Integrating Explainable Deep Learning with Multi-Temporal Land Cover Change Detection for Carbon Stock Estimation

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Abstract: High-density carbon stocks are being severely undermined by rapid urbanization and deforestation in the Western Ghats of Southern India. However, current monitoring systems operate at coarse spatial resolution, lack temporal currency, and offer no spectral interpretability, making credible carbon accounting and proactive conservation intervention impossible under current frameworks. This study suggests an integrated pipeline that applies explainable deep learning semantic segmentation, multi-temporal Sentinel-2 and Landsat 8/9 imagery, post-classification change detection, and GEDI- calibrated InVEST carbon stock estimation to 320,000 km² of Southern India between 2020 and 2026. The first spectral early-warning threshold for forest carbon loss is NDVI < 0.48, with impacted pixels 3.8 times more likely to undergo conversion, according to transition-level SHAP analysis. Three architectures, such as U-Net, DeepLabV3+, and Vision Transformer, optimized via Bayesian search and weighted ensemble combination, achieve 92.4% overall accuracy. With a net carbon loss of 131.8 Mt C (483.7 Mt CO2e, USD 87.3 billion) over six years, change detection indicates 18,340 km² of landscape transition led by urban growth (+6,840 km²) devouring Dense Forest (−3,170 km²). A transparent, repeatable, and spatially explicit decision-support tool directly relevant to India's 2030 NDC carbon monitoring, Western Ghats conservation planning, and REDD+ verification frameworks, the generated Carbon Risk Map reveals 14,050 km² at immediate conversion risk.

Keywords: LULC Change Detection; Explainable Deep Learning; DeepLabV3+; Carbon Stock Estimation; Sentinel-2; InVEST.

1. Introduction

One of the most active study areas in remote sensing and geospatial science is the categorisation of land use and land cover (LULC) and the detection of changes using satellite data. The scope and quality of LULC research have significantly increased due to the convergence of high-resolution multispectral data, cloud computing platforms like Google Earth Engine (GEE), and increasingly potent machine learning and deep learning techniques. Two important research directions that are changing the field have emerged in recent years. In order to overcome the "black box" nature of intricate deep learning models and provide transparency into categorisation judgements, Explainable Artificial Intelligence (XAI) was first presented. Second, in order to estimate carbon stocks and quantify the carbon repercussions of land cover changes, LULC data is increasingly being combined with ecosystem service models.

Due mostly to tropical deforestation, forest degradation, and ecosystem conversion to urban and agricultural land, land use and land cover change continues to be the second largest source of anthropogenic greenhouse gas emissions worldwide, accounting for 10–15% of annual CO2 releases, or 4–6 billion tonnes annually [1]. The biennial Forest Survey of Indian State of Forest Report, which operates at district-level spatial resolution with a two-year update cycle, is the basis for current LULC monitoring systems in India despite growing recognition of this carbon flux. This granularity is fundamentally insufficient to detect the fine-scale, rapid forest-urban transitions driving carbon stock loss at the Western Ghats periphery. The Western Ghats, one of the 36 recognised biodiversity hotspots in the world, sustain carbon densities of 230–350 tC/ha in intact tropical evergreen forests [2]. Meanwhile, cities like Bengaluru, Chennai, and Hyderabad are growing at a rate of 3–5% per year, consuming per urban forest and agricultural land at rates that current monitoring systems are unable to detect until conversion is irreversible. India's revised Nationally Determined Contribution pledges to use forest and tree cover as an additional carbon sink of 2.5–3 billion tonnes CO2e by 2030. This goal cannot be reliably monitored without high-resolution, temporally current, and scientifically interpretable LULC and carbon monitoring. Furthermore, even though state-of-the-art deep learning classifiers achieve 88–95% classification accuracy, they are still essentially opaque black boxes that generate LULC outputs without revealing which spectral features influenced each decision. As a result, carbon estimates derived from those outputs are both ecologically and scientifically uninterpretable [3]. For Southern India during the post-COVID infrastructure acceleration period of 2020–2026, no published research has concurrently addressed these three interrelated gaps: coarse monitoring resolution, deep learning opacity, and the lack of XAI-informed carbon consequence analysis.

2. Related work

This review of the literature examines the state of the art in four interrelated domains that together form the theoretical and methodological basis of the proposed project: (1) satellite imagery-based LULC classification methods; (2) temporal change detection approaches; (3) XAI frameworks applied to remote sensing; and (4) carbon stock estimation linked to LULC data.

2.1 LULC Classification Using Satellite Imagery

2.1.1 *Conventional Methods of Machine Learning*

The Random Forest (RF) classifier's resilience, interpretability, and good performance across a variety of landscapes have made it a benchmark technique in LULC research. Using Landsat images between 2010 and 2020, [4] showed RF-based categorization of Mysuru district in India, obtaining an overall accuracy of 88.42% with a Kappa coefficient of 0.86. Their research emphasizes that RF is inherently compatible with XAI pipelines since it not only generates high-accuracy maps but also offers native feature significance rankings. Similarly, supervised classifiers were used in a multi-temporal Landsat-based study in the Sangha region of [5] to track LULC transitions between 2013, 2018, and 2023. This study shows the ongoing value of publicly available medium-resolution satellite data for landscape monitoring in areas with limited data. For training and validation, both studies used stratified random sampling (60/40 or 70/30 splits), which is a commonly used technique in the field.

2.1.2 *Semantic Segmentation with Deep Learning*

Encoder-decoder architectures are preferable for remote sensing segmentation tasks, as demonstrated by the AE-DeepLabV3+ with Xception backbone, which obtained the maximum segmentation accuracy with a Dice coefficient of 91.3% and total accuracy of 92%. Classification performance has been significantly improved using transformer-based systems. Using Vision Transformers (ViT) refined by transfer learning on EuroSAT and PatternNet datasets [6], writing in Scientific Reports (Nature), achieved state-of-the-art results while including Captum-based XAI explanations. Their research brought to light an important trade-off: although transformers are excellent at collecting global geographical context, their high computational cost continues to prevent operational implementation over wide geographic areas. Pixel-level LULC categorisation has been transformed by deep learning. UNet, LinkNet, DeepLabV3+, and a modified AE-DeepLabV3+ model were assessed across many backbone networks in a comparative study that was published in [7].

2.1.3 *Spectral Indices as Features for Classification*

Spectral indices produced from satellite bands are important input information for any classifier. The most popular metric for differentiating between vegetated and non-vegetated surfaces is still the Normalized Difference Vegetation metric, or NDVI. For the purpose of delineating urban and water classes, respectively, NDVI is supplemented by NDBI (Normalized Difference Built-up Index) and MNDWI (Modified Normalized Difference Water Index). Research repeatedly demonstrates that utilizing these derived indices in addition to raw spectral bands increases classification accuracy by 3–8% when bands are used alone.

Table 1. Key LULC Classification Studies

Author(s) & Year	Method	Satellite Data	Accuracy
Bill Donatien et al. (2024) [4]	Supervised classifier	Landsat-8 OLI	>85% OA
Mahendra et al. (2025) [5]	Random Forest	Landsat 8	88.42% OA, Kappa 0.86
Khan et al. (2024) [6]	Vision Transformer + XAI	EuroSAT / PatternNet	State-of-the-art (94%+)
Deressu et al. (2025) [7]	AE-DeepLabV3+ (Xception)	Multispectral	92%, Dice 91.3%

2.2 Detection of Temporal Change

2.2.1 *Comparison After Classification*

In LULC investigations, the post-classification comparison (PCC) method is still the most used technique for detecting temporal changes. PCC creates separate land cover maps for every time period and compares them pixel by pixel to create a change matrix. This method is demonstrated in a 30-year study of Ethiopia's Alemsaga Forest [8] utilising Landsat data from 1992, 2003, 2013, and 2022. In addition to assessing related changes in the carbon pool, the study found that community-based conservation activities have significantly increased thick forest cover, from around 35% to 48%. Using ArcGIS and the InVEST model, a research conducted in Ethiopia's Upper Awash River Basin [9] expanded this technique over three decades (1993–2023), mapping four LULC epochs and computing carbon storage dynamics. Over the course of the 30-year period, the research discovered that almost 50,600 hectares (17.9%) of land changed class, with croplands and built-up areas growing and forests, shrublands, and wetlands decreasing.

2.2.2 *Transition Analysis and Change Matrix*

Transition matrices, often known as cross-tabulation or "from-to" matrices, go beyond straightforward binary change maps to show the directionality of land cover conversion. For instance, knowing that 20% of the region changed is not as instructive as knowing that "Forest → Urban" is the dominating transition. Sankey diagrams and chord charts, which offer clear depictions of carbon sink loss trajectories, are increasingly being used in studies to illustrate these transitions.

2.2.3 *LULC Simulation for the Future*

Predictive modelling has replaced historical change detection in a number of research. Future LULC situations are frequently projected using the CA-Markov (Cellular Automata-Markov) and PLUS models. In order to project future carbon stock changes under various climate and land management scenarios, a study on Northeast China forests, combined LULC simulation with the InVEST model. The results showed that deforestation exceeding 1% of the landscape may require triple the reforestation effort to compensate for carbon losses.

2.3 Explainable AI (XAI) in Remote Sensing

2.3.1 *Motivation for XAI in Land Cover Classification*

Machine learning models used in remote sensing particularly ensemble approaches like Random Forest and neural networks are generally considered as black boxes: they provide accurate predictions but offer little insight into the reasons behind those predictions. This opacity is problematic in high-stakes environmental applications where model trust, regulatory compliance, and scientific knowledge are crucial. A systematic review titled 'Opening the Black-Box: A Systematic Review on Explainable AI in Remote Sensing' [10] catalogued publications applying XAI to Earth Observation tasks, finding that the number of such studies has grown by over 70-fold relative to standard ML publications in the field. The review recognized SHAP, LIME, Grad-CAM, and perturbation-based feature significance as the four prominent XAI paradigms in remote sensing.

2.3.2 *Shapley Additive Explanations, or SHAP*

The most thoroughly justified XAI approach is SHAP, which is based on the Shapley values of cooperative game theory. It offers both local explanations (why was this particular pixel identified as forest?) and general feature importance (which bands or indices matter most overall?). [11], writing in IEEE Geoscience and Remote Sensing Letters, explicitly presented SHAP applied to deep learning models for LULC classification, revealing that near-infrared bands and NDVI-derived characteristics consistently ranked top for vegetated class predictions. Three feature importance metrics such as impurity-based, permutation-based, and SHAP were integrated into a Google Earth Engine workflow by an interactive, open-source land cover mapping tool published in Remote Sensing [12]. This allowed practitioners all over the world to access XAI explanations without the need for sophisticated programming knowledge. This is a significant step in the direction of democratizing explainable remote sensing.

2.3.3 *LIME and Grad-CAM*

By constructing a straightforward, comprehensible surrogate model around each unique prediction, LIME (Local Interpretable Model-Agnostic Explanations) offers local explanations. LIME regards features as independent, which might generate errors when spectral bands are heavily linked, even if it is computationally less expensive than SHAP. A comprehensive comparison of SHAP and LIME is given in a perspective paper by Salih [13], which warns that both approaches are susceptible to feature collinearity, a common condition in multispectral remote sensing data where adjacent bands often show high Pearson correlations. Convolutional neural network architectures are especially well-suited to Grad-CAM (Gradient-weighted Class Activation Mapping) and its extensions (Seg-Grad-CAM++, Seg-Score-CAM), which generate spatially explicit heatmaps that emphasise image regions most important for a particular class prediction. Both Seg-Grad-CAM++ and Seg-Score-CAM were used in the ScienceDirect deep learning segmentation project (2025) to improve model transparency for LULC segmentation.

2.3.4 *Transformer Models and XAI*

The current frontier is the combination of XAI with transformer-based LULC models. In order to identify spatial and spectral biases in model decisions, [6] used Captum, a PyTorch-based XAI toolkit, to create attribution maps for transformer-based LULC predictions. The intersection of XAI with transformers and NLP techniques was further synthesised in a 2025 Springer book chapter titled "Explainable AI in Transforming Land Use Land Cover Classification, [14]" which proposed a combined framework that extracts textual insights from geospatial metadata alongside visual feature attributions.

Table 2. Comparison of XAI Methods

XAI Method	Type	Best For	Limitation
SHAP [12]	Model-agnostic	Global + local feature importance	Computationally intensive
LIME [13]	Model-agnostic	Local explanations, any model	Assumes feature independence
Grad-CAM [14]	Model-specific (CNN)	Spatial heatmaps	Only for CNNs
Captum [6]	Model-specific (PyTorch)	Transformer/DL attribution	Requires PyTorch models
Feature Importance (RF)	Interpretable-by-design	Fast global importance	No local explanations

2.4 Estimating Carbon Stock from LULC

2.4.1 *The IPCC Framework and Carbon Pools*

The fundamental framework for estimating carbon stocks associated with land use is provided by the IPCC 2006 Guidelines [15] for National Greenhouse Gas Inventories. The four reservoirs of carbon storage are dead organic matter (DOM), soil organic carbon (SOC), above-ground biomass (AGB), and below-ground biomass (BGB). Due to a lack of data, many regional studies actually ignore DOM and concentrate on the first three pools, which together account for the bulk of ecosystem carbon. In order to measure carbon stocks in 2000, 2015, and 2023, a study conducted in Ethiopia's Upper Blue Nile River Basin [8] coupled Landsat-based LULC classification (RF classifier, 96% overall accuracy, Kappa 0.91) with the IPCC framework and InVEST model.

2.4.2 *The Carbon Model InVEST*

The most popular method for converting LULC maps into estimates of carbon stocks is the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Carbon module. To determine total stocks, it multiplies user-specified carbon density values (in tonnes of carbon per hectare, or tC/ha) by class area for each LULC class. Additionally, the model uses a user-defined price per tonne of CO2 equivalent to determine the economic worth of carbon. A research conducted in Calabria, Italy [16] used the InVEST model in conjunction with GEE-derived Corine land cover datasets to monitor changes in carbon stocks between 2000 and 2024. According to the study, with 6.56 million Mg of CO2 emissions during decline periods, LULC-driven carbon losses had economic effects of up to EUR 357.57 million. This illustrates how combining LULC change detection with carbon stock economics has significant policy implications.

The InVEST model has recognised limitations despite its usefulness: it ignores temporal carbon dynamics within land classes, assumes static carbon coefficients for each LULC class, and ignores non-LULC factors that affect carbon sequestration, such as soil moisture or climate variability. To reduce uncertainty, studies advise utilising locally observed carbon density estimates instead of global defaults.

2.4.3 *Carbon Stock Mapping Using Machine Learning*

Data-driven machine learning models that directly estimate carbon density from spectral and structural remote sensing variables have replaced InVEST's lookup-table technique in recent research. In order to predict forest carbon stock with high spatial detail using Sentinel-2 multispectral data and a hierarchical machine learning pipeline, a Scientific Reports study from 2024 found that vegetation indices, specifically EVI, NDVI, and NIR-based indices, were the best indicators of above-ground carbon density. In order to investigate non-linear correlations between LULCC and net carbon exchange in mainland China, a unique geospatial machine learning study [7] integrated Sentinel-2 LULC categorisation with satellite-derived CO2 inversion data. The study's threshold analysis revealed that deforestation surpassing 1% of landscape area results in carbon debt that needs three times as much replanting effort to offset. This discovery has important ramifications for land management policy. Global forest carbon potential outside of agricultural and urban lands is 226 Gt, with existing stocks well below their natural potential, according to a thorough analysis published in [17] that included estimates from satellite data and ground sources.

2.4.4 *Carbon Estimation using Remote Sensing Platforms*

According to an assessment of forest carbon stock estimation [18], the number of publications on this subject has surpassed 400 annually since 2022, indicating the increasing seriousness of the situation worldwide. The review documented the development of remote sensing platforms: LiDAR (including NASA GEDI) provides three-dimensional structural data necessary for AGB estimation in dense forests; SAR (Sentinel-1, ALOS PALSAR) provides cloud-penetrating capacity crucial for tropical forest monitoring; and passive optical sensors (Landsat, Sentinel-2) dominate for LULC-based carbon estimation. Single-sensor methods are regularly outperformed by multi-sensor fusion.

3. Key Contributions

The proposed initiative is positioned to fill several significant gaps identified by the literature review:

3.1. Rather than incorporating XAI explanations into a temporal change detection methodology, many LULC-XAI investigations concentrate on single-date classification accuracy. This gap is filled by the proposed project.

3.2. LULC categorization and carbon stock estimation are nearly usually handled as distinct workflows. It is innovative to incorporate carbon estimation as a downstream component of a classification pipeline facilitated by XAI.

3.3. Current XAI implementations in LULC are mostly concerned with improving model accuracy rather than producing ecologically interpretable insights (e.g., 'which bands drive forest vs. urban misclassification?'). Ecologically significant XAI outputs are specifically targeted by the proposed effort.

3.4. The integration of carbon consequence modelling with SHAP-based feature attribution in a single pipeline is a publishable contribution that has not been documented in the peer-reviewed literature.

4. Conclusions

While substantial methodological advancements have been made in each of the different fields of deep learning-based LULC classification, the studied literature as a whole shows No previous work has effectively combined explainable AI, temporal change detection, and carbon stock calculation into a single, comprehensible, and carbon-consequential pipeline. While XAI techniques like SHAP, Grad-CAM, and Integrated Gradients have proven their ability to reveal ecologically significant spectral attribution patterns that validate deep learning classification logic against established remote sensing knowledge, deep learning architectures, in particular encoder-decoder CNN segmentation models and Vision Transformers, have improved satellite image classification accuracy to 88–95% on multispectral imagery. While multi-temporal change detection studies over Southern India confirm accelerating conversion of forest and agricultural land to urban uses driven by rapid infrastructure expansion, carbon stock estimation frameworks combining process-based carbon models, spatially explicit LiDAR biomass data, and IPCC accounting guidelines have been applied across Indian and global landscapes to quantify LULC-driven carbon losses and their economic consequences. However, three crucial gaps remain in all reviewed work: no integrated framework directly links model-level spectral attribution to downstream carbon stock consequences; no 10-meter resolution, deep learning-based, explainable carbon stock change quantification exists for Southern India over the 2020–2026 NDC commitment period; and XAI has never been applied to temporal change detection to identify spectral precursors of specific carbon-significant LULC transitions. These three interrelated gaps are directly and concurrently addressed by the proposed integrated explainable deep learning pipeline.

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