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Influence of Land Use and Cover Transformations on Ecosystem Carbon Storage over Gandak River Basin, India

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ABSTRACT

This study investigates the changes in land use/land cover (LULC) and their impact on ecosystem carbon sequestration, greenhouse gas (GHG) dynamics, and environmental sustainability in the Gandak River Basin (GRB), India, focusing on the period between 2014 and 2024. LULC changes significantly influence ecosystem functions, including carbon storage potential, biodiversity, and air quality regulation. Using Google Earth Engine (GEE)-based machine learning (ML) algorithms for LULC classification, the study identified substantial transformations in land cover patterns. In 2014, the basin was predominantly covered by agricultural land, followed by forests, water bodies, and urban areas. By 2024, rapid urbanization and infrastructural expansion caused a corresponding decline in farming and the forested regions. Using the InVEST model, carbon storage estimates revealed a net increase of 23,415,542.10 Mg of carbon (C) over the decade, primarily attributed to improved agricultural management, afforestation initiatives, and soil carbon enhancement. However, intensified urban growth and industrialization led to higher emissions of GHGs, including formaldehyde (HCHO), carbon monoxide (CO), nitrogen dioxide (NO_2), and carbon dioxide (CO_2), contributing to degraded air quality and increased regional warming potential. Elevated concentrations of these gases were closely linked to forest loss, declining vegetation cover, soil degradation, and growing anthropogenic pressures, highlighting the dual challenge of enhancing carbon sequestration while mitigating environmental risks. This study underscores the importance of integrated and sustainable LULC planning to control emissions, enhance carbon storage, and reduce the basin's vulnerability to climate change. These findings provide critical insights for policymakers to formulate evidence-based strategies that promote eco-friendly development, resource conservation, and climate resilience in the GRB.

Keywords: LULC, InVEST, Carbon sequestration, Greenhouse gases, GRB, Geospatial tools.

INTRODUCTION

Carbon emissions remain a key contributor to global warming (Fahad et al., 2019; Zhang et al., 2021). Understanding the relationship between LULC dynamics and carbon emissions is essential for assessing climate change impacts at regional and global scales. Carbon storage is a vital indicator of terrestrial ecosystems' response to climate change (Gupta et al., 2021, 2022; Ito et al., 2016). Enhancing carbon sequestration reduces atmospheric CO_2, mitigating the greenhouse effect (Groshans et al., 2018; LI 2004; Liang et al., 2021). Terrestrial ecosystems store carbon in biomass, soil organic matter, and decomposed material, totaling 2000–2500 Pg globally, with 500–600 Pg in vegetation and 1500-2300 Pg in the top 100 cm of soil (Groshans et al., 2018; LI, 2004; Liang et al., 2021). These estimates emphasize the crucial role of vegetation and soil in global carbon cycling and highlight the potential consequences of ecosystem degradation. Temperature and precipitation changes significantly affect this cycle (Fahad et al., 2019; Jia et al., 2021; Tauqeer et al., 2022).

Over recent decades, ecosystem services have declined by at least 4% per decade, mainly due to human activity (Gond et al., 2023a; Gond et al., 2023b; Gupta et al., 2021a). Land Use/Land Cover (LULC) changes, driven by climate and anthropogenic influences, substantially impact terrestrial carbon storage (Jodhani et al., 2024; Zaehle et al., 2007). These changes are the second largest source of atmospheric CO_2 after fossil fuels (Baumann et al., 2017; Foley et al., 2005; Shekhar et al., 2022; Jodhani et al., 2024a; Jodhani et al., 2024b; Zhu et al., 2020). Thus, assessing carbon storage across spatial and temporal scales is critical. Therefore, understanding spatiotemporal variations in carbon storage is essential for designing sustainable land management strategies and developing climate change mitigation policies.

Carbon sequestration capacity varies across LULC types, with transitions altering vegetation and soil function (Jodhani et al., 2023; L. Li et al., 2020; Ni 2013; Shekhar et al., 2022; Vyas et al., 2024). Vegetation and soil, key carbon reservoirs, are highly sensitive to LULC changes. Shifts in vegetation growth and soil traits lead to marked differences in ecosystem carbon storage. The conversion of non-construction land to urban areas, for example, significantly reduces regional carbon storage, with limited short-term recovery (Muñoz-Rojas et al., 2015). LULC changes are estimated to emit 1.5 Pg of carbon annually, disrupting global carbon cycling (Landman, 2010). In China, terrestrial ecosystems lost 279 Tg of carbon between 1980 and 2010 due to such dynamics (Zhang et al., 2015).

Current methods for evaluating ecosystem carbon storage use field surveys, remote sensing, and models (Gupta et al., 2025; Mishra et al., 2024). Models like CLUE-S and LUSD forecast land-use changes (Zhao et al., 2019), with the CA-Markov model widely used for incorporating terrain and policy factors (Chen et al., 2021; Mokarram et al., 2021). The InVEST model further quantifies LULC effects on carbon with user-friendly precision (Jiang et al., 2017). Combining these models with machine learning (ML) classification enhances predictive accuracy and provides a robust framework for assessing ecosystem responses.

CA-Markov and InVEST have proven effective in analyzing LULC impacts on carbon (Lai et al., 2016; Maanan et al., 2019; Sarathchandra et al., 2021; Wang et al., 2012; Xia et al., 2020; Xiao et al., 2021; Zhou et al., 2020). Studies have assessed carbon storage variations at multiple scale watersheds (Zhu et al., 2020), climate zones (Zhou et al., 2020), administrative boundaries (C. Li et al., 2018; Tang et al., 2020), conservation areas (Chu et al., 2019), and hill belts (Ma et al., 2021). Yet, uncertainties in scale-specific LULC impacts persist (Calle et al., 2016; Zhou et al., 2020), especially in ecologically sensitive coastal zones. However, uncertainties remain regarding the relative contributions of socio-economic, policy-driven, and climatic drivers to LULC-induced carbon storage changes, particularly at local scales.

Remote Sensing (RS) and GIS enhance temporal-spatial LULC analyses (Baidya et al., 1970; J. Wang et al., 2011; Weng, 2002), enabling LUCC assessments globally using satellite data (J. Chen et al., 2015; Hansen et al., 2000; Klein Goldewijk et al., 2011; Loveland et al., 2000). These tools are also widely applied in studies of the Gandak River Basin (GRB) (Rimal, 2012; Rimal et al., 2015). Despite significant advancements in remote sensing, GIS, and machine learning (ML) techniques, studies assessing land use/land cover (LULC) dynamics and their impact on carbon sequestration in the Gandak River Basin (GRB) remain limited. Previous research has primarily focused on broader regional or national scales, often neglecting localized socio-economic drivers, policy influences, and climate variability that directly affect carbon storage. Furthermore, earlier studies have generally used conventional classification techniques and static datasets, lacking high-resolution temporal analyses and robust machine learning-based approaches integrated with dynamic carbon modeling. These limitations create uncertainty in understanding how LULC transitions influence ecosystem carbon balance, greenhouse gas (GHG) emissions, and environmental sustainability at the basin level.

This study aims to address the identified research gap by integrating machine learning-based LULC classification with the InVEST carbon storage model to comprehensively evaluate spatiotemporal carbon dynamics in the Gandak River Basin from 2014 to 2024. Therefore, the key objectives are to (i) evaluate a decade of LULC transformations, (ii) quantify changes in carbon storage using the InVEST model, and (iii) assess the combined impact of LULC dynamics and greenhouse gas emissions on ecosystem health. The findings aim to provide actionable insights for sustainable land use planning and climate change mitigation in the GRB. Objectives include evaluating 10-year LULC trends, estimating carbon storage using the InVEST model, and assessing LULC impacts on carbon storage offering insights for sustainable land use and climate change mitigation. The remainder of this paper is organized as follows: The next section describes the study area and data sources, followed by a section that explains the methodology, including machine learning-based LULC classification and carbon storage estimation using the InVEST model. Then, we present the results and discussion, focusing on LULC dynamics, carbon sequestration patterns, and greenhouse gas emissions. Finally, the last section concludes the study with key findings, policy recommendations, and potential directions for future research.

MATERIALS AND METHODOLOGY

This study utilized machine learning (ML)-based classification to generate land use/land cover (LULC) maps for the Gandak River Basin (GRB) for the years 2014 and 2024. High-resolution satellite imagery was processed to classify major land cover types, including agricultural land, forests, water bodies, and urban areas. The InVEST model was employed to estimate carbon storage variations by integrating LULC data with carbon pool parameters. Additionally, atmospheric datasets were analyzed to assess greenhouse gas (GHG) emissions, specifically formaldehyde (HCHO), carbon monoxide (CO), nitrogen dioxide (NO_2), and carbon dioxide (CO_2), providing insights into the environmental impact of LULC transformations.

Study Area

The Gandak River Basin (GRB) is a significant hydrological unit of northern India, covering parts of Bihar and Uttar Pradesh (Raj & Roy, 2025). It lies between latitudes 25°30′N to 27°40′N and longitudes 83°50′E to 85°50′E (Fig. 1).

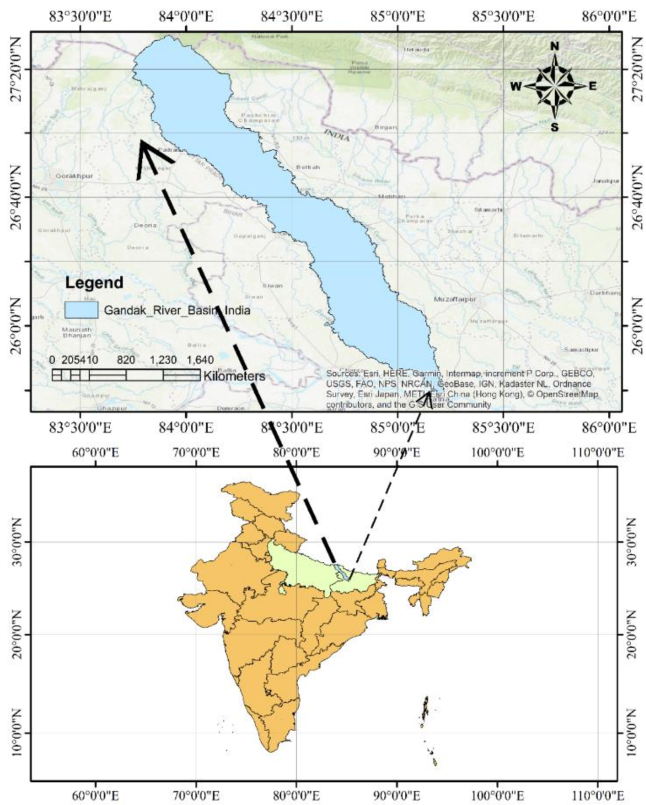

Figure 1. Gandak river basin, India as the study area for the present study

Originating from the glaciers of the central Nepal Himalayas, the Gandak is a perennial river and a key tributary of the Ganges. The basin encompasses approximately 22,000 square kilometers within India, characterized by fertile alluvial plains and a mosaic of land use/land cover (LULC) types. The GRB includes agricultural fields, forested regions, wetlands, urban centers, and rural settlements, making it ecologically and economically significant. Agricultural practices, predominantly focused on rice and wheat cultivation, are heavily reliant on the southwest monsoon and are supported by irrigation sourced from the river network. Wetlands and riparian zones within the basin contribute essential ecosystem functions, such as biodiversity preservation and groundwater recharge. Climatically, the GRB experiences a humid sub-tropical climate, with annual rainfall ranging from 1,000 mm to 1,600 mm, the majority of which falls during the monsoon period (from June to September). The basin is subject to periodic flooding, driven by intense monsoonal rains and snowmelt from the Himalayas. Although these floods enhance soil fertility, they also pose significant risks to agriculture and human habitation.

The GRB (chiefly West Champaran, East Champaran, Gopalganj and Siwan) combines land use dynamics with people and infrastructure. ML-based LULC maps indicate a decade of rapid peri-urban expansion along district and national corridors, with built-up area growing at the expense of agricultural mosaics and scattered tree cover, while water bodies show seasonal contraction/fragmentation; these patterns align with field notes and are mapped in the results. Demographically, this is a very densely settled landscape: Census 2011 district figures report population densities of ~753 persons/km² in West Champaran, ~1,281–1,285 persons/km² in East Champaran, ~1,260 persons/km² in Gopalganj, and ~1,501 persons/km² in Siwan, underscoring intense human pressure on land and ecosystems. Transport access is a major driver of change: the all-India East–West corridor (NH-27) threads through Gopalganj and Mehsi (East Champaran), complemented by the (old-numbered) NH-28 corridor that historically linked Lucknow–Gorakhpur with Muzaffarpur *via* East Champaran/Gopalganj; together with East Central Railway lines (notably the Muzaffarpur–Sagauli–Bettiah and Siwan–Mairwa sections). These routes have catalyzed settlement densification, market integration and land conversion along road/rail spines. The basin also contains high-value natural assets, including the 880–900 km² Valmiki Tiger Reserve/National Park block in West Champaran adjoining Nepal's Chitwan, which anchors remaining Terai forests, but faces edge pressures from agriculture and expanding villages. Today's spatial picture is therefore a tight co-existence of (i) intensively farmed floodplain tracts, (ii) fast-growing market towns and border-trade nodes (e.g. Raxaul–Birgunj) tied into national corridors, and (iii) protected forest cores and riparian buffers; this mix helps explain our observed LULC transitions and the carbon-and-air-quality trade-offs. This study investigates the spatio-temporal changes in LULC and carbon storage within the basin, offering vital insights into ecological sustainability and informing future land management strategies.

Datasets Used

The datasets utilized for LULC analysis in the Gandak River Basin (GRB) are critical for understanding historical trends, current conditions, and future projections. Satellite imagery from Landsat (5 TM, 7 ETM+, 8 OLI) with a spatial resolution of 30 meters was used for LULC classification for a decade (2014-2024). Carbon pool data for above-ground biomass, below-ground biomass, and soil organic carbon was sourced from IPCC reports and regional studies. Additional datasets included administrative boundaries, hydrological layers from the Survey of India and NRSC, and climate data from the Indian Meteorological Department (IMD) to account for environmental drivers of LULC change. Ground truth data from field surveys and Google Earth high-resolution imagery supported training and validation. These datasets were processed using supervised classification techniques, with accuracy validated through metrics enabling comprehensive LULC mapping and scenario simulation for the GRB.

Methodology

The methodology involved using high-resolution satellite imagery to perform ML-based LULC classification for the GRB in 2014 and 2024, identifying key land cover types and their spatial distribution. The InVEST model was applied to estimate carbon storage for both years by integrating LULC data with carbon pool parameters. Atmospheric data on greenhouse gases (HCHO, CO, NO_2, and CO_2) was analyzed to assess variations in their concentrations due to LULC changes. The findings were synthesized to evaluate the combined impact of LULC dynamics on carbon sequestration, air quality, and greenhouse gas emissions in the region.

LULC Classification

The classification of Land Use and Land Cover (LULC) in the Gandak River Basin (GRB) was conducted using machine learning algorithms on satellite data from Landsat 8 OLI (2014) and Sentinel-2 MSI (2024) *via* Google Earth Engine (GEE). Pre-processing steps, such as atmospheric correction, geometric correction, and cloud masking, were applied to enhance image quality. Five major LULC classes were delineated: agricultural land, forest cover, water bodies, built-up areas, and barren land. Spectral indices, like NDVI and NDWI, were used to improve class separability. Change detection analysis quantified spatial and temporal dynamics, and outputs were integrated into the InVEST model to assess carbon storage impacts.

ML Techniques Implemented

In this study, Land Use/Land Cover (LULC) classification for 2014 and 2024 was carried out using the Random Forest (RF) algorithm implemented in Google Earth Engine (GEE), following approaches similar to Jodhani et al., (2023, 2024). Several machine learning techniques, such as Support Vector Machines (SVM), Classification and Regression Trees (CART), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANNs), were initially reviewed for their potential applications in LULC mapping. However, RF was selected due to its proven robustness, ability to handle high-dimensional multi-spectral data, and superior performance in heterogeneous landscapes. Input features included surface reflectance bands from Landsat-8 and Sentinel-2, along with derived spectral indices, such as NDVI, NDBI, and NDWI, consistent with methodologies adopted by Jodhani et al. (2023). Topographic variables, including elevation and slope from the SRTM DEM, were also integrated to improve class separability. The RF classifier was trained with 500 decision trees using a 70% training and 30% validation split. Accuracy assessment was conducted using multiple metrics, including Overall Accuracy (OA), Kappa Coefficient, Producer's Accuracy (PA), and User's Accuracy (UA), as recommended by Jodhani et al., (2024). The classification achieved an OA of 91.3% and a Kappa value of 0.87, demonstrating high reliability and comparable performance to similar RF-based studies by Jodhani et al., (2024).

InVEST Model

Carbon stock changes in the GRB from 2014 to 2024 were analyzed using the InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model. The model used classified LULC maps to estimate net carbon storage change per pixel, attributing changes to transitions between LULC types (Mannan et al., 2019). Four carbon pools were considered: above-ground biomass (Cabove), below-ground biomass (Cbelow), soil organic carbon (Csoil), and dead organic matter (Cdead) (Sharp et al., 2017).

- **Cabove** represents carbon in vegetation above ground,
- **Cbelow** in roots,
- **Csoil** in soil organic matter,
- **Cdead** in litter and decomposed material.

Due to data limitations, only **Cabove, Cbelow, and Csoil** were included (Lai et al., 2016; Zhou et al., 2020). Despite using static carbon density values, studies confirm that this approach still effectively evaluates LULC-driven carbon changes (Chu et al., 2019). LULC data paired with carbon pools allowed accurate spatial estimation of carbon stocks.

RESULTS

The study analyzed LULC changes in the GRB from 2014 to 2024 and their impact on carbon sequestration and greenhouse gas emissions.

Spatio-temporal Analysis of LULCC

LULC maps for 2014 and 2024 were generated using a Random Forest (RF) classifier implemented in Google Earth Engine. Input features included surface reflectance bands, spectral indices (NDVI, NDWI, NDBI), and topographic covariates (slope, elevation). Ground truth data consisted of GPS-referenced field samples and high-resolution Google Earth points, stratified across five LULC classes (agriculture, forest, built-up, water, barren). The dataset was split into training (≈70%) and independent validation (≈30%)

sub-sets. RF was trained with 500 trees; hyper-parameters were tuned *via* out-of-bag error and cross-validation. Classification accuracy was assessed using a confusion matrix; Overall Accuracy (OA) = 91.3%, Kappa = 0.87. These results are comparable with other recent GEE-ML studies in India (e.g. Jodhani et al., 2024; Vyas et al., 2024) that reported high classification reliability using RF coupled with spectral indices.

The RF classifier achieved robust accuracy: OA = 91.3% and Kappa = 0.87. Water bodies were identified with the highest reliability (UA > 98%), while mixed/barren classes had relatively lower producer accuracies (≈80%), likely due to small patch sizes and seasonal dynamics. Errors of commission and omission for each class are explained and were propagated into carbon stock uncertainties for InVEST analysis.

GEE-based ML classification revealed major LULC shifts in GRB due to expanding agriculture, deforestation, and rapid urban growth. Agricultural land increasingly replaced natural vegetation and water bodies. Urban expansion, driven by population growth, led to hydrological consequences, such as increased run-off and reduced groundwater recharge, heightening flood vulnerability in Bihar. Declining forests and water bodies also compromise biodiversity and ecosystem services. Structural flood controls, like embankments, showed mixed outcomes, often intensifying flood severity. Sustainable land use and integrated water resource management are necessary to ensure ecological balance.

LULC Classification in 2014

In 2014 (Fig. 2), GRB's landscape comprised agricultural fields, forests, built-up zones, water bodies, and barren land. Forests made up 33.22%, mainly midstream and downstream, while croplands dominated midstream (29.03%) and downstream (69.11%) areas. The upstream was marked by snow/glacier cover (7.27%) and barren zones (13.75%), with intermittent grasslands and shrubs. Urban areas were still limited, but showing early signs of expansion. These LULC patterns significantly influenced regional hydrology and carbon sequestration.

LULC Classification in 2024

By 2024, notable LULC transformations have occurred. Between 2008 and 2018, the Burhi Gandak River catchment, part of the GRB, saw agricultural land increase by 6.51%, settlements by 58.20%, and wastelands by 34.05%, while natural vegetation declined by 33.58%, and water bodies shrank by 54.23%. Similar trends are evident in the GRB, with urbanization and agriculture expanding at the expense of forests and water bodies.

LULC Changes: 2014 *vs*. 2024

Between 2014 and 2024, the Gandak River Basin (GRB) in India witnessed substantial transformations in land use and land cover (LULC), shaped by the combined effects of population growth, urbanization, and agricultural intensification. These changes reflect both anthropogenic pressures and natural processes influencing the region's evolving landscape.

Agricultural land and built-up areas expanded significantly during this period, often replacing natural vegetation and water bodies. Built-up areas, in particular, grew by approximately 58.20%, highlighting the rapid pace of urban development and increasing demands for infrastructure and housing. Although built-up regions remained relatively limited in area compared to other land types, their growth trajectory suggests an ongoing trend of urban sprawl. Simultaneously, the basin experienced a marked decline in ecological zones. Forests and water bodies, critical to regional biodiversity and hydrological stability, saw considerable reductions. Studies on the Burhi Gandak River catchment (a sub-region within the GRB) reported a 33.58% loss in natural vegetation and a 54.23% reduction in water bodies between 2008 and 2018, trends that are mirrored across the broader basin up to 2024. These losses are largely attributed to deforestation, encroachment, and the absence of regulated land use planning.

Such land conversions have far-reaching environmental implications. The loss of forests and wetlands has significantly reduced the basin's carbon sequestration potential, disrupted local ecosystems, and degraded habitat quality. Hydrologically, increased impervious surfaces due to urban expansion have altered run-off dynamics, reduced groundwater recharge, and heightened flood risks, particularly in downstream regions like Bihar. Structural flood control interventions, such as embankments, have shown mixed results at times, exacerbating the intensity of flood events rather than mitigating them.

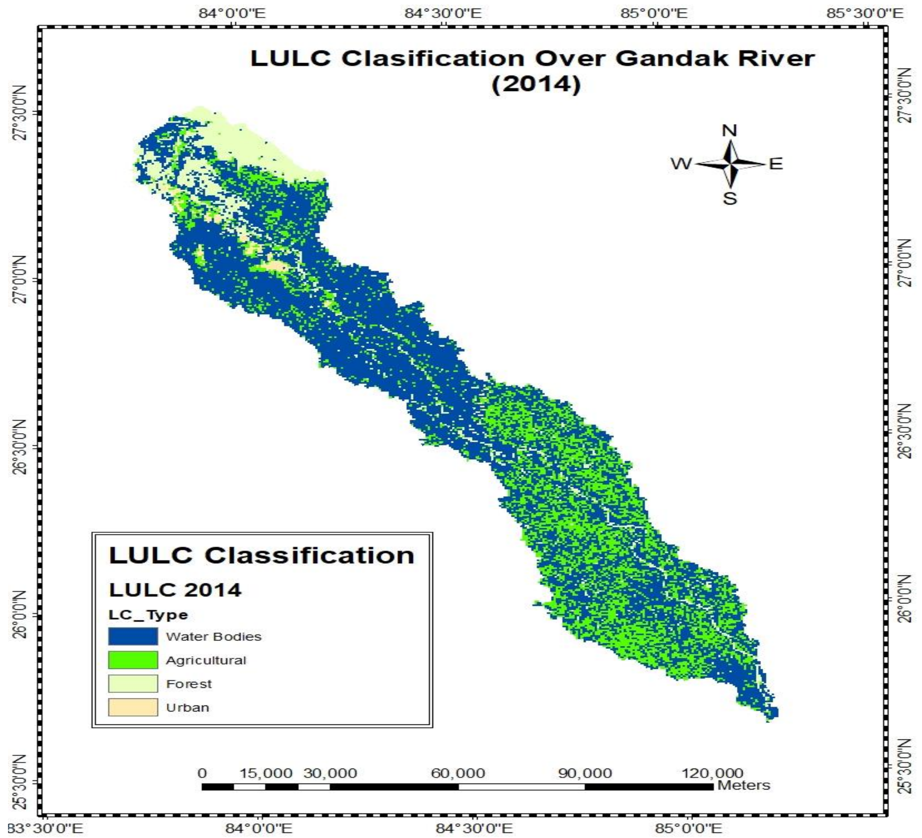

Figure 2. Land use land cover classification for the year 2014 over GRB

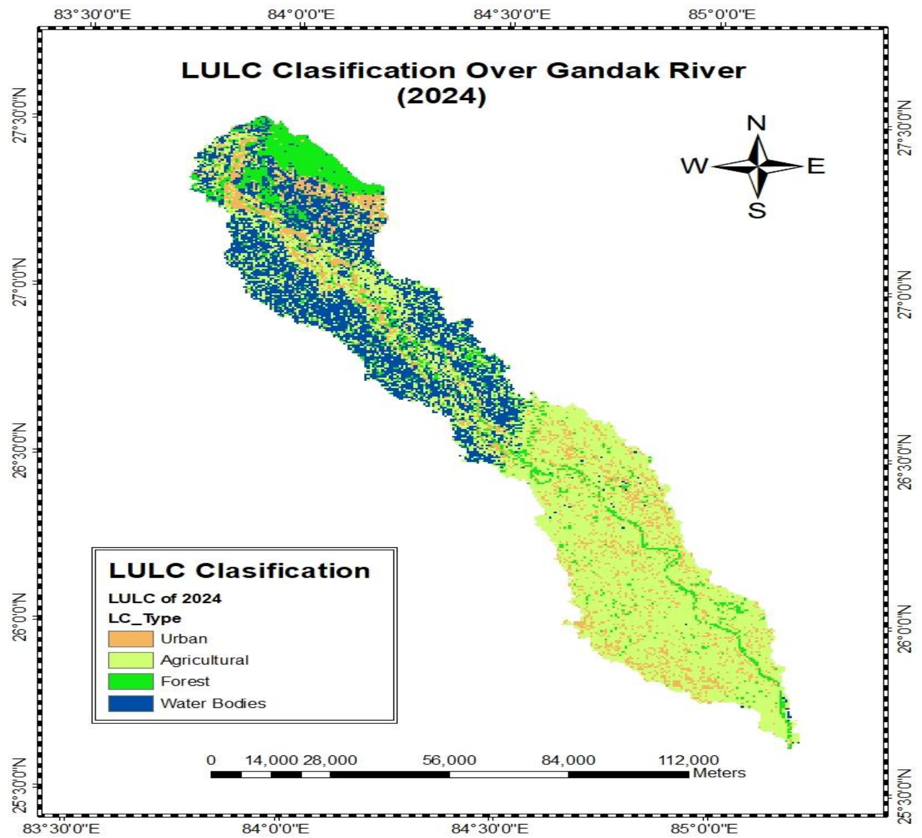

Figure 3. Land use land cover classification in 2024 over GRB

The comparison of LULC patterns from 2014 to 2024 underscores an urgent need for sustainable land management practices and integrated watershed planning. Continuous monitoring of land changes and the implementation of conservation-focused development strategies are essential to safeguard ecological integrity while accommodating socio-economic growth in the GRB.

Greenhouse Gas Emissions

The GRB, encompassing a significant area across India and Nepal, has undergone extensive land-use and land-cover (LULC) changes in the past decade, resulting in notable greenhouse gas (GHG) and pollutant emissions. The basin's transformation, particularly from agricultural and forested land to urban and industrial zones, has contributed to increasing concentrations of HCHO (formaldehyde), NO_2 (nitrogen dioxide), CO (carbon monoxide), and CO_2 (carbon dioxide). Between 2014 and 2024, LULC changes saw agricultural land decrease from 67.32% to 62.78%, and built-up areas expanded from 3.21% to 6.19%, accompanied by deforestation and soil degradation. These LULC dynamics have accelerated emissions of HCHO and NO_2 due to intensified industrial activities, vehicular emissions, and biomass burning. CO levels have risen due to incomplete combustion processes in expanding urban areas, while CO_2 emissions have surged from fossil fuel use and land conversion, with the latter releasing stored carbon from soil and vegetation. Despite the increase in carbon sequestration from 18,701,438.27 Mg of C in 2014 to 42,116,980.34 Mg of C in 2024, the growing urban and industrial footprint significantly offsets these gains by contributing to higher GHG levels.

HCHO

The spatial and temporal variation of formaldehyde (HCHO) in the Gandak River Basin (GRB) is shaped by land use and land cover (LULC) changes. As a byproduct of volatile organic compound (VOC) oxidation, HCHO indicates both primary emissions and secondary atmospheric processes. In the GRB, major sources include biomass burning, vehicular exhaust, industrial discharges, and vegetation.

Between 2014 and 2024, deforestation, urban growth, and intensive agriculture have raised VOC emissions, leading to higher HCHO levels. This degrades air quality and promotes tropospheric ozone and secondary organic aerosol formation, both contributing to climate change. Reduced vegetative sinks and increased fossil fuel use have further amplified emissions. Elevated HCHO enhances greenhouse effects by participating in photochemical reactions that increase ozone, a strong greenhouse gas. These dual impacts on air quality and climate highlight the need for sustainable land management and emission controls in the GRB. Between 2014 and 2024, LULC changes, such as deforestation, urban expansion, and intensive agriculture, have led to increased VOC emissions, resulting in elevated atmospheric HCHO levels.

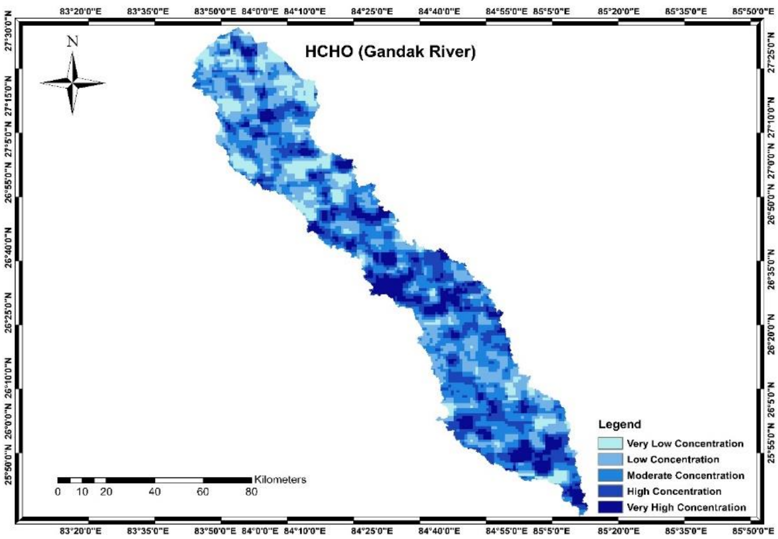

Figure 4. Spatial Variation in concentration of HCHO over GRB in 2024

These elevated concentrations not only degrade air quality, but also enhance tropospheric ozone formation and the production of secondary organic aerosols, both of which contribute significantly to radiative forcing and regional climate change. The reduction in vegetative carbon sinks, combined with intensified fossil fuel use and land surface alterations, has further amplified HCHO emissions in the GRB.

CO Concentration

CO levels in the GRB are similarly affected by LULC changes. Emitted mainly from biomass burning, vehicles, industries, and agriculture, CO has risen due to deforestation, urbanization, and intensified farming.

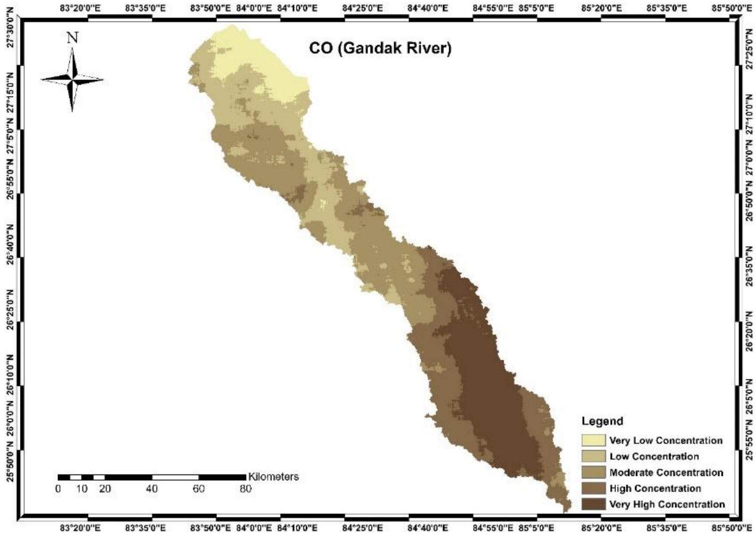

Figure 5. Spatial variation of CO concentration over GRB in 2024

These changes reduce forests that act as carbon sinks and increase CO sources. CO worsens air quality by depleting atmospheric hydroxyl radicals (OH), limiting the breakdown of methane and prolonging its warming effect. Elevated CO near urban and agricultural areas signals deteriorating air quality and climate impacts. Mitigation requires emission reductions, sustainable land practices, and cleaner technologies.

NO_2 Concentration

Nitrogen dioxide (NO_2) levels in the GRB show notable variations due to LULC changes, directly impacting air quality and greenhouse gas formation (Fig. 6).

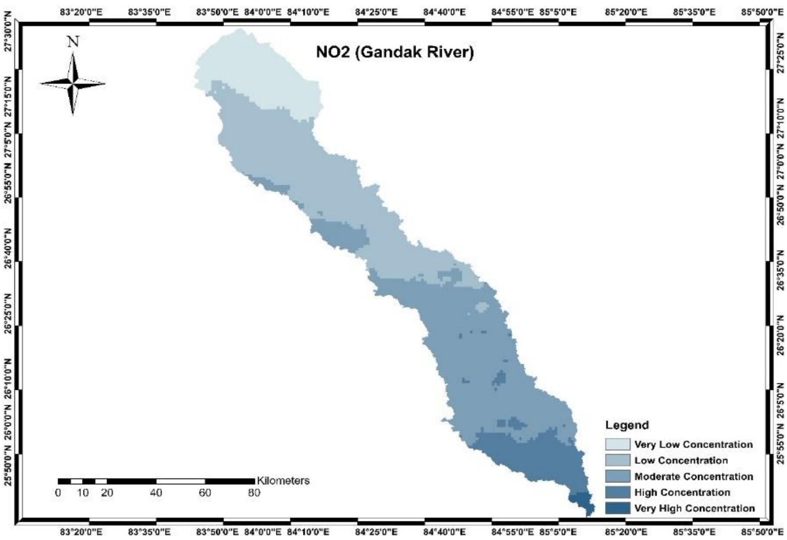

Figure 6. Spatial Variation in concentration of NO_2 over GRB in 2024

Major sources include vehicular emissions, industries, biomass burning, and fertilizer use in agriculture. Urbanization and intensive farming have elevated NO_2 emissions, especially in densely populated and agricultural zones. These shifts have not only boosted emissions, but also reduced vegetation that naturally absorbs nitrogen compounds. Elevated NO_2 worsens air quality by forming ground-level ozone and particulate matter, posing severe health hazards. It also acts as a precursor for tropospheric ozone, intensifying global warming. Additionally, NO_2 leads to acid rain, damaging soil, water systems, and biodiversity in the GRB.

Carbon Sequestration

The carbon sequestration potential of the GRB in 2014 was assessed using the InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) tool based on LULC classification (Fig. 7). The analysis estimated a total carbon stock of 18,701,438.27 Mg of C, distributed across various land cover categories in the basin. InVEST modeled carbon storage using data on above-ground biomass, below-ground biomass, soil organic carbon, and dead organic matter for each LULC type, providing a holistic estimate of the region's carbon holding capacity. Forested zones emerged as the primary contributors, with dense vegetation accounting for a substantial portion of both above- and below-ground biomass pools.

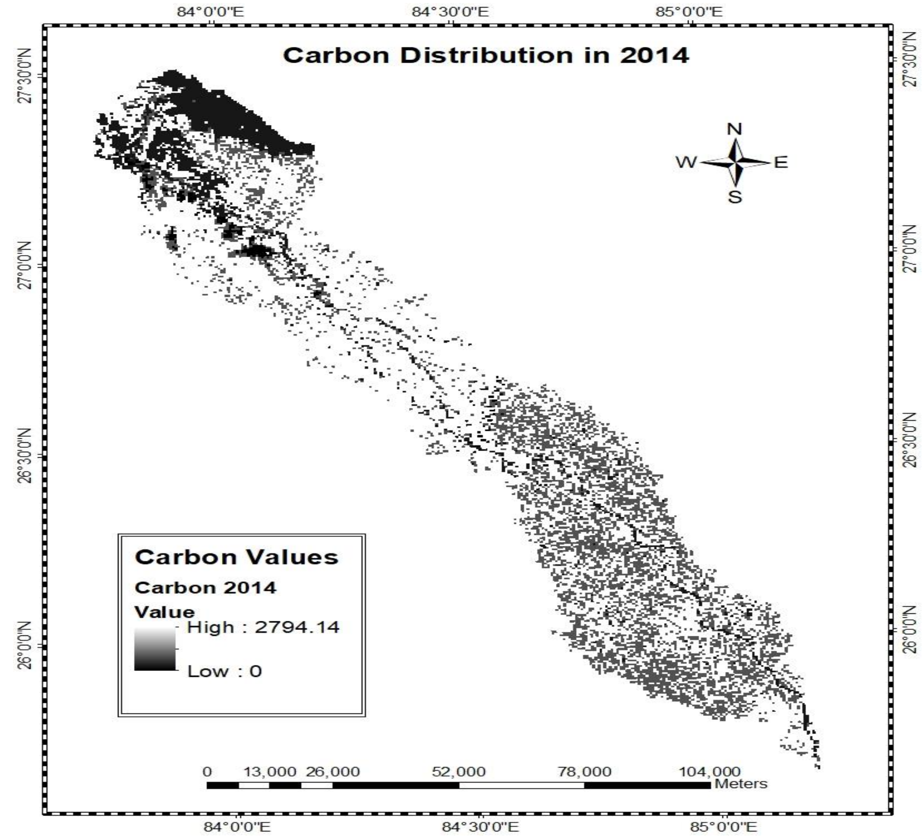

Figure 7. Spatial distribution of carbon in 2014 over GRB

Agricultural lands and grasslands contributed to the soil organic carbon pool, though their sequestration capacity remained lower than that of forests. Conversely, urban areas showed minimal carbon storage, due to scarce vegetation cover and widespread impervious surfaces. This evaluation underscores the pivotal influence of LULC patterns on carbon sequestration dynamics in the GRB, highlighting the necessity for sustainable land use practices to boost carbon storage and mitigate climate risks. In 2024, the InVEST analysis projected a total carbon stock of 42,116,980.34 Mg of C, based on updated LULC classifications (Fig. 8).

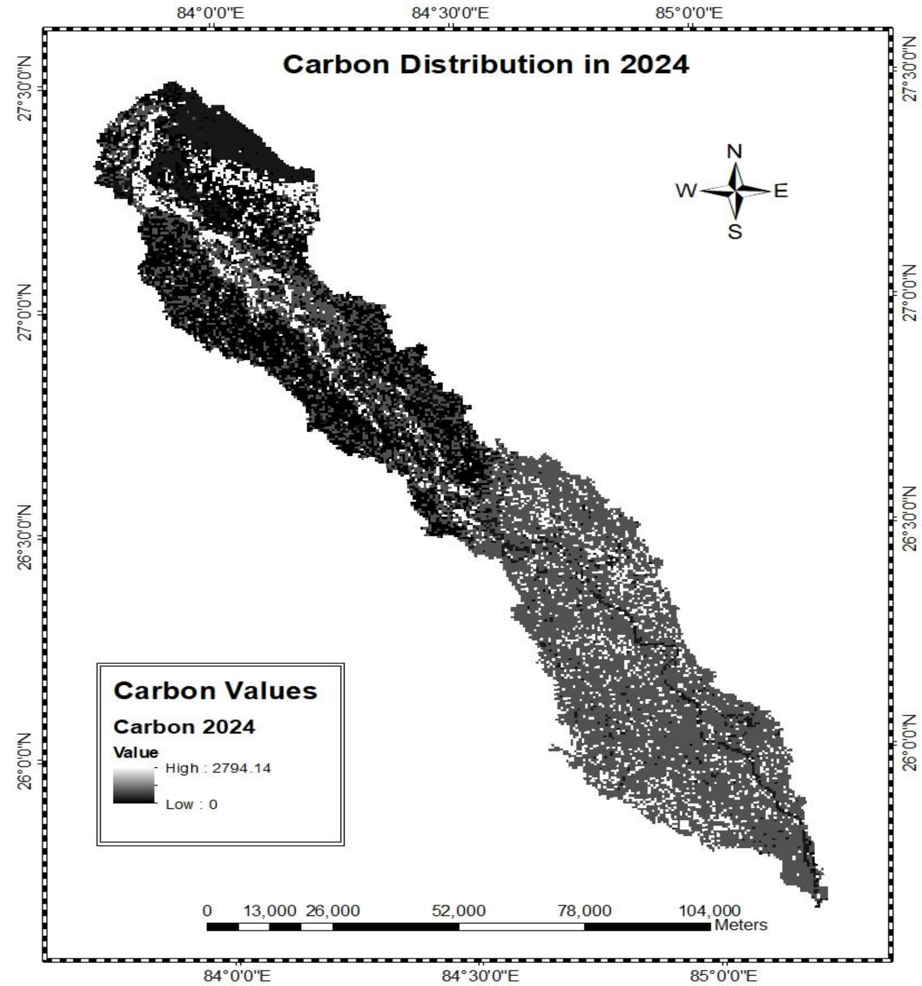

Figure 8. Spatial distribution of carbon in 2024 over GRB

This marked rise in carbon stock mirrors evolving land use patterns and cover changes across the basin. Forest ecosystems continued to lead in carbon storage, reflecting the success of afforestation drives and conservation measures that enhanced both biomass and soil carbon pools. Agricultural zones also showed gains in soil organic carbon, credited to improved land management strategies. However, expanding urban areas maintained their low carbon contribution, underscoring the ongoing challenge of aligning urban growth with ecological sustainability.

The comparison of GRB's carbon dynamics between 2014 and 2024 indicates significant ecosystem shifts, as analyzed through the InVEST model (Fig. 6). The increase from 18.7 million Mg of C in 2014 to 42.1 million Mg of C in 2024 reflects a remarkable net gain of 23,415,542.10 Mg of C over the decade. This rise highlights the positive impact of improved land management and natural vegetation restoration in the basin. Afforestation, reforestation, and conservation have played a decisive role, particularly by boosting vegetation cover and enhancing soil organic carbon. Forest and agricultural lands were key drivers of this gain, whereas urban expansion slightly offset the benefits by reducing sequestration in some localities.

These findings highlight the critical importance of sustainable LULC management in mitigating climate change and enhancing ecosystem services in the GRB. The study provides robust evidence for policymakers and planners to prioritize land-use strategies that optimize carbon sequestration while balancing developmental needs in the region.

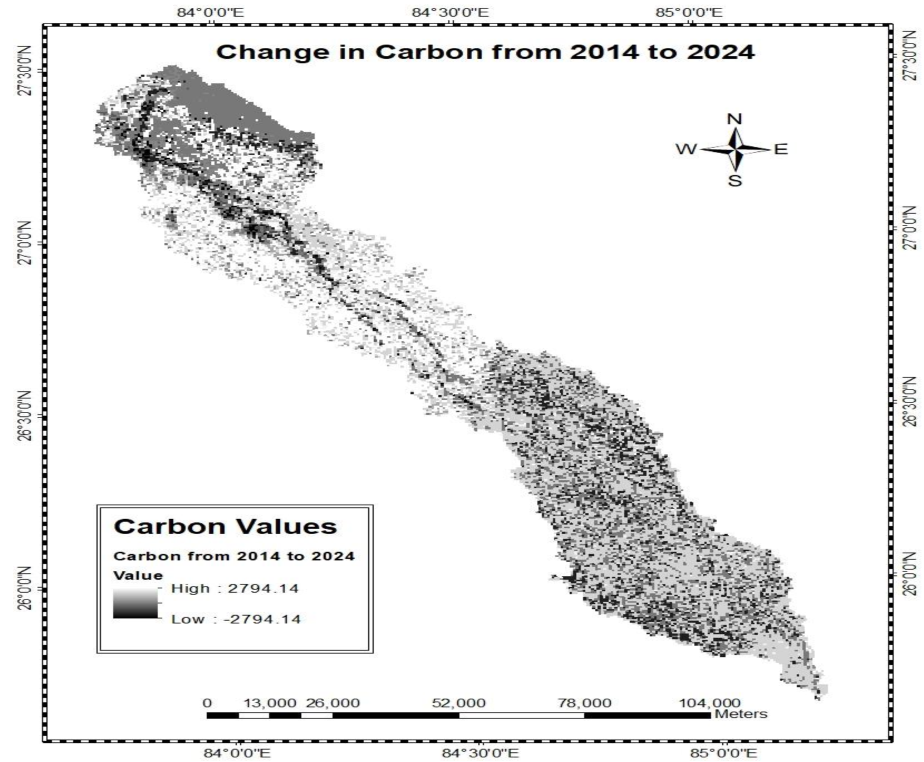

Figure 9. Spatial distribution of carbon from 2014 to 2024 over GRB

DISCUSSION

LULC classification within Google Earth Engine (GEE) was performed using the Random Forest (RF) machine learning algorithm on Landsat 8 and Sentinel-2 imagery for 2014 and 2024, enabling efficient and scalable mapping of land cover dynamics in the Gandak River Basin (GRB). The comparative analysis reveals significant spatial transformations over the last decade that directly influence carbon sequestration potential, ecosystem resilience, and environmental sustainability. In 2014, the GRB landscape was dominated by agricultural lands (~65%), followed by natural vegetation (~18%), water bodies (~7%), built-up areas (~6%), and barren land (~4%). By 2024, agricultural zones expanded to ~69% and built-up regions nearly doubled (~12%), largely driven by rapid urbanization, infrastructural growth, and economic development. Conversely, natural vegetation declined to ~12% and water bodies reduced to ~5%, indicating substantial pressure on high-carbon-density ecosystems.

The observed LULC transitions are influenced by multiple socio-economic and policy-driven factors in addition to climatic variability. Population growth, migration, and increasing population density in districts, such as East Champaran, Gopalganj, and Siwan, have intensified land conversion for agriculture, settlements, and industrial development. Enhanced transportation infrastructure, including NH-27 and NH-28 corridors and expanded railway connectivity, has accelerated urban sprawl and commercial activity. Policy initiatives promoting agricultural intensification and irrigation expansion have further encouraged cropland conversion, while inadequate enforcement of wetland protection and forest conservation policies has contributed to ecosystem degradation. These socio-economic and governance factors, together with environmental stressors, collectively explain the rapid transformations observed in the GRB's landscape.

These LULC shifts have significantly impacted the basin's carbon sequestration dynamics. The total carbon storage was 18,701,438.27 Mg of C in 2014 and increased to 42,116,980.34 Mg of C by 2024, representing a net gain of 23,415,542.10 Mg of C over the decade. This gain is primarily associated with agricultural expansion and improved crop and soil management practices that enhance carbon uptake. However, the simultaneous loss of natural vegetation and wetland ecosystems threatens long-term carbon sink potential, as these ecosystems typically store higher carbon densities than croplands.

Rapid population growth, increased urbanization, expansion of transportation networks, and agricultural intensification have significantly influenced land conversion in the Gandak River Basin. Additionally, policy decisions promoting irrigation and settlement development, along with inadequate enforcement of wetland and forest conservation measures, have accelerated ecosystem degradation. Integrating these socio-economic and governance factors provides a more comprehensive understanding of the drivers behind the observed land cover transformations. Overall, the findings demonstrate a complex interplay between land use dynamics, carbon storage, socio-economic development, and policy decisions. While enhanced agricultural practices may temporarily boost carbon stocks, continued deforestation, wetland encroachment, and unregulated urban growth risk undermining the basin's capacity to function as a sustainable carbon. This highlights the urgent need for integrated land use strategies that balance agricultural productivity, urban development, and ecosystem conservation, ensuring long-term ecological stability and optimized carbon sequestration in the GRB.

CONCLUSION

This study analyzed land use/land cover (LULC) dynamics and their impact on carbon sequestration in the Gandak River Basin (GRB) between 2014 and 2024 using a machine learning-based Random Forest (RF) classifier within Google Earth Engine (GEE) and the InVEST carbon storage model. The LULC classification achieved a high overall accuracy of 91.3% and a Kappa coefficient of 0.87, ensuring reliable mapping results. The comparative analysis revealed significant transformations over the last decade, with agricultural land increasing from ~65% in 2014 to ~69% in 2024 and built-up areas nearly doubling from ~6% to ~12% due to rapid urbanization and infrastructural expansion. Conversely, natural vegetation decreased from ~18% to ~12%, and water bodies declined from ~7% to ~5%, indicating growing pressure on ecologically sensitive landscapes.

The total carbon storage in the GRB was estimated at 18,701,438.27 Mg of C in 2014, which increased to 42,116,980.34 Mg of C in 2024, reflecting a substantial net gain of 23,415,542.10 Mg of carbon over the decade. This increase is largely attributed to improved agricultural management practices and enhanced soil carbon sequestration in cultivated areas. However, the simultaneous loss of forests, wetlands, and other high-carbon-density ecosystems raises concerns about the long-term stability of carbon stocks and the basin's capacity to act as a sustainable carbon sink.

Furthermore, the analysis highlights that LULC transitions in the GRB are not solely driven by environmental factors, but are significantly influenced by socio-economic dynamics, population growth, policy-driven agricultural expansion, infrastructure development, and inadequate enforcement of conservation measures. These interlinked drivers underline the urgent need for an integrated and data-driven land management strategy that balances economic growth with ecosystem preservation. The study's findings provide valuable insights for policymakers, planners, and environmental managers. Implementing sustainable agricultural practices, conserving forests and wetlands, regulating urban expansion, and adopting real-time geospatial monitoring systems can help maintain ecological stability and optimize carbon sequestration. Future research should integrate high-resolution spatio-temporal datasets, socio-economic indicators, biodiversity assessments, and AI-based predictive modeling to better forecast LULC changes and design climate-resilient land use strategies for the GRB.

Recommendations/Future Directions

The findings of this study highlight the urgent need for integrated and sustainable land management practices in the Gandak River Basin (GRB) to balance agricultural productivity, urban development, and ecosystem conservation. Based on the observed LULC transitions and carbon dynamics, the following recommendations are proposed:

1. **Promote sustainable agricultural practices** — Encourage crop diversification, precision farming, and organic soil management to enhance carbon sequestration while reducing greenhouse gas emissions.
2. **Strengthen forest and wetland conservation** — Implement strict land-use regulations to protect high-carbon-density ecosystems, particularly remaining forest patches and wetlands, which are critical for long-term carbon storage.
3. **Integrate urban planning with ecosystem services** — Establish green belts, enforce zoning regulations,

and adopt low-impact infrastructure designs to mitigate uncontrolled urban sprawl and its environmental impacts.

4. **Develop data-driven land use policies** — Utilize remote sensing, machine learning, and geospatial analysis for real-time LULC monitoring to inform adaptive policy frameworks and improve enforcement of land-use regulations.
5. **Enhance community participation and awareness** — Engage local stakeholders through capacity-building programs to foster collective responsibility in managing land resources sustainably.

For future research, expanding the current analysis to include high-resolution spatio-temporal datasets, integrating socio-economic drivers, and assessing biodiversity impacts would provide deeper insights into ecosystem health. Additionally, incorporating advanced AI-based predictive modeling, coupled with scenario-based planning, could help forecast future LULC transitions and optimize carbon management strategies under changing climate and policy conditions.

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Conflict of Interests

The authors have no conflict of interests to declare.

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