Advances in AI-Based Land Use and Land Cover Classification: A Review of Deep Learning and Remote Sensing Integration

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The integration of Artificial Intelligence (AI) with remote sensing has transformed Land Use and Land Cover (LULC) classification, enabling more accurate, efficient, and scalable environmental monitoring. This review synthesizes recent advancements in AI-driven LULC classification, with a focus on deep learning, transfer learning, hybrid approaches, and explainable AI (XAI). Recent studies demonstrate that AI techniques significantly enhance classification accuracy and adaptability across diverse geospatial datasets, supporting applications such as urban expansion monitoring, ecological assessment, reforestation analysis, and real-time land management. Despite these advancements, challenges remain regarding spectral resolution, model interpretability, computational efficiency, and data scarcity. This review highlights these limitations and discusses emerging solutions, including multimodal data fusion, lightweight AI models, and scalable MLOps frameworks. The findings provide insights for researchers, practitioners, and policymakers to guide future work in sustainable land management and environmental monitoring.

Keywords: Land Use and Land Cover (LULC); Remote Sensing; Artificial Intelligence (AI); Deep Learning; Machine Learning; Satellite Imagery; Image Classification

Introduction:

Land use and land cover (LULC) classification has long been a focal point in Earth observation studies [1]. Land cover refers to the observable physical characteristics of the land at a given time, while land use indicates the extent of human activities related to the utilization of land and its resources [2]. Land use is closely linked with changes in land cover, both of which play a significant role in altering the environment [3]. Land cover, in particular, is continuously modified by urbanization processes [4]. Mapping land use and land cover consistently draws the attention of researchers, governments, and international organizations due to its strong association with diverse environmental conditions [5]. The most obvious manifestation of changes to the surface of the Earth is the change in land use and land cover (LULC) [6]. Investigation of land use and land cover (exploration of LULC) is required in order to understand the complicated interconnection between human activity and the environment. It highlights the diverse ways land is utilized, such as in forestry, modern agriculture, urban and rural planning, disaster response, environmental protection, and the promotion of sustainable practices [7]. LULC data is important in many geospatial applications such as urban and regional planning, monitoring of the environment, and management [8]. The design of infrastructure projects in urban and rural areas needs an understanding of land use and land cover (LULC) [9]. Effective land management plans can be formulated by policymakers and academicians by conducting their studies on change analysis of land use and land cover [7]. Therefore, it is essential to conduct regular observations and assessments of land use and land cover worldwide to understand both the positive and negative changes occurring on the land [10].

Satellite-derived information is widely recognized for its significant impact on scientific investigations [11]. LULC mapping has heavily applied the use of remote sensing [12]. Satellite imagery and other remote sensing data are applied in r-s (remote sensing) analysis for land cover (LC) classification in an attempt to group different types of land cover [11]. Advancements in technologies for remote sensing have greatly promoted the availability of satellite imagery at anyone's reach, hence triggering innovativeness and entrepreneurship [13]. With its cost-effectiveness, high efficiency, and broad applicability, remote sensing technology offers robust technical support for the classification of land use and land cover [14]. Traditional LULC classification methods have evolved from manual visual interpretation, which was often subjective and inefficient, to more automated approaches that utilize remote sensing and advanced image processing techniques [15].

Currently, the majority of techniques used to classify land cover may generally be categorized into two classes. Machine learning and deep learning are the two chief sub-categories of AI [14]. Artificial intelligence (AI) has attracted the attention of academics, researchers, and professionals across various fields, whose work and innovations continue to drive the advancement and success of AI techniques [16]. Instead of conventional methods, researchers suggest the use of powerful and efficient AI-based machine learning algorithms to go beyond the intrinsic limitations and attain the necessary degrees of precision [17]. Land use classification can now be automated using machine learning, which employs both supervised and unsupervised approaches to deliver significant improvements across various applications [15]. However, these techniques lack in respect of scalability and precision.

The abstract term "deep learning" (DL) describes a set of various algorithm architectures based on neural networks [18]. The field of computer vision has been significantly impacted by deep learning [19]. Deep learning algorithms have also been widely used in many different use cases related to remote sensing [20]. Unlike traditional methods, they can automatically extract image features, capture complex non-linear relationships while offer enhanced generalization capabilities. This advancement enhances the interpretability of land cover classifications, providing not only higher accuracy but also clearer insights into the model's decision-making process [14]. Several key challenges remain, including improving classification performance in terms of efficiency and accuracy, reducing computational costs, and enhancing adaptability to diverse geographical contexts.

To address the growing need for accurate, efficient, and scalable LULC classification, this review explores recent advances in AI-based approaches, particularly those leveraging deep learning and remote sensing technologies. It highlights the evolution from traditional classification methods to sophisticated AI models such as convolutional neural networks (CNNs), vision transformers (ViTs), and hybrid architectures. The study integrates insights from recent research, evaluates model performance across various datasets and regions, and examines the impact of explainable AI alongside cloud-based computational approaches. By doing so, this review aims to provide a comprehensive understanding of current capabilities, key challenges, and future directions in AI-driven LULC classification to guide researchers, policymakers, and practitioners in land management and environmental monitoring.

"From Traditional Methods to AI-Driven Approaches":

While traditional remote sensing and manual classification approaches have laid the foundation for LULC studies, they are often limited by subjectivity, scalability issues, and reduced accuracy in complex or heterogeneous landscapes. The emergence of Artificial Intelligence (AI), particularly machine learning and deep learning methods, represents a transformative shift in this field. Unlike conventional techniques, AI-based approaches can automatically learn spatial and spectral patterns, adapt to diverse geographical contexts, and process large-scale satellite data with greater efficiency and precision. This transition underscores the significance of reviewing AI-driven methodologies, as they not only overcome the limitations of earlier techniques but also open new possibilities for real-time monitoring, explainability, and integration with cloud-based platforms.

A general workflow diagram of how the process of LULC classification takes place is shown in Figure 1.

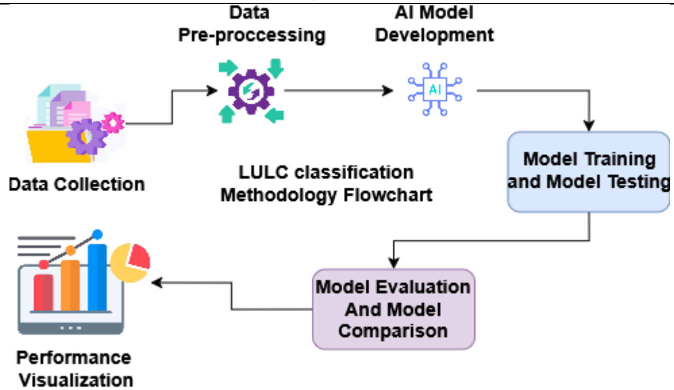

Figure 1. General workflow diagram for AI-based LULC classification

Objectives:

The primary objectives of this review article are as follows:

To provide a comprehensive overview of recent advancements in Artificial Intelligence (AI) techniques, particularly machine learning and deep learning models, for Land Use and Land Cover (LULC) classification using remote sensing data.

To critically analyze and compare the performance of different AI models (e.g., CNNs, Vision Transformers, AutoML, and hybrid approaches) across various datasets, spatial resolutions, and numbers of land cover classes.

To highlight the strengths, limitations, and challenges encountered in AI-based LULC classification, including issues of scalability, computational cost, spectral variability, and model interpretability.

To synthesize future research directions by identifying potential solutions, such as the integration of Explainable AI (XAI), lightweight architectures, multi-spectral and spatiotemporal data, and MLOps-driven frameworks.

To support researchers, policymakers, and practitioners by presenting consolidated knowledge that can guide sustainable land management, environmental monitoring, and urban planning through improved LULC classification.

Literature Review:

Transformer-Based Approaches:

The author [7] proposed an efficient framework for Land Use and Land Cover (LULC) analysis using transfer learning and strategic fine-tuning on transformer-based models. The study integrates insights from recent research, evaluates model performance across various datasets and regions, and examines the impact of explainable AI alongside cloud-based computational approaches. Experiments were conducted on the EuroSAT and PatternNet datasets using models pre-trained on ImageNet-21k and run on Google Colab Pro GPUs. Ten models from CNN and transformer families were compared—ResNet50, ResNet101, Inception V3, DenseNet161, GoogleNet, ViT Base, ViT-Large, DeiT-Base, SwinT-Small, and

SwinT-Large—with the proposed method showing competitive performance. Preprocessing steps included image resizing and normalization. Explainable AI (XAI) was implemented using Captum, whose model-agnostic framework generates detailed attribution maps without modifying the network, offering greater interpretability compared to Grad-CAM. This framework demonstrates the potential of combining transformers and XAI for scalable, transparent LULC classification. Future work includes expanding to more spectral bands and broader computer vision tasks.

The author in [13] presented a transformer-based framework for remote sensing scene classification, achieving 99.19% accuracy using transfer learning (TL) and fine-tuning on RGB bands. Using the EuroSAT dataset, which comprises 27,000 georeferenced Sentinel-2 images across ten land use classes, Vision Transformer (ViT) models pre-trained on ImageNet-21k were trained both with and without data augmentation. Augmentation techniques such as cropping and flipping enhanced generalization, particularly for the Forest and Sea/Lake classes, whereas the Pasture class exhibited the lowest classification accuracy. Training was limited to 15 epochs using cross-entropy loss, Adam optimizer, early stopping, dropout, weight decay, and gradient clipping (1.0), all within a PyTorch-GPU environment on Google Colab. ViT outperformed ResNet50 and VGG16 in accuracy, though VGG16 trained faster. The model was further evaluated on Sentinel-2A imagery (2018–2020) over Kreis Borken using Google Earth Engine, where 64×64 image tiles were classified and color-mapped. While effective, the RGB-only input limits the model's full potential; future work will explore multi-spectral data, other pre-trained models, and applications like change detection and land cover prediction.

The author in [14] presented a deep learning-based approach to extract large-scale land cover data from medium-resolution Landsat imagery (2000–2023) for assessing the ecological health of coastal regions along the China-Pakistan Economic Corridor (CPEC). Land cover classification was conducted using the MSNet model, trained on 24,000 samples and validated on 10,300, incorporating NDVI and NDWI indices along with cloud-free imagery processed through the CFMask algorithm on the Google Earth Engine platform. The model outperformed U-Net, SegNet, RF, and SVM in accuracy. Land cover data from six time periods were analyzed using ArcGIS, and ecological health was assessed through the VOR model, evaluating ecosystem vigour, organisation, and resilience (EV, EO, ER). Results of the study presented by the authors in [14] showed the CPEC coastal region to be "Unhealthy" but with signs of moderate improvement. Supporting datasets, including ESA_WorldCover, GlobeLand30, and GLC_FCS30, were incorporated alongside data augmentation and spatial processing techniques. Despite limitations such as sample optimization and a lack of spatiotemporal modeling, the framework demonstrates strong potential. Future work includes testing DDPM-SegFormer, incorporating higher-resolution and spatiotemporal attention modules, and exploring lightweight model enhancements and causal mechanisms driving landscape changes.

CNN-Based and Joint Deep Learning Frameworks:

The author in [10] investigated LULC changes in Nanjangud taluk, Mysuru district, India, using LISS-III satellite imagery from 2010 and 2020 with a CNN-based deep learning model. Traditional manual classification methods lack accuracy, while the proposed CNN approach achieved 94.08% and 95.30% accuracy for 2010 and 2020, respectively. The LISS-III sensor provides medium resolution (5.8–23.5 m) multispectral data with a 24-day revisit cycle. Preprocessing included radiometric, atmospheric, and geometric correction, followed by band composition and feature extraction using spectral indices. The inclusion of auxiliary data, such as topographic and soil maps, further improved classification accuracy. Using a 60:20:20 data split, the model outperformed traditional machine learning methods and existing approaches in both accuracy and computational efficiency. Results of the study conducted by the authors in [10] showed increases in built-up areas, agriculture, and water bodies, while forest cover declined. Despite computational demands and resolution limitations, the model proved effective for medium resolution, mixed-region classification. The study employed tools such as MATLAB, QGIS, and Python. Future work will explore deeper models, utilize higher-resolution data, and expand the analysis to a district-wide scale to provide enhanced insights for land management.

The author in [4] developed an AI-based land cover classification model using high-resolution remote sensing (HRRS) images to enable rapid land cover mapping. The model consists of three modules: pre-processing, classification, and post-processing. In the pre-processing stage, a sliding window algorithm partitions HRRS images into overlapping segments, while the classification stage employs a FusionNet-based convolutional neural network (CNN) to perform image classification. The post-processing module aggregates the results to generate final land cover maps. The model was trained using land cover maps from Jeonnam province, Korea, with validation conducted at two different sites. Results of the study introduced by the authors in [4] showed overall accuracies of 0.81 and 0.71, with higher performance in agricultural areas. The model shows strong potential for rapid updates in agricultural regions but highlights the need for further refinement, including the integration of field boundary delineation and training with specialized datasets for wetlands and barren lands. The CNN-based model classifies land cover on a pixel level, and future improvements could involve integrating land parcel boundaries for better accuracy.

The researcher in [19] proposed a hybrid HEVGG19 deep learning model for land cover classification and change detection, combining one-hot encoding with transfer learning from a pre-trained ResNet50. Drawing on datasets from the National Remote Sensing Centre and Sentinel-2 (27,000 images across 10 classes), the model applies transfer learning, fine-tuning, and a modified VGG19 architecture, attaining an accuracy of 98.5%. Historical satellite and aerial imagery from Chennai and Coimbatore (spanning 20 years) are preprocessed, augmented, and segmented using a Feature Pyramid Network with EfficientNet-B3, and converted into textual data for land cover change tracking. The model outperforms other CNN-based approaches and aids in predicting urban expansion to support environmental planning and climate mitigation efforts.

The author in [8] presented the Scale Sequence Joint Deep Learning (SS-JDL) method for joint Land Use (LU) and Land Cover (LC) classification, addressing key challenges in traditional pixel- and object-based approaches, including scale selection and classification hierarchy. SS-JDL introduces a sequence of image patch sizes (scales) derived using a Forward Scale Sequence (FSS) sampling scheme, enabling progressive information transfer from small to large scales. At each scale, LU and LC are jointly classified using a pixel-based MLP and a patch-based OCNN. When tested on aerial imagery from Bournemouth, Southampton, and Manchester, SS-JDL outperformed state-of-the-art methods, including JDL, achieving LU and LC overall accuracies of 88.94% and 91.06%, respectively, for S1. The method is simple, generalizable, and offers a robust framework for higher-order feature classification in remote sensing.

AutoML and Hybrid ML Approaches:

The author in another study [15] applied automatic machine learning (AutoML) techniques to classify land use changes in the Qarhan Salt Lake area from 2000 to 2020 using Landsat-5 TM and Landsat-8 OLI imagery. Eight land cover classes, exposed lakes, saline lands, salt flats, salt fields, construction land, water, and agricultural land were identified, with 400 stratified sample points selected annually. Using FLAML and Scikit-learn, six machine learning algorithms (LRL2, RF, ET, LGBM, XGBoost, and XGBLD) were compared, with XGBLD outperforming the others by reaching 77% accuracy. Bayesian optimization is used for hyperparameter tuning, offering efficiency over traditional methods. AutoML proved effective in handling spectral variability and limited data in this arid, complex environment. Image preprocessing includes atmospheric correction, normalization, and resampling to 90m resolution, while classification results are integrated into GIS for spatial analysis. Land cover changes are analyzed in relation to human water usage, temperature, precipitation, and evaporation, revealing strong anthropogenic and climatic influences. Despite challenges like computational demands, data sensitivity, and model interpretability, the study demonstrates AutoML's value for dynamic, large-scale environmental monitoring. Future work should focus on improving model explainability, addressing exposed lakes as key indicators, and advancing sustainable land and water management strategies.

The author in [16] aimed to enhance the accuracy of land use/land cover (LULC) classification by combining artificial neural networks (ANN) and random forest (RF) techniques into a novel approach called ANN_RF, applied to Sentinel-2A and Landsat-8 multispectral satellite data for Sana'a city in 2016. The proposed method outperforms individual ANN classifiers, offering better performance in both speed and accuracy. The study utilizes SAGA GIS software for data processing, which includes geometric and radiometric corrections of the satellite images, and a confusion matrix and kappa coefficient are employed to evaluate classification accuracy. Results show an accuracy of 82.52% and a kappa of 0.58 for Sentinel-2A, and 80.00% accuracy with a kappa of 0.71 for Landsat-8. The study demonstrates that merging ANN and RF techniques improves LULC classification compared to other methods like RF+SVM, MLC+SVM, and ANN+SVM. Future work is suggested to further explore the integration of RF and ANN with other satellites and under different environmental conditions to enhance model performance.

In [2], the researcher models Uttarakhand's land use and land cover (LULC) patterns for 2032 and examines changes from 1992 to 2022 using 30 m Landsat imagery, applying a semi-automated hybrid classification that integrates Maximum Likelihood and Object-Based Image Analysis (OBIA) for improved accuracy. Future LULC prediction is performed using the Cellular Automata–Artificial Neural Network (CA-ANN) model within the MOLUSCE plugin in QGIS, leveraging its spatiotemporal simulation capabilities and transition probability matrices. The study incorporates population, road network, and satellite data to assess six LULC classes in this mountainous region. Results of the study presented by the authors in [2] highlight the effectiveness of CA-ANN in forecasting complex landscape dynamics, though challenges include model opacity, potential ANN overfitting, resolution discrepancies among datasets, and sample bias. Future work should explore integrating multi-resolution satellite data, advanced remote sensing techniques, and ensemble machine learning approaches to enhance spatial detail, classification accuracy, and robustness of LULC change analysis.

Explainable and Interpretable AI:

The author in [9] presented an interpretable deep learning framework for land use and land cover (LULC) classification using Shapley additive explanations (SHAPs) to improve classification results from satellite images. The framework utilizes a compact convolutional neural network (CNN) trained on the EuroSAT dataset, with three-band combinations (red, green, near-infrared, and short-wave infrared) instead of the full 13 spectral bands. The proposed approach achieved an overall accuracy of 94.72%, outperforming standard methods with larger trainable parameters. By incorporating SHAP, the framework provides both local and global explanations, offering insights into how different spectral bands influence classification, particularly in urban and rural areas. The model was compared to several CNN architectures (e.g., GoogleNet, DenseNet121, ResNet50), and results demonstrated that the use of three-band combinations significantly improved classification accuracy. Additionally, SHAP's explainability enhanced the interpretability of model predictions, revealing correlations between image features and LULC classes.

In [20], Land Cover/Land Use (LCLU) in Talassemtane National Park (TNP) is classified using Sentinel-2 imagery and a Deep Neural Network (DNN) model, which employs five spectral indices—NDVI, GNDVI, SAVI, MNDWI, and NDWI—to separate six distinct land use classes. The DNN model is optimized using three hyperparameter optimization algorithms: Random Search, Hyperband, and Bayesian optimization. The results showed that spectral indices significantly improved classification, especially for classes with similar reflectance. The Hyperband optimization method outperformed the others, increasing classification accuracy by 12.5%, achieving an overall accuracy of 94.5%. Dropout regularization was applied to prevent overfitting. The study conducted by the authors in [20] aimed to classify the 2022 LCLU in TNP, evaluate optimization methods for DNN, and provide an updated LCLU map. The study employs Sentinel-2 MSI Level 2A imagery at 10 m resolution, supplemented with ground truth data provided by local managers. The study highlights the challenges of selecting spectral indices, DNN model sensitivity, and data limitations, and suggests future improvements through advanced deep learning architectures and multi-source remote sensing data integration to enhance classification accuracy.

The author in [11] outlined the development of an end-to-end MLOps workflow integrating land cover classification models using Big Data strategies to process large-scale, high-resolution spatial data. The workflow, implemented in a Kubernetes environment, ensures on-demand auto-scaling, distributed computing, and load balancing for efficient satellite imagery processing. By incorporating automated data ingestion, preprocessing, model training, and evaluation, this MLOps framework ensures that land cover models remain up-to-date and reflect current conditions. An AI-as-a-service (AIaaS) solution, using Sentinel-2 and ASTER data with over 40,000 manually validated locations across nine classes, achieves over 75% pixel-level classification accuracy. The system allows users to obtain terrain classification through a REST or gRPC API. Future work focuses on integrating drift detection mechanisms to autonomously identify shifts in data distributions and incorporating explicability components to improve model transparency and reliability.

Other Machine Learning and Specialized Applications:

In [17], coal mine overburden reclamation through reforestation is assessed using high-resolution Sentinel-2 imagery, with classification performed through multiple machine learning (ML) techniques, including SVM, RF, ANN, and MLC. The results show that SVM outperforms RF and MLC in accurately delineating land use and vegetation classes, particularly in distinguishing reclamation plantations into age classes (young, middle-aged, and mature). The study, carried out in the Korba coalfields, applies Sentinel-2 imagery (10 m resolution) from 2020 to 2022 to map nine land cover categories: forests, plantations at various growth stages (young, middle-aged, mature), agriculture, fallow land, built-up areas, water bodies, mining zones, and barren overburdens without vegetation. SVM achieved the highest accuracy of 96.4%. The study highlights gaps in plantation development and soil reclamation in coal mine overburdens, with the recommendation to integrate advanced ML and AI techniques to overcome spectral and spatial limitations and improve classifier performance.

The author in [3] analyzed land use and land cover change (LULCC) in the River Tea SCI (Galicia, NW Spain) between 2015 and 2023, utilizing Sentinel-2 and Planet Labs (RapidEye, PlanetScope) imagery in combination with Object-Based Image Analysis (OBIA) and Artificial Neural Network (ANN) classification methods. The fragmented and low-variability landscape posed challenges to achieving high classification accuracy. OBIA with Planet Labs data achieved the highest accuracy (80%), followed by Sentinel-2 + OBIA (77%) and Planet Labs + ANN (55%). The methodology incorporated multispectral indices (NDVI, NDWI), PCA, and post-classification analysis using QGIS's MOLUSCE tool to simulate land cover for 2031. The approach integrated both free (QGIS, SNAP, OTB) and proprietary (Erdas Imagine, MATLAB) tools. Eight land cover classes are identified, and models are trained using 21 images (10 Sentinel, 11 Planet Labs) across seasons. The study highlights the potential of combining optical sensors of varying resolutions and object-based techniques for accurate classification of riparian zones. Limitations of the study introduced by authors in [3] include randomized parameter selection (e.g., ANN layer size), and future improvements may involve adopting CNN architectures for better pixel-patch analysis and adapting the framework for different terrain and land cover types.

In [21], land use/land cover (LULC) changes in the Manipur River basin are assessed and projected using the Land Change Modeller (LCM) within TerrSet, drawing on Landsat images from 2007, 2014, and 2017. The study applies Markov Chain and artificial neural network (ANN) models, incorporating driving variables such as distance from roads, settlements, elevation, and slope, to predict future LULC for 2030. The findings indicate substantial shifts in urbanization and herbaceous wetland areas, underscoring the importance of implementing effective urban planning and environmental conservation policies. The LULC maps achieved high accuracy rates, with 88%, 92%, and 93% for 2007, 2014, and 2017, respectively, and an R2 value of 0.86 for the predicted and actual 2017 maps. The study concludes that LCM can effectively predict future LULC changes, providing valuable insights for sustainable resource management and policy formulation. Using higher-resolution datasets in future studies may improve the accuracy of LULC classification and allow for a more detailed assessment of habitat dynamics in sensitive regions like the Loktak Lake Wetland.

The author in [23] assessed land use and land cover (LULC) changes in Ethiopia's Tana Basin using Landsat imagery from 1986, 2002, and 2018, processed with ENVI and ArcGIS software. Six land cover classes were identified through supervised classification using the maximum likelihood algorithm, with accuracy evaluated using the Kappa coefficient. The results revealed a notable 32-year increase in agricultural land (15.61%) and residential areas (8.05%), largely at the expense of forests, bushland, and grazing lands, whereas water bodies remained relatively stable due to reservoir development. The findings underscore the value of remote sensing and GIS in monitoring LULC changes and inform sustainable land management and planning efforts.

The author in [18] compared the performance of four machine learning algorithms—SVM, RF, XGBoost, and DL—in classifying land cover and land use (LCLU) in a complex boreal landscape in south-central Sweden using multi-temporal Sentinel-2 data. The dataset included 11,816 samples, split into 70% training and 30% evaluation, with 10 spectral bands and vegetation indices (NDVI, MNDWI, NDBI) for enhanced classification. SVM achieved the highest accuracy (0.758), followed by XGBoost, RF, and DL. Accuracy comparisons revealed significant differences among algorithm pairings and class-wise predictions. The study highlighted the importance of red edge and shortwave infrared bands, particularly from spring and summer scenes. A major limitation was the poor performance of DL, attributed to the "vanishing gradient problem" caused by the tanh activation function. Future studies may focus on improving accuracy through parameter tuning, examining the utility of red edge bands in forested regions, and contrasting mono-temporal with multi-temporal Sentinel-2 datasets for LCLU classification.

Dynamic World is a near real-time (NRT) land use and land cover (LULC) classification product that leverages deep learning on 10 m Sentinel-2 imagery to deliver high-resolution, continuously updated LULC maps via cloud platforms like Earth Engine [22]. In contrast to traditional products updated annually, it delivers single-date snapshots synchronized with satellite acquisitions, allowing for dynamic monitoring and flexible applications. Using a semi-supervised Fully Convolutional Neural Network trained on dense, polygon-based annotations from globally distributed regions, the model achieves 73.8% agreement with expert labels and outperforms existing LULC products. While highly accurate in temperate, tree-dominated regions, it struggles to distinguish between crops and shrubs in arid landscapes. Nevertheless, Dynamic World supports scalable, timely, and customizable LULC analysis across a wide range of applications.

Comparative Insights from Reviewed Studies:

Transformer-based models consistently demonstrate superior performance (>99% accuracy in some cases) and strong adaptability to diverse datasets. Their integration with explainability tools enhances interpretability, but reliance on RGB bands or medium-resolution data can limit potential.

CNN-based models and joint deep learning frameworks remain robust and computationally efficient, with accuracies ranging from ~90–98%. While CNNs excel in pixel-level classification, approaches like SS-JDL address the challenge of multi-scale feature extraction and hierarchical classification, offering a more generalizable framework.

AutoML and hybrid methods reduce manual parameter tuning and provide flexibility for diverse environments. However, their accuracy lags behind transformer and advanced CNN models, particularly in complex landscapes.

Explainable AI and MLOps frameworks emphasize transparency and operational deployment. While accuracy may be slightly lower than that of transformers, these approaches are crucial for trust, adoption, and real-world scalability.

Traditional ML, OBIA, and statistical approaches remain valuable for regional studies and long-term change analysis. However, they often underperform compared to CNNs and transformers, especially in large-scale, heterogeneous, or real-time applications.

The various methods used by different researchers for AI-based LULC classification, as mentioned in the literature, along with their results, key limitations, and suggested improvements to overcome these limitations, are listed in Table 1.

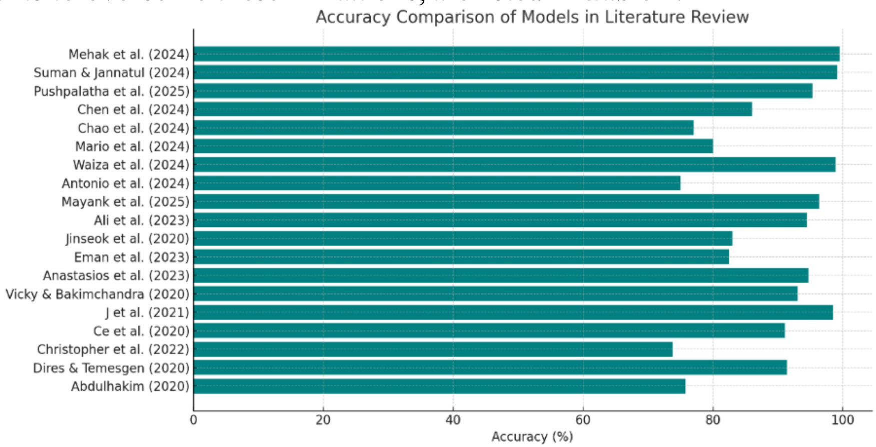

Figure 2. Accuracy Comparison of various AI Models used in the literature by different researchers for LULC Classification, showing better classification performance with complex model architectures

Figure 2 compares the reported accuracies of different AI-based models used in the literature for Land Use and Land Cover (LULC) classification. Transformer-based architectures (e.g., ViT and SwinT) achieved the highest accuracies (>99%), outperforming traditional CNNs and machine learning models. Although CNN-based models such as HEVGG19, DNN, and hybrid approaches achieved high accuracies (94–98%), methods like AutoML and FCNN performed less effectively, largely due to dataset constraints and spatiotemporal variability. This underscores the advantage of transformer-based models in exploiting large-scale datasets to achieve high accuracy, while CNN-based and hybrid frameworks continue to offer strong performance in certain applications.

This bubble chart 3 illustrates the relationship between AI models, datasets, and the number of classes considered in LULC classification tasks. The x-axis represents the number of classes, the y-axis lists the models, and the bubble size indicates the accuracy achieved. Models like Vision Transformers (ViT, SwinT) and hybrid CNNs were tested on datasets with larger class diversity (up to 38 classes) and still achieved high accuracies (>99%). In contrast, models such as AutoML and OBIA+ANN, when applied to medium-class datasets (6–10 classes), yielded comparatively lower accuracies. The visualization demonstrates that advanced deep learning models scale more effectively with class complexity and generalize well across diverse datasets, positioning them as highly suitable for operational LULC monitoring.

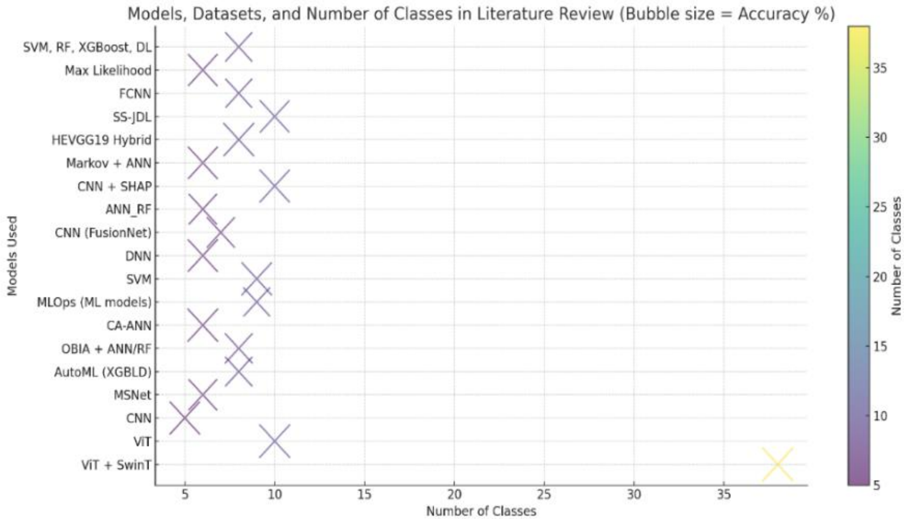

Figure 3. Models, Datasets, and Number of Classes in the Past LULC Studies (Bubble Chart), presenting the relationship between dataset complexity, no. of target classes, and models used for classification, along with their impact on the classification performance

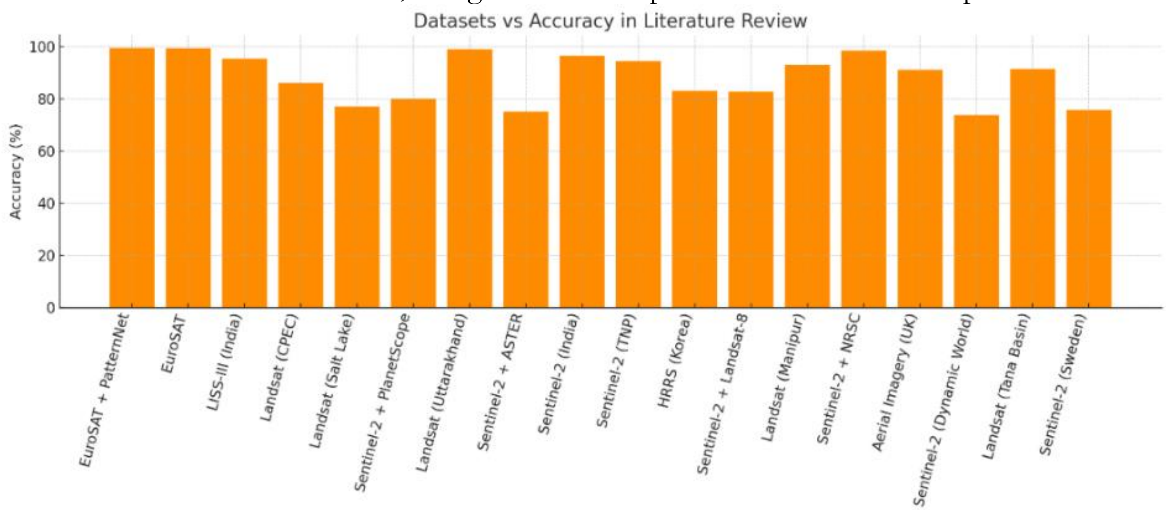

Figure 4. Accuracy of AI Models used in the Previous Studies across Different Datasets for LULC Classification, demonstrating superior classification performance of complex model architectures when applied to larger datasets as compared to smaller datasets

Table 1. Different approaches used in the literature for AI-based LULC classification

S.NO	Author	Year	Methods	Result	Dataset & study area	No. of classes	Limitation	Future Work
1	Mehak et al.,	2024	Vision Transformer (ViT) and Swin Transformer (SwinT), Captum for XAI	> 99% accuracy	EuroSAT dataset, 27,000 images, RGB bands, spatial resolution 10m PatternNet dataset for additional experiments, 800 images per class, spatial resolution ~0.3m SA: Global	10 LULC classes, 38 classes	Not mentioned.	Larger datasets, using a wider range of spectral bands
2	Suman & Jannatul	2024	ViT	99.19% accuracy	EuroSAT dataset SA: Global, Kreis Borken area for evaluating the model further	10 LULC classes	Only using RGB bands	Other datasets, other models, multi-temporal data, and more spectral bands
3	Pushpalatha et al.,	2025	CNN	accuracy of 94.08% for the 2010 data and 95.30% for the 2020 data	Linear imaging self-scanning sensor- III (LISS-III) remote sensing images, 4 spectral bands: blue, green, red, and near-infrared, spatial resolutions ranging from 5.8 m to 23.5 m. SA: Nanjangud taluk, Mysuru district, Karnataka, India	5	extensive computational resources, medium resolution restricts accuracy	Deeper architectures, longer training cycles, and higher-resolution satellite data.
4	Chen et al.,	2024	MSNet model	accuracy >86%	(Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI) satellite images, spatial resolution 30m, 8,8,11 bands SA: coastal regions that extend 50 km offshore along the CPEC	6	Optimization Samples, Spatiotemporal factors ignored, Modelling adjustment	higher-resolution imagery, spatiotemporal attention module, using the DDPM-SegFormer model

5	Chao et al.,	2024	Auto ML algorithms (6 ML models)	XGBLD with 77% accuracy	Landsat-5 TM and Landsat-8 OLI images, spatial resolution 90mX90m, blue (B), G, R, NIR, shortwave infrared 1 (SWIR1), and shortwave infrared 2 (SWIR2) spectral bands SA: Qarhan Salt Lake area	8	Reliance on data quality, computational demands of Auto ML, and the "black-box" nature of AutoML	Complementary methods for result validation and interpretation
6	Mario et al.,	2024	object-based image analysis (OBIA) Classification via RF and Artificial Neural Network (ANN) (pixel-based approach)	Highest accuracy Planet Labs+OBIA 80%, Sentinel+OBIA 77%, Planet Labs+ANN 55%	Images from the Sentinel-2 (10m) and Planet Labs (3m) (RapidEye and PlanetScope) multispectral satellite platforms. SA: River Tea SCI (Site of Community Importance) (Galicia, NW Spain)	8	Random model parameters' optimization, different landscapes' data need to be adjusted for classification.	ANN can be replaced by CNN for better performance
7	Waiza et al.,	2024	Cellular automata and Artificial neural networks (CA-ANN)	The accuracy of LULC for the years 1992, 2002, 2012, and 2022 was 96.94 %, 97.77 %, 98.61 % and 98.87 % respectively	Population, road network, and satellite data (Landsat), with a spatial resolution of 30 m. SA: Uttarakhand, a mountainous and hilly state.	6	CA-ANN algorithm being opaque, ANN prone to overfitting, Biases in sample selection, Differences in resolution in satellite images, and data from other sources.	Integrating multi-resolution satellite data, Alternative ML and ensemble techniques incorporated with CA and using additional parameters.
8	Antonio et al.,	2024	ML models	a pixel-level classification	Sentinel-2 and ASTER data incorporating over	9	Not mentioned.	incorporating a robust drift detection mechanism and

				accuracy of over 75%	SA: 40,000 manually validated locations			integrating an explicability component
9	Mayank et al.,	2025	ML models (SVM, RF, Maximum Likelihood Classifier)	SVM with an accuracy rate of 96.4%	Sentinel-2 satellite data, with a 10-m spatial resolution free of clouds, Visible (Red, Green) and Infrared (NIR) bands SA: Korba coalfields	9	Spectral and Spatial Limitations, Classifier Performance Variability	Integrate advanced machine learning and artificial intelligence techniques to overcome spectral and spatial limitations
10	Ali et al.,	2023	Deep Neural Network (DNN)	accuracy of 94.5%	Sentinel-2 satellite imagery, 10m spatial resolution, the vector dataset used, including ground truth data, was provided by local managers and validated by visits to the NPT territory. SA: Talassemtane National Park (TNP)	6	The selection and number of spectral indices used to classify land cover, DNN's sensitivity to model layers, overfitting, and Challenges gathering ground truthing data	Advanced DL architectures, incorporating ancillary data to enhance classification accuracy, combining multi-source RS data to augment spectral information
11	Jinseok et al.,	2020	CNN model based on the FusionNet network architecture	accuracy of 0.83%	The orthographic images obtained from the National Geographic Information Institute (NGII), red, green, and blue spectral bands, spatial resolution 51 cm/pixel, image size 256 x 256. SA: The area from the Jeonnam province in Korea was used to train the model, Subuk-myeon of Jeonnam province,	three different categories based on the level of detail; seven items in the main category, 22 items in the parent subcategory, and 41 items in the child subcategory	Some land cover classes had small data, and a CNN-based model classifies land cover on a pixel unit, which can be different from the actual land use of the parcel unit	Using more than four such classes and using NDVI and NDWI, considering land parcel boundaries into pixel-based land cover can improve the classification accuracy substantially

					and Daseo-myeon of Chungbuk province, used for model validation			
12	Eman et al.,	2023	merging of the two neural-based and object-based approaches, the ANN_RF model	82.52% Accuracy for sentinel-2A, 80.00% Accuracy for landsat-8.	Sentinel-2A and Landsat-8 satellite images, Medium resolution, RGB 432 spectral bands SA: Sana'a is Yemen's capital	6	Deep learning has various downsides, such as complexity, expense, and the need to wait longer for results.	merging these RF and ANN algorithms with other satellites and other times and environmental conditions
13	Anastasios et al.,	2023	CNN model, SHAP for XAI	accuracy 94.72%	EuroSAT dataset, red, green, near infrared (NIR-Band 8), short-wave infrared (SWIR-Band 11) spectral bands using a combination of 3 bands via these bands SA: Global	10	Not mentioned	Not mentioned
14	Vicky & Bakimchandra	2020	Markov Chain and artificial neural network (ANN) for developing a future LULC map of the study area	accuracy 93%	Landsat satellite images SA: Manipur River basin,	6	Not mentioned	Use of high-resolution data for the second level of land use classification
15	J et al.,	2021	hybrid HEVGG19 deep learning model	98.5% accuracy	Sentinel-2 satellite images and aerial images SA: regions of Chennai and Coimbatore	8	Not mentioned	Not mentioned
16	Ce et al.,	2020	Scale Sequence Joint Deep Learning (SS-JDL) method	Accuracy: (LC: 91.06%, LU: 88.94%) for S1	Aerial photos with four spectral bands (RGB and NIR) with 50-cm spatial	Classes S1 (LC 10: LU: 11), Classes S2 (LC 9: LU:	Not mentioned	Not mentioned

			for joint Land Use (LU) and Land Cover (LC) classification iteratively using a pixel-based MLP and a patch-based OCNN		resolution were selected. SA: Bournemouth (S1), Southampton (S2), and Manchester (S3), and their surrounding terrestrial regions	10), and Classes S3 (LC 9: LU: 9) were included		
17	Christopher et al.,	2022	Fully Convolutional Neural Network (FCNN)	73.8% agreement with expert labels (agreement between reference annotations and our Top-1 NRT labels is the primary validation metric)	10 m Sentinel-2 imagery with all bands retained except B1, B8A, B9, and B10 SA: (Western Hemisphere, Eastern Hemisphere-1, and Eastern Hemisphere-2	8	Performed better for some regions and performed less accurately for some other regions	Not mentioned
18	Dires & Temesgen	2020	supervised classification using the maximum likelihood algorithm	accuracy 91.40%	Landsat TM satellite imagery, 30m spatial resolution, RGB spectral bands SA: Lake Tana Basin, Northwest Ethiopia	6	Not mentioned	Not mentioned
19	Abdulhakim	2020	Support Vector Machines (SVM), Random Forests (RF), Extreme Gradient Boosting (XGBoost), and Deep Learning (DL)	SVM achieved the highest accuracy (0.758 ± 0.017)	Multi-temporal Sentinel-2 imagery from all four seasons was used with 10 m spatial resolution, ten spectral bands covering the red, blue, green, red edge, near- and short-wave infrared.	8	In DL use of the tanh activation function, which can saturate and cause the "vanishing gradient problem," slowing training with	ReLU activation function for better results due to its non-saturating nature, the use of user-defined parameters for each algorithm for better performance, to evaluate the role of Sentinel-2's red edge bands compared to vegetation indices, and

					SA: Boreal landscape in south central Sweden.		high-dimensional data, there is no use of user-defined parameters for each algorithm, meaning the reported accuracies may not represent the maximum achievable performance.	to assess whether optimally-timed mono-temporal Sentinel-2 scenes can match or outperform multi-temporal stacks in classifying LULC

Figure 4 illustrates the reported classification accuracies of AI models applied to various remote sensing datasets in the reviewed studies. Datasets such as EuroSAT, PatternNet, and Sentinel-2 consistently enabled high accuracies (>95%) when combined with advanced deep learning models like Vision Transformers and hybrid CNNs. Medium-resolution datasets such as LISS-III, Landsat (CPEC, Salt Lake, Tana Basin), and HRRS resulted in lower accuracies (75–86%) due to spatial resolution limitations, mixed land cover features, and spectral variability. Interestingly, studies integrating multi-source datasets (e.g., Sentinel-2 with ASTER or PlanetScope) improved classification diversity but faced challenges in model generalization. These findings emphasize that dataset resolution, spectral richness, and pre-processing quality strongly influence model performance, highlighting the importance of dataset selection for future LULC research.

Methodology Used for Conducting the Review:

A methodology flow diagram showing the flow of steps through which the LULC classification review has been conducted is shown in **Figure 5** below.

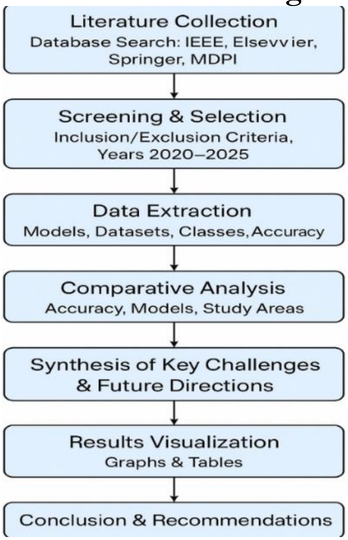

Figure 5. Methodology Flow Diagram of the Review conducted for the LULC classification.

Diagram 5 illustrates the structured methodology followed in this review article. Literature is collected from leading scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The search timeframe is limited to studies published between 2020 and 2025, ensuring coverage of the most recent advancements in AI-based LULC classification. Predefined inclusion criteria required studies to (i) apply AI, machine learning, or deep learning techniques to LULC classification, (ii) utilize satellite or aerial imagery, and (iii) report performance metrics such as accuracy, F1-score, or kappa coefficient. Studies are excluded if they (i) focus solely on traditional/manual classification methods without AI integration, (ii) lack sufficient methodological details, or (iii) are not peer-reviewed.

Following the screening process, data extraction focuses on capturing details of the AI models used, datasets, study areas, number of classes, and reported accuracies. A comparative analysis is then conducted across studies, highlighting performance trends, limitations, and methodological differences. Insights are synthesized into a summary of key challenges and the future research directions proposed in the literature. To enhance clarity and interpretability, the findings are further visualized using comparative graphs and tables. The process culminates in the formulation of conclusions and recommendations, aligning recent advances with future opportunities for scalable, explainable, and operational AI-based LULC classification.

Challenges in AI-based LULC Classification Along with their Feasible Solutions:

To consolidate insights from the literature and highlight broader research trends, Table 2 presents a comparative analysis of key challenges and future directions in AI-based LULC classification. The table summarizes recurring limitations across different methods, datasets, and regions, including dependence on limited spectral bands, risks of model overfitting, challenges in interpretability, and spatiotemporal inconsistencies. It also highlights promising solutions proposed by recent studies, including the adoption of multi-spectral and high-resolution data, the use of explainable AI tools, hybrid model architectures, and integration of temporal and ancillary data. The goal of this synthesis is to provide a clear roadmap for future research that addresses current technical constraints and enhances the operational scalability and reliability of AI-powered LULC systems.

Table 2: Key Challenges encountered in AI-Based LULC Classification and Future Directions to resolve these challenges

Key Challenges	Future Directions to Overcome Challenges
Reliance on limited spectral bands (e.g., only RGB)	Use of multi-spectral and hyperspectral data; integration of red edge, SWIR, and thermal bands
Low-resolution or medium-resolution satellite imagery	Adoption of high-resolution imagery (e.g., PlanetScope, Sentinel-2, commercial satellites)
Computational cost and resource constraints	Implementation of lightweight models, optimization algorithms, and cloud-based solutions like Google Earth Engine or AI-as-a-Service (AIaaS)
Lack of generalization across different geographies and land types	Use of data augmentation, transfer learning, and training on global multi-source datasets
Model interpretability and explainability	Integration of Explainable AI tools (e.g., SHAP, Captum) to visualize decision processes and build trust

Overfitting and sensitivity to hyperparameters in deep models	Use of regularization, dropout, early stopping, and automated hyperparameter tuning (e.g., Bayesian optimization, AutoML)
Black-box nature of ML/AutoML approaches	Combine model performance with interpretability layers and validation using expert annotations.
Spatiotemporal inconsistency and lack of temporal modeling	Integrate temporal modeling techniques (e.g., RNNs, transformers with temporal embeddings); explore change detection using multi-date imagery
Manual feature engineering or parameter selection	Adoption of end-to-end deep learning pipelines and hybrid models with self-learned features
Difficulty in classifying complex or fragmented landscapes	Employ object-based image analysis (OBIA), CNNs with patch-level context, and spatial attention mechanisms
Inadequate ground truth or labeled data	Leverage semi-supervised learning, crowd-sourced annotations, and synthetic data generation.
Landscape-specific limitations (e.g., coalfields, urban-rural boundaries)	Tailor classification frameworks by region, integrate ancillary data (e.g., elevation, land parcel maps), and adopt hierarchical classification strategies

In addition to accuracy comparisons, it is important to recognize that variations in reported results are often influenced by factors beyond the model architecture itself. Dataset diversity plays a critical role, as models trained on high-resolution or multispectral imagery typically outperform those using medium-resolution or RGB-only data. Similarly, preprocessing quality, including atmospheric correction, normalization, data augmentation, and handling of noise, directly impacts model generalization. Furthermore, geographic variability introduces additional complexity, since heterogeneous landscapes, seasonal changes, and region-specific land cover patterns can make classification more challenging. These underlying factors must therefore be carefully considered when interpreting performance differences, as they shape not only accuracy outcomes but also the scalability and robustness of AI-based LULC systems across diverse contexts.

Conclusion:

The evolution of Land Use and Land Cover (LULC) classification has been profoundly shaped by the integration of artificial intelligence (AI) with remote sensing, marking a decisive shift from traditional approaches to data-driven, automated methods. This review has gone beyond summarizing individual studies by thematically clustering and critically comparing AI techniques, including transformer-based models, CNNs, hybrid deep learning frameworks, AutoML pipelines, and explainable AI approaches. Through this comparative analysis, the review highlights not only the performance levels achieved but also the underlying causes of variability across studies, such as dataset diversity, preprocessing strategies, and geographic complexity. A key novelty of this review lies in the synthesis of recurring challenges with their feasible solutions, as consolidated in Table 2, which provides a roadmap for advancing AI-based LULC research. Unlike prior reviews that focus predominantly on accuracy, this work emphasizes scalability, interpretability, and operationalization—factors that will determine the real-world impact of these models. Looking forward, future research should prioritize multi-spectral and multi-temporal integration, lightweight and interpretable architectures, scalable MLOps frameworks, and the incorporation of ancillary data sources. By framing these directions, this review not only identifies current limitations but also sets the stage for the development of next-generation AI-powered LULC systems capable of supporting sustainable land management, ecological monitoring, and urban planning at scale.

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Conflict of interest:

There is no conflict of interest among the authors.

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