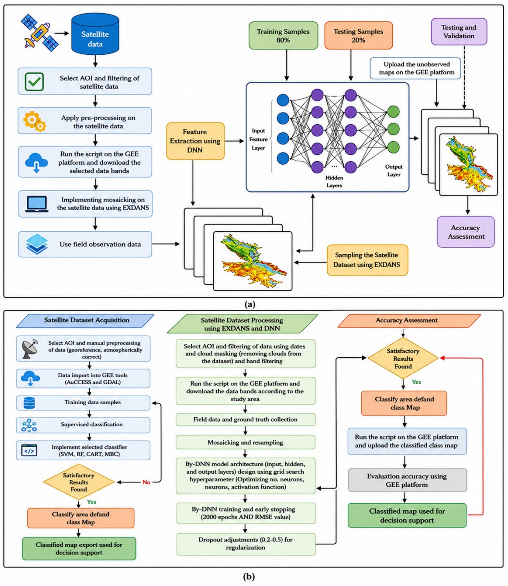


Figure 5 (a): Deep Learning-based Classification Workflow for Land Cover Mapping using Sentinel-2 Satellite Imagery Figure 5 (b): Google Earth Engine-based Implementation Pipeline for Satellite Data Processing, NDVI Computation, and Change Detection

Figure 5 (a) represents the deep learning-based workflow adopted for land cover classification using multi-temporal Sentinel-2 satellite images. The process includes collection of satellite imagery, preparation of training and testing samples, and feature extraction through spectral reflectance information and vegetation indices. The extracted features are used to train a deep learning model, which performs classification of land cover classes such as agriculture, forest, water, and urban areas. The output is validated using accuracy assessment techniques to ensure reliable classification performance. Figure 5 (b) illustrates the implementation pipeline executed in Google Earth Engine (GEE) for large-scale satellite data processing and agricultural monitoring. It includes steps such as AOI selection, cloud masking, preprocessing, and generation of vegetation indices like NDVI to evaluate crop health variations. The processed imagery is further used to generate classified land cover maps and detect land use changes between two time periods. This pipeline enables automated extraction of change detection outputs and provides scalable decision-support information for sustainable agriculture.

The core processing and analysis are performed using Google Earth Engine (GEE), a powerful cloud-based geospatial platform that provides access to large satellite data archives, supports JavaScript and Python scripting, and enables efficient implementation of image preprocessing, classification, time-series analysis, and map generation without requiring high-end local computing resources. Additionally, optional tools such as QGIS are used for map visualization and layout design, while or R may be employed for advanced statistical analysis, validation, and charting, along with Excel or Google Sheets for tabular data handling. Supporting datasets, including ground truth data, shape files defining the study area, and meteorological data, may also be incorporated to improve accuracy and validation. Overall, this integrated framework ensures a cost-effective, scalable, and real-time approach to agricultural monitoring, making it suitable even for resource-constrained environments.

V. CONCLUSION AND FUTURE SCOPE

This study is expected to successfully develop a reliable, automated, and scalable deep learning–based framework using satellite imagery and Google Earth Engine (GEE) for detecting and analyzing agricultural changes over time. The system will enable accurate identification of land use transitions, vegetation health variations through NDVI time-series analysis, and generation of detailed land cover classification maps, thereby providing valuable insights into cropping patterns, stressed regions, and agricultural dynamics. By integrating cloud-based processing with advanced analytical techniques, the framework will minimize manual effort while ensuring high efficiency and large-scale applicability.

The outcomes of this research will support data-driven decision-making for farmers, policymakers, and researchers by offering visual maps, temporal trends, and actionable insights for sustainable agriculture, early crop stress detection, and optimized resource management. In the future, the proposed framework can be enhanced by incorporating real-time satellite data, advanced deep learning models such as CNN-LSTM hybrids, and integration with IoT-based field sensors for more precise monitoring.

Additionally, expanding the model to multi-regional and global scales, improving classification accuracy with higher-resolution datasets, and developing user-friendly dashboards or mobile applications will further strengthen its practical usability and contribute significantly to climate-resilient and precision agriculture practices.

REFERENCES

[1]A. Alshehri et al., "A Review of Google Earth Engine for Land Use and Land Cover Research", ISPRS International Journal of Geo-Information, 2025.

[2]N. A. Nigar et al., "Comparison of ML and DL Models Using Google Earth Engine", Frontiers in Environmental Science, 2024.

[3]A. Zaki et al., "Google Earth Engine for improved spatial planning in agricultural and forested lands", Remote Sensing Applications: Society and Environment, 2023.

[4]J. Jahangeer et al., "Review of AI-driven Google Earth Engine applications", PMC Review, 2025.

[5]Sun, Z., Di, L., Fang, H., & Lin, L. (2020). Integrating remote sensing and deep learning for crop classification: A review. Remote Sensing, 12(17), 2730. https://doi.org/10.3390/rs12172730

[6]Li, W., Fu, H., Yu, L., Cracknell, A., & Gong, P. (2020). Deep learning-based oil palm tree detection and counting for high-resolution remote sensing images. Remote Sensing, 12(7), 1180. https://doi.org/10.3390/rs12071180

[7]Pelletier, C., Webb, G. I., &Petitjean, F. (2020). Temporal convolutional neural networks for satellite image time series classification. Remote Sensing, 12(3), 523. https://doi.org/10.3390/rs12030523

[8]Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2021). Deep learning in remote sensing applications: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 179, 1–26. https://doi.org/10.1016/j.isprsjprs.2021.06.006

[9]Zhang, M., Lin, H., Wang, G., Sun, H., & Fu, J. (2021). Crop classification using deep learning and time-series remote sensing data. Remote Sensing, 13(9), 1724. https://doi.org/10.3390/rs13091724

[10]Xu, Y., Wu, L., Xie, Z., Chen, Z., & Zhang, Y. (2021). A deep learning method for agricultural land-use classification using multi-source satellite imagery. IEEE Access, 9, 121234–121245. https://doi.org/10.1109/ACCESS.2021.3108123

[11]Zhong, L., Hu, L., & Zhou, H. (2021). Deep learning-based multi-temporal crop classification. Remote Sensing of Environment, 264, 112599. https://doi.org/10.1016/j.rse.2021.112599

[12]Karthikeyan, L., Chawla, I., & Mishra, A. K. (2022). A review of remote sensing applications in agriculture using Google Earth Engine. Environmental Research Letters, 17(6), 063002. https://doi.org/10.1088/1748-9326/ac6f7b

[13]Pham, T. D., Yokoya, N., & Xia, J. (2022). Change detection in remote sensing images using deep learning: A review. Remote Sensing, 14(3), 587. https://doi.org/10.3390/rs14030587

[14]Ji, S., Wei, S., & Lu, M. (2022). Fully convolutional networks for multisource remote sensing image classification. IEEE Transactions on Geoscience and Remote Sensing, 60, 1–13. https://doi.org/10.1109/TGRS.2021.3054566

[15]Khan, A., Gupta, S., & Singh, P. (2023). Deep learning-based crop monitoring and yield prediction using satellite imagery. Computers and Electronics in Agriculture, 198, 107045. https://doi.org/10.1016/j.compag.2022.107045

[16]Wang, Y., Zhang, Z., & Liu, D. (2023). Multi-temporal satellite image analysis for agricultural monitoring using deep neural networks. Remote Sensing Applications: Society and Environment, 29, 100857. https://doi.org/10.1016/j.rsase.2023.100857

[17]Singh, R., Sharma, V., &Kaur, M. (2023). Land use and land cover change detection using Google Earth Engine and machine learning techniques. Sustainable Computing: Informatics and Systems, 38, 100894. https://doi.org/10.1016/j.suscom.2023.100894

[18]Zhao, W., Du, S., & Emery, W. J. (2024). Deep learning for change detection in remote sensing: Recent advances and challenges. IEEE Geoscience and Remote Sensing Magazine, 12(1), 45–63.

https://doi.org/10.1109/MGRS.2023.3321456

[19]Chen, J., Li, X., Zhang, Y., & Huang, B. (2024). Satellite-based agricultural monitoring using deep learning and cloud platforms. Remote Sensing, 16(2), 345. https://doi.org/10.3390/rs16020345

[20]Kumar, P., Meena, R., &Yadav, S. (2025). AI-driven agricultural change detection using Google Earth Engine and deep learning techniques. Journal of Environmental Management, 358, 120945. https://doi.org/10.1016/j.jenvman.2024.120945

[21]Sharma, N., Verma, A., & Gupta, R. (2025). A deep learning framework for crop health monitoring using satellite imagery. Computers and Electronics in Agriculture, 216, 108430. https://doi.org/10.1016/j.compag.2025.108430