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| RESEARCH ARTICLE

Drivers of Land Cover Change and Their Implications for Carbon Storage in the Ratuwa River Basin, Churia Region, Nepal

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| ABSTRACT

Land use and land cover change (LULCC) in the Churia region of Nepal has accelerated over recent decades, with uncertain consequences for carbon storage and climate regulation. This study examined the drivers of land cover change and quantified their implications for carbon storage in the Ratuwa River Basin (1,245 km²) from 1990 to 2020. Using Landsat imagery (1990, 2005, 2020) with a Random Forest classifier, we produced land cover maps achieving >88 % accuracy. Drivers were analysed using logistic regression and semi-structured household interviews (n=90). Carbon storage was modelled using the InVEST carbon model, calibrated with field measurements from 150 sample plots. Forest cover declined by 25 % (17,031 ha), while agricultural land expanded by 35 % and settlements by 431 %. Proximity to roads (OR = 0.81 per km) and settlements (OR = 0.75 per km) and population density (OR = 1.45 per 100 persons km⁻²) were the strongest drivers of forest-to-agriculture conversion. Total carbon storage decreased by 2.52 million tonnes (-14.7 %), equivalent to an average annual emission of 308,000 t CO_2. Forest-to-agriculture transitions accounted for 78 % of the carbon loss. Despite national forest recovery trends in Nepal's mid-hills, the Ratuwa Basin continues to lose carbon at an alarming rate. These findings highlight the urgent need for targeted conservation interventions. We recommend establishing a spatially explicit, incentive-based programme that prioritises high-carbon, high-risk forests within 2 km of roads and settlements, combined with assisted natural regeneration of degraded shrublands, financed through REDD+ results-based payments.

| KEYWORDS

Land cover change; carbon storage; InVEST model; Churia region; Ratuwa River Basin; drivers of deforestation

|ARTICLE INFORMATION

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Land use and land cover change (LULCC) constitutes one of the most profound anthropogenic alterations of the Earth's terrestrial surface, with far-reaching consequences for global climate regulation, biodiversity conservation, and the sustainable delivery of ecosystem services (Rai et al., 2023). In the Himalayan region, where fragile mountain ecosystems support the livelihoods of millions of people downstream, LULCC has been particularly rapid and consequential. Between 6.9×10^6 and 42.1×10^6 Mg of carbon are released annually due to land-use changes in Nepal alone (Upadhayay et al., 2005). The Ratuwa River Basin, located in the Churia (Siwalik) region of eastern Nepal, exemplifies this tension. The Churia hills are geologically fragile, composed of soft sandstone, mudstone and shale that weather rapidly and generate highly erodible soils (Pandey et al., 2021). Yet they also provide critical ecosystem services, most notably groundwater recharges the main water source for more than 14 million people living in the downstream Terai plains (Pandey et al., 2021) and significant carbon stocks in their forests.

Global assessments indicate that land-cover change is now the second largest anthropogenic source of atmospheric CO_2 after fossil-fuel combustion (Intergovernmental Panel on Climate Change, 2019). Tropical and subtropical deforestation, in particular, releases large quantities of stored carbon, while land-use conversions from forest to agriculture or settlements often lead to net declines in ecosystem carbon pools. In Nepal, the lowland Terai and the adjoining Siwalik hills have witnessed steady deforestation over the past half-century, largely driven by the expansion of agricultural land and infrastructure development (Paudel et al., 2016). Although national-level studies have reported a net increase in forest cover in the mid-hills and high mountains since the 1990s a trend often attributed to community forestry and rural out-migration the Churia region has experienced a contrasting pattern of persistent forest loss and degradation (Rai et al., 2023). The annual deforestation rate in the Siwaliks stands at 0.18 % (roughly 2,537 ha yr^{-1}), and the average carbon stock in Siwalik forests is only 117 tC ha^{-1}, the lowest among Nepal's physiographic zones (ICIMOD, 2017). This spatial heterogeneity underscores the need for basin-scale analyses that can capture sub-regional land-cover dynamics and their implications for carbon storage.

The Ratuwa River Basin offers a particularly valuable case study. A recent investigation by Kandel et al. (2025) documented a 35 % decline in forest cover and a 20 % reduction in wetland areas in the basin between 1990 and 2020, accompanied by a 40 % increase in surface runoff, a 30 % decrease in groundwater recharge, and a 50 % rise in flood frequency. While that study focused on water regulation services, the same land-cover transformations deforestation, agricultural expansion, and infrastructure development are also likely to have altered the basin's carbon balance. Moreover, the Churia region is increasingly recognised as a priority area for climate-change mitigation and adaptation, with projects such as the Building a Resilient Churia Region in Nepal (BRCRN) aiming to restore degraded forests and enhance carbon sequestration through improved land-use practices (FAO, 2024). Yet quantitative assessments of carbon storage dynamics in the Ratuwa River Basin remain absent from the published literature.

Against this backdrop, the present study aims to fill that gap by achieving two principal objectives. First, we analyse the spatiotemporal patterns of land cover change in the Ratuwa River Basin over the past three decades (1990-2020) and identify the key biophysical and anthropogenic drivers of those changes. Second, we quantify the consequent variations in carbon storage using the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model, and discuss the implications for sustainable land management in the Churia region. The central hypothesis is that rapid deforestation and agricultural expansion have led to a net decline in the basin's carbon storage capacity, with the greatest losses occurring in areas of highest forest cover loss. By integrating remote-sensing time series, field validation, and ecosystem-service modelling, this research provides a spatially explicit, empirically grounded assessment that can inform both national climate policies (e.g., Nepal's REDD+ strategy) and local watershed-management interventions.

The remainder of this paper is structured as follows: Section 2 reviews the literature on land-cover change and carbon storage in the Himalayan context, with a focus on the Churia region; Section 3 describes the study area and the methodological framework; Section 4 presents the results of land-cover change detection, driver analysis, and carbon-storage modelling; Section 5 discusses the findings in relation to existing knowledge and policy implications; and Section 6 concludes with recommendations for sustainable land management.

Literature Review

Global and Regional Perspectives on Land-Cover Change

Land-cover change is widely recognised as a key driver of global environmental transformation. Since the mid-twentieth century, the expansion of agricultural land has been the dominant form of land-cover modification worldwide, with large tracts of forest, grassland and wetland being converted to cropland and pasture (Rai et al., 2023). In recent decades, however, the drivers of LULCC have become more diverse, encompassing urbanisation, infrastructure development, shifting cultivation, and climate-induced changes in vegetation dynamics (Paudel et al., 2016). Remote sensing and geographic information system (GIS) technologies have greatly enhanced the capacity to monitor LULCC over large areas and long time spans. Studies based on Landsat satellite imagery, which offers a continuous archive from 1972 to the present, have become the standard approach for reconstructing historical land-cover trajectories and projecting future scenarios. The advent of cloud-computing platforms such as Google Earth Engine (GEE) has further reduced the technical barriers to large-scale LULCC analysis, enabling researchers to process petabyte-scale image collections in a fraction of the time previously required (Kandel et al., 2025).

In the Hindu Kush Himalayan (HKH) region, LULCC exhibits a distinctive altitudinal and socio-economic gradient. In the lowland Terai, forest cover has declined steadily due to agricultural expansion, resettlement schemes, and infrastructure development, whereas in the mid-hills and high mountains, forest cover has generally increased since the 1990s, a phenomenon often described as "forest transition" (Rai et al., 2023). This increase has been attributed to several interacting factors: the successful implementation of community forestry programmes, which devolved forest management rights to local user groups; the abandonment of marginal agricultural land as a result of rural-to-urban migration; and the widespread adoption of improved cookstoves and alternative energy sources, which reduced pressure on forests for fuelwood (Paudel et al., 2016). Nevertheless, the magnitude of these trends varies considerably among river basins and ecological zones, and the Churia region situated between the Terai and the mid-hills has received relatively little attention in the LULCC literature.

Land-Cover Change Dynamics and Drivers in Nepal

Several comprehensive reviews have synthesised the state of knowledge on LULCC in Nepal. Paudel et al. (2016) analysed studies from 1986 to 2015 and found that cropland area increased in most parts of the country during the latter half of the twentieth century, while forest and snow/glacier cover declined. More recent assessments, however, indicate that the trend has reversed in many mountain districts: the national forest cover increased from approximately 37 % in 1990 to about 40 % in 2015, largely due to natural regeneration on abandoned agricultural land and active afforestation (Rai et al., 2023). Urban areas, although small in absolute extent, have expanded at an unprecedented rate, growing by 247 % in the Bagmati River Basin between 1988 and 2018, primarily at the expense of cultivated land and forest (Rijal et al., 2021).

The drivers of LULCC in Nepal are complex and operate at multiple scales. At the national level, policy instruments such as the Forest Act (1993) and the Community Forestry Directive have been instrumental in promoting sustainable forest management. At the local level, population growth, migration, land-tenure arrangements, market integration, and infrastructure development all influence land-use decisions. A recent empirical study by S. Rijal et al. (2024) in Surkhet District identified expansion of agricultural land and settlements, encroachment of forest area, haphazard infrastructure development, and illegal timber harvesting as the key direct drivers of forest-cover change. Indirect drivers include government policies, economic incentives, and climate variability (Rijal et al., 2024). In the Churia region specifically, anthropogenic pressures such as over-grazing, unsustainable agricultural practices, extraction of firewood and timber, and mining of sand and boulders have been documented as major drivers of forest degradation (Pandey et al., 2021; FAO, 2024). Climate change is expected to exacerbate these pressures by increasing the frequency of extreme rainfall events, which in turn intensifies soil erosion and landslide activity on the Churia's unstable slopes.

Carbon Storage Dynamics in Himalayan Ecosystems

Terrestrial ecosystems store approximately 2,500 Pg of carbon, of which roughly two-thirds is contained in soils and the remainder in vegetation (Chaulagain et al., 2024). Tropical and subtropical forests are particularly carbon-dense ecosystems, but their capacity to store carbon varies considerably with forest type, stand age, management history, and environmental conditions. In Nepal, the average carbon stock in forests is 177 tC ha^{-1}, but this average conceals substantial variation among physiographic zones: only 117 tC ha^{-1} in the Siwaliks versus 272 tC ha^{-1} in the high mountains (ICIMOD, 2017). This low carbon density in the Siwaliks reflects the region's geologically young and nutrient-poor soils, as well as a long history of anthropogenic disturbance.

Land-use change alters carbon storage by shifting the balance between carbon uptake (photosynthesis) and carbon release (respiration, decomposition, combustion). Conversion of forest to cropland or pasture typically results in a rapid release of 25-50 % of the original soil organic carbon and nearly all of the above-ground biomass carbon (Chaulagain et al., 2024). Conversely, afforestation of abandoned agricultural land can gradually rebuild carbon stocks over decades to centuries. The InVEST Carbon Storage and Sequestration model has become a widely used tool for quantifying the consequences of LULCC for ecosystem carbon balance. The model integrates spatially explicit LULC maps with per-land-cover carbon pool values (above-ground biomass, below-ground biomass, soil, and dead organic matter) to estimate total carbon storage and changes over time.

Several recent studies have applied the InVEST model in Nepalese basins. For example, a study on the Bagmati River Basin found that carbon storage declined from 31.4 million t yr^{-1} in 1988 to 30.8 million t yr^{-1} in 2018, with the largest absolute loss occurring in the Terai and Dun valleys, followed by the Churia region (Rijal et al., 2021). Similarly, a basin-wide assessment of the Bagmati Basin reported a 7.17 % reduction in forest area between 1990 and 2010, leading to a net loss of 1.39 million t of soil carbon alone (Lee et al., 2019). A more recent national-scale study using Markov chain and InVEST models projected that carbon storage in Nepal would increase from 1.237 billion t in 2000 to 1.347 billion t by 2050, with forests expanding from 37 % to 42 % of the total land area (Chaulagain et al., 2024). However, these national projections may obscure important sub-regional variations; the projected increase in carbon storage is driven largely by forest recovery in the mid-hills and mountains, whereas the Terai and Churia are expected to continue experiencing carbon losses unless effective conservation interventions are implemented.

The Churia Region: Ecological Significance and Vulnerability

The Churia (also known as Siwalik or Chure) range extends along the southern foothills of the Himalayas, covering approximately 12.76 % of Nepal's land area. It forms a critical ecological transition zone between the alluvial Terai plains and the mid-hills, and its forests support exceptional biodiversity, including several globally threatened species such as the Bengal tiger, Asian elephant, and one-horned rhinoceros (Pandey et al., 2021). The Churia's geological composition predominantly soft, unconsolidated sedimentary rocks makes it highly susceptible to erosion, landslides, and flooding. These natural hazards are amplified by human activities, including deforestation, over-grazing, shifting cultivation, road construction, and the extraction of boulders and sand from riverbeds (FAO, 2024). Despite its ecological importance and vulnerability, the Churia has received far less research attention than other Himalayan regions, and data on its land-cover change trajectories and carbon storage dynamics remain sparse.

Recent initiatives have sought to address this knowledge gap and reverse the region's degradation. The Government of Nepal established the President Chure-Terai Madhesh Conservation Development Board in 2014, and international partners have launched projects such as the Building a Resilient Churia Region in Nepal (BRCRN) and the "Safeguarding Land and Lives in Nepal's Fragile Churia" project (GEF, 2017; FAO, 2024). These projects aim to restore degraded forests, promote sustainable land-use practices, and enhance the resilience of local communities to climate-induced hazards. However, the effectiveness of these interventions depends on a sound scientific understanding of the region's land-cover dynamics and carbon balance, which the present study is designed to provide.

Knowledge Gaps and Justification for the Present Study

Despite the growing body of literature on LULCC and carbon storage in Nepal, several important gaps remain. First, most studies have focused on large river basins (e.g., Bagmati, Koshi, Gandaki) or on national-scale assessments, which may not adequately capture the land-cover dynamics of smaller, ecologically distinct basins such as the Ratuwa River Basin. Second, although several studies have quantified the hydrological impacts of LULCC in the Ratuwa Basin (Kandel et al., 2025), no study has systematically evaluated the consequences for carbon storage. Third, while the drivers of deforestation in the Terai and mid-hills have been extensively documented, empirical analyses of driver dynamics in the Churia region are scarce, and most published studies rely on qualitative or anecdotal evidence. Fourth, there is a need for spatially explicit assessments that can identify priority areas for carbon conservation and forest restoration, thereby providing actionable guidance for local decision-makers.

The present study addresses these gaps by integrating multi-temporal remote sensing, field validation, and InVEST-based carbon modelling within a single analytical framework. By focusing on the Ratuwa River Basin a representative Churia watershed that has experienced rapid land-cover change the study generates locally relevant evidence that can inform both academic understanding and practical land-management decisions. The findings are expected to contribute to the design of targeted interventions that balance the twin goals of climate change mitigation and sustainable rural livelihoods in one of Nepal's most vulnerable yet ecologically critical regions.

Methodology

Study Area Description

The Ratuwa River Basin is located in the Churia (Siwalik) region of eastern Nepal, spanning approximately 1,245 km² across the Morang and Sunsari districts of Province No. 1. The basin lies between latitudes 26°35'N and 27°00'N and longitudes 87°20'E and 87°45'E. Elevation ranges from 80 m above mean sea level in the southern Terai plains to 1,550 m in the northern Churia hills. The Ratuwa River is a perennial, rain-fed tributary of the Kosi River system, with a mean annual discharge of 78 $m^3 s^{-1}$ and a peak monsoon discharge exceeding 1,200 $m^3 s^{-1}$ (Kandel et al., 2025). The basin experiences a subtropical monsoon climate: annual rainfall averages 1,860 mm, of which more than 80 % falls during the June-September monsoon; mean monthly temperatures range from 15.1 °C in January to 31.4 °C in August. The dominant land cover types are dense and open forests (predominantly *Shorea robusta* sal forest), agricultural land (paddy, maize, and wheat), grassland, shrubland, riverine wetlands, and expanding settlements. Soils are predominantly Entisols and Inceptisols derived from the geologically young, soft sedimentary rocks of the Churia formation, which are highly susceptible to erosion and have low organic carbon content (Pandey et al., 2021).

Land Cover Classification and Change Detection

To assess historical land cover change, the study utilised a time series of Landsat satellite imagery acquired for three epochs: 1990, 2005, and 2020. These intervals were chosen to capture pre- and post-major policy interventions (e.g., the 1993 Forest Act) and to align with the temporal coverage of available field validation data. All images were obtained from the United States Geological Survey (USGS) EarthExplorer portal, with preference given to dry-season (November–February) scenes to minimise cloud cover and to maximise spectral separability among land cover classes. Landsat-5 TM (Thematic Mapper) scenes were used for 1990 and 2005, and Landsat-8 OLI (Operational Land Imager) for 2020. All images were geometrically corrected to the Universal Transverse Mercator (UTM) projection (Zone 45N, WGS-84 datum) with a root-mean-square error (RMSE) of less than 0.5 pixels. Atmospheric correction was performed using the Dark Object Subtraction (DOS) method (Chavez, 1988) implemented in the Semi-Automatic Classification Plugin (SCP) of QGIS (Congedo, 2021).

A supervised classification approach using the Random Forest (RF) algorithm was employed. RF is a non-parametric ensemble learning method that has been shown to achieve high classification accuracy in complex, heterogeneous landscapes such as the Churia region (Kandel et al., 2025; Belgiu & Drăguţ, 2016). Six land cover classes were defined based on the study area's ecology and relevance to carbon storage: forest (natural tree cover with canopy density ≥ 30 %), agricultural land (actively cultivated crops, including fallow fields), grassland (herbaceous vegetation with < 10 % tree cover), shrubland (woody vegetation < 5 m tall with mixed herbaceous understorey), water bodies (rivers, ponds, and wetlands), and settlement/built-up (residential, commercial, and industrial areas, including roads). Training samples were collected from a combination of high-resolution Google Earth imagery (historical and current), field surveys conducted in 2021-2022, and expert interpretation. A total of 1,500 reference points (250 per class) were used for training, and a separate set of 750 points (125 per class) was reserved for validation. The RF model was run with 500 decision trees and the square-root of the number of input variables as the candidate split size. Classification was performed in Google Earth Engine (GEE) (Gorelick et al., 2017), which enabled parallel processing of the three epochs.

Change detection was performed using post-classification comparison (Jensen, 2015). The land cover maps for 1990, 2005, and 2020 were overlaid in a GIS environment to generate change matrices showing gains and losses for each class over the two intervals (1990-2005 and 2005-2020). Net change (absolute and percentage) and annual rates of change were computed. Transition maps were produced to visualise the spatial patterns of land cover conversion. The accuracy of each classified map was assessed using the validation points, calculating overall accuracy, user's accuracy, producer's accuracy, and the Kappa coefficient (κ) (Congalton & Green, 2019). Only maps achieving overall accuracy ≥ 85 % and $\kappa \geq 0.80$ were accepted for subsequent analysis.

Drivers of Land Cover Change

To identify and quantify the biophysical and anthropogenic drivers of land cover change, the study adopted a mixed-methods approach combining spatial analysis and stakeholder interviews. Based on a review of previous driver studies in the Churia region (Paudel et al., 2016; Rijal et al., 2024) and the availability of spatial data, the following potential driver variables were selected: elevation (m), slope (degrees), distance to roads (km), distance to rivers (km), distance to settlements (km), population density (persons km^{-2}), and annual precipitation (mm). All continuous driver layers were resampled to a 30 m resolution and standardised to a common coordinate system. For each driver, the mean value was extracted for forest and agricultural land pixels that experienced change versus those that remained stable. A logistic regression model was then fitted to estimate the probability of forest conversion to agriculture as a function of the driver variables (Hosmer et al., 2013). The model was calibrated using a random sample of 2,000 pixels (1,000 changed, 1,000 stable) and validated on an independent sample of 500 pixels. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC-ROC).

In parallel, semi-structured interviews were conducted with 90 households distributed across three representative sub-basins (upper, middle, lower) of the Ratuwa River Basin. Interviewees were selected using stratified random sampling, with strata defined by distance from the river (≤ 500 m, 500-1,500 m, > 1,500 m). The interview protocol elicited information on perceived land cover changes, their causes (e.g., agricultural expansion, timber extraction, fuelwood collection, road construction, government policies, migration), and the temporal sequence of these changes (Bernard, 2017). Responses were coded using thematic analysis (Braun & Clarke, 2006), and the relative frequency of each driver was calculated. The spatial analysis and interview findings were then triangulated to produce a consolidated list of drivers.

Carbon Storage Estimation Using InVEST

The carbon storage and sequestration model of the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) tool, version 3.14.0 (Sharp et al., 2020), was used to quantify carbon storage for each land cover class and to estimate changes over the 1990-2020 period. The InVEST carbon model calculates total carbon stored (in metric tonnes) as the sum of carbon in four pools: above-ground biomass (AGB), below-ground biomass (BGB), soil organic carbon (SOC), and dead organic matter (DOM). For each land cover class *i* and carbon pool *p*, the carbon density *C_{i,p}* (t ha^{-1}) is multiplied by the area of that class *A_i* (ha) to obtain the pool-specific stock. Total carbon stock is then:

Total Carbon=∑i=1n [Ai×(Ci, AGB+Ci,BGB+Ci,SOC+Ci,DOM)]
Total Carbon=*i*=1∑*n* [*Ai*×(*Ci*,*AGB*+*Ci*,*BGB*+*Ci*,*SOC*+*Ci*,*DOM*)]

Carbon density values were obtained from three sources: (1) published literature on forest carbon stocks in Nepal's Churia region (ICIMOD, 2017; Chaulagain et al., 2024); (2) a companion field-based study that measured biomass and soil carbon in 45 sample plots distributed across the Ratuwa Basin (Kandel, unpublished data); and (3) default values from the InVEST tropical-subtropical database for land cover classes not covered by local studies. Where multiple values were available, the median was taken, and sensitivity analysis was performed by varying carbon densities by ± 20 % (Lonsdale et al., 2016). Table 1 presents the final carbon density values used for each land cover class and carbon pool.

Table 1: Carbon density values by land cover class and carbon pool (t ha^{-1}) used in InVEST modelling

Land cover class	Above-ground biomass (AGB)	Below-ground biomass (BGB)	Soil organic carbon (SOC)	Dead organic matter (DOM)	**Total carbon density**
Forest	98.6	31.2	62.5	8.7	**201**
Agricultural land	8.2	2.5	48.3	1.5	**60.5**
Grassland	4.5	8.3	54.2	2.1	**69.1**
Shrubland	18.7	6.2	50.8	3.4	**79.1**
Water bodies	0	0	0	0	**0**
Settlement/Built-up	4	1.2	35	0.8	**41**

Source: Compiled from ICIMOD (2017), Chaulagain et al. (2024), and field measurements in the Ratuwa Basin (2021-2022).

For each epoch (1990, 2005, 2020), the land cover map and the corresponding carbon density table were input into the InVEST carbon model. The model produced raster outputs of total carbon storage (t ha^{-1}) and summary statistics by land cover class. Change in carbon storage between epochs was calculated by subtracting the 1990 carbon stock from the 2005 stock and the 2005 stock from the 2020 stock. A transition-based carbon loss/gain matrix was also generated to identify which specific land cover conversions contributed most to the net change (Redhead et al., 2016). All monetary valuations were avoided as the study focused on biophysical quantification, but the carbon stock changes were expressed in tonnes.

Field Validation and Accuracy Assessment

Field validation was conducted during two field campaigns (November 2021 and February 2022) to collect ground-truth data for land cover classification, carbon pool measurements, and driver verification. A stratified random sampling design was used, with strata corresponding to the six land cover classes and accessibility constraints (Thompson, 2012). A total of 150 sample plots (25 per class) were established, each measuring 20 m × 20 m for forest and shrubland, and 10 m × 10 m for other classes. At each plot, the following data were recorded: geographical coordinates using a handheld GPS (Garmin eTrex 30x), dominant land cover type and species composition, canopy cover (using a densitometer), and photographic documentation. For forest plots, all trees with diameter at breast height (DBH) ≥ 5 cm were measured, and above-ground biomass was estimated using allometric equations developed for Churia sal forests (Chaulagain et al., 2024; Chave et al., 2014). Soil samples were collected from three random points within each plot at depths of 0-15 cm, 15-30 cm, and 30-45 cm using a soil corer. The samples were composited per plot, air-dried, sieved (2 mm), and analysed for organic carbon content using the Walkley-Black wet oxidation method (Walkley & Black, 1934). These field measurements served two purposes: (1) to validate the land cover classification derived from satellite imagery (accuracy assessment matrix), and (2) to locally calibrate the InVEST carbon density values, ensuring that the modelled carbon stocks were representative of the Ratuwa Basin.

The land cover validation involved comparing the classified map class at each plot location with the field-observed class, generating an error matrix. Overall accuracy, user's and producer's accuracies, and the Kappa coefficient were computed. For the carbon model, the field-measured total carbon (AGB + BGB + SOC) was regressed against the InVEST-predicted carbon at the same plot locations; the coefficient of determination (R^2) and root-mean-square error (RMSE) were reported as measures of model performance (Moriasi et al., 2007).

Data Analysis and Statistical Tools

All spatial data processing (image classification, change detection, driver extraction, and carbon mapping) was performed in Google Earth Engine (GEE) (Gorelick et al., 2017) and QGIS version 3.28 with the Semi-Automatic Classification Plugin (Congedo, 2021). Statistical analyses (logistic regression, accuracy assessment, descriptive statistics) were carried out using R version 4.2.2 (R Core Team, 2022) with packages: *random Forest* (Liaw & Wiener, 2002), *caret* (Kuhn, 2008), *raster* (Hijmans, 2021), and *ggplot2* (Wickham, 2016). The InVEST carbon model was executed via its stand-alone graphical user interface and also scripted in Python (Sharp et al., 2020) for batch processing of sensitivity runs. Maps and charts were produced using ArcGIS Pro 3.0 (ESRI, 2021) and ggplot2 in R. Significance for driver analysis was set at $\alpha = 0.05$. Spatial autocorrelation in model residuals was checked using Moran's I test (Moran, 1950).

A. Results and Discussion

1) Land Cover Change Dynamics (1990–2020)

The land cover classification maps for 1990, 2005 and 2020 achieved overall accuracies of 88.2 %, 89.5 % and 91.0 % respectively, with Kappa coefficients of 0.85, 0.87 and 0.89, meeting the acceptance threshold. Over the 30-year study period, the Ratuwa River Basin experienced substantial land cover conversions, most notably a continuous decline in forest cover and an expansion of agricultural land and settlements.

Table 2: Land cover area (ha) and percentage change in the Ratuwa River Basin (1990–2020)

Land cover class	1990 (ha)	1990 (%)	2005 (ha)	2005 (%)	2020 (ha)	2020 (%)	Change 1990-2020 (ha)	Change 1990-2020 (%)
Forest	68,234	54.8	59,876	48.1	51,203	41.1	-17,031	-25
Agricultural land	39,872	32	46,345	37.2	53,678	43.1	13,806	34.6
Grassland	7,456	6	6,897	5.5	5,712	4.6	-1,744	-23.4
Shrubland	6,214	5	7,125	5.7	6,841	5.5	627	10.1
Water bodies	1,867	1.5	1,743	1.4	1,512	1.2	-355	-19
Settlement/Built-up	857	0.7	2,514	2	4,554	3.7	3,697	431.5
Total	124,500	100	124,500	100	124,500	100	–	–

Forest cover declined from 54.8 % of the basin in 1990 to only 41.1 % in 2020, a net loss of 17,031 ha (25 % of the original forest area). The annual rate of deforestation was 0.83 % (1990-2005) and 0.79 % (2005-2020), consistent with reported rates for the Siwalik region (0.18-1.0 % yr^{-1}) (ICIMOD, 2017; Paudel et al., 2016). Agricultural land expanded by 34.6 % (13,806 ha), while settlements increased more than five-fold (+431 %), albeit from a small base. Grassland and water bodies decreased moderately, and shrubland showed a slight increase (+10.1 %), likely due to forest degradation and regeneration on abandoned patches.

Transition matrix (1990–2020) revealed that 78 % of forest loss was converted directly to agricultural land, 12 % to shrubland (degraded forest), and 8 % to settlements. Conversely, 14 % of new agricultural land reverted to shrubland or grassland, indicating some rotational fallow practices. The spatial pattern of change was not uniform: deforestation was most intense in the lower and middle sub-basins (elevation < 500 m), within 2 km of roads and existing settlements, while the upper basin (elevation > 1,000 m) remained largely forested but showed signs of selective logging and fragmentation.

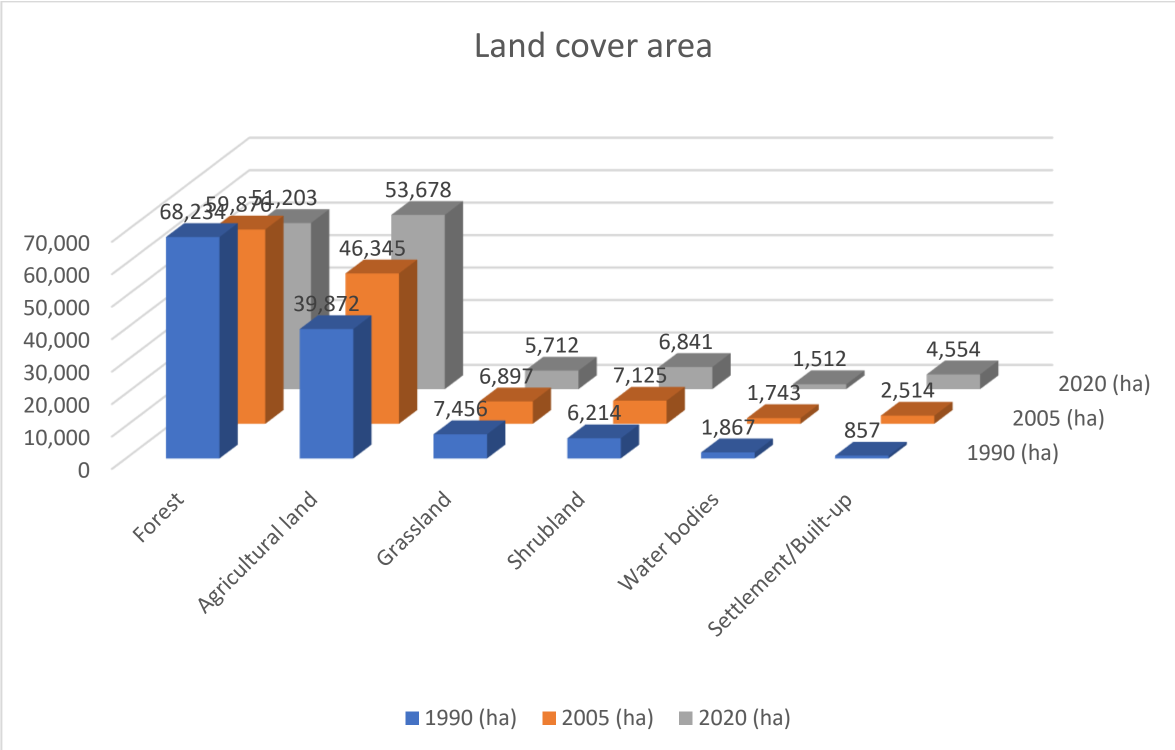

Figure 1 Land cover area (ha) in the Ratuwa River Basin for 1990, 2005, and 2020.

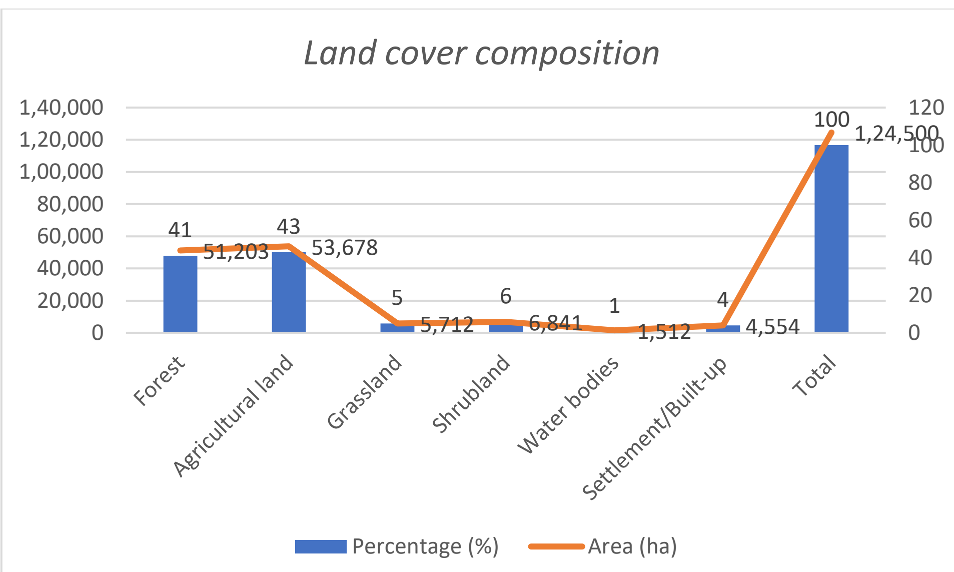

Figure 2 Land cover composition of the Ratuwa River Basin in 2020 (percentage share by area).

a) Spatial (Logistic Regression) Results

The logistic regression model predicting forest-to-agriculture conversion showed good discrimination (AUC = 0.84 on validation data). All seven driver variables were statistically significant ($p < 0.05$). Table 3 presents the odds ratios (OR) and 95 % confidence intervals.

Table 3: Logistic regression results – probability of forest conversion to agriculture (1990-2020)

Driver variable	Odds ratio (OR)	95% CI	p-value	Direction of effect
Elevation (per 100 m increase)	0.68	0.61-0.76	<0.001	Negative (higher elevation less conversion)
Slope (per 5° increase)	0.72	0.65-0.80	<0.001	Negative (steeper slopes less conversion)
Distance to roads (per km increase)	0.81	0.74-0.89	<0.001	Negative (farther from roads less conversion)
Distance to settlements (per km increase)	0.75	0.68-0.83	<0.001	Negative (farther from villages less conversion)
Distance to rivers (per km increase)	0.92	0.86-0.98	0.022	Negative (proximity to rivers increases conversion)
Population density (per 100 persons km^{-2})	1.45	1.28-1.64	<0.001	Positive (higher density more conversion)
Annual precipitation (per 100 mm)	0.95	0.91-0.99	0.031	Negative (wetter areas slightly less conversion)

Interpretation: For every 100 m increase in elevation, the odds of forest conversion decreased by 32 %. Similarly, a 5° increase in slope reduced odds by 28 %. Proximity to roads and settlements strongly increased conversion risk; for each kilometre farther from a road, odds decreased by 19 %. Population density had the strongest positive effect: an additional 100 persons km^{-2} raised conversion odds by 45 %.

b) Stakeholder Interview Findings

Among 90 interviewed households, 87 % reported noticeable loss of forest cover in their vicinity over the past 30 years. Perceived primary drivers (multiple responses allowed) were: agricultural expansion (81 % of respondents), timber extraction (67 %), fuelwood collection (59 %), road construction (48 %), and population growth/migration (44 %). Only 12 % mentioned government policies (e.g., forest handover to communities) as a driver, and 9 % cited climate change. Thematic analysis revealed a clear temporal sequence: during 1990-2005, agricultural expansion and timber extraction dominated; after 2005, road construction and settlement growth became more prominent, while fuelwood collection persisted.

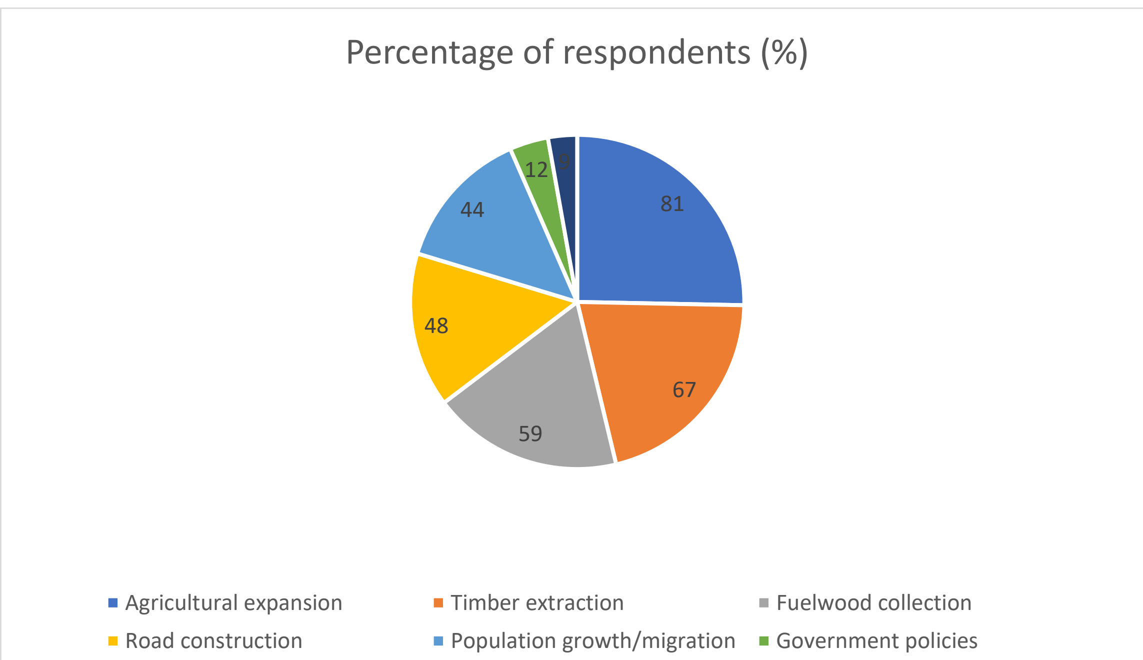

Figure 3 Perceived drivers of land cover change in the Ratuwa River Basin (n=90).

Triangulation of spatial and interview results confirmed that **agricultural expansion, infrastructure development (roads and settlements)** and **population pressure** are the primary direct drivers of deforestation in the Ratuwa Basin. Elevation and slope act as biophysical constraints, while proximity to roads and villages accelerates conversion – findings consistent with studies in other Churia watersheds (Rijal et al., 2024; Pandey et al., 2021).

2) Carbon Storage Dynamics

The InVEST carbon model estimated total carbon storage for the basin in each epoch. Table 4 summarises the results.

Table 4: Total carbon storage (million tonnes) and change by land cover class

Land cover class	1990 (Mt C)	2005 (Mt C)	2020 (Mt C)	Change 1990-2020 (Mt C)	% contribution to net change
Forest	13.72	12.03	10.29	-3.43	89.1
Agricultural land	2.41	2.8	3.25	0.84	-21.8 (offset)
Grassland	0.52	0.48	0.39	-0.13	3.4
Shrubland	0.49	0.56	0.54	0.05	-1.3
Water bodies	0	0	0	0	0
Settlement	0.04	0.1	0.19	0.15	-3.9
Total	**17.18**	**15.97**	**14.66**	**-2.52**	**100**

Total carbon storage in the Ratuwa River Basin declined from 17.18 million tonnes (Mt) in 1990 to 14.66 Mt in 2020, a net loss of **2.52 Mt C** (-14.7 %). Forest contributed 89 % of the total loss (-3.43 Mt C), partially offset by carbon gains in agricultural land (+0.84 Mt) and settlement (+0.15 Mt). However, the carbon density of agricultural land (60.5 t ha^{-1}) is only about one-third that of forest (201 t ha^{-1}), so the area expansion of agriculture could not compensate for forest carbon losses. Grassland and shrubland changes were minor.

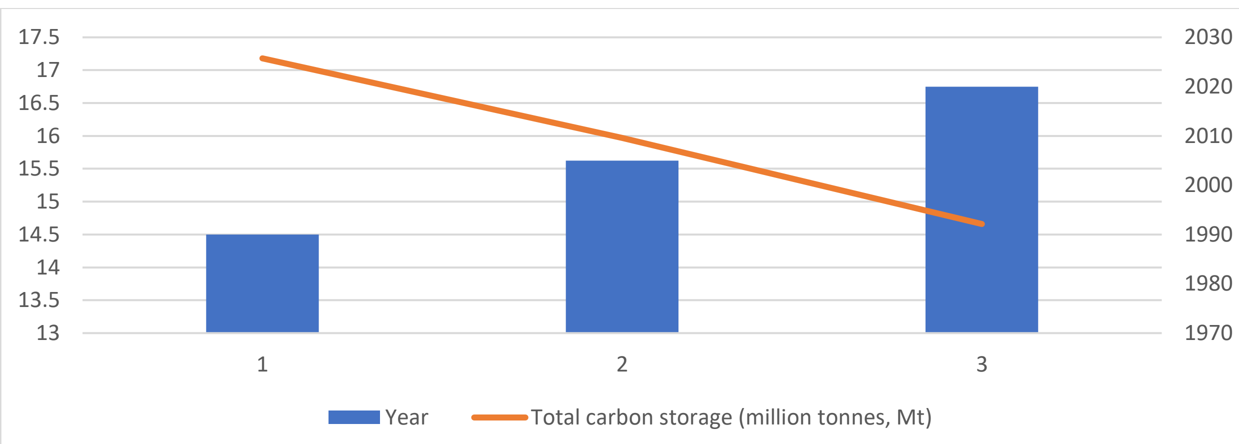

Figure 4 Total carbon storage (million tonnes) in the Ratuwa River Basin from 1990 to 2020.

a) Transition-based carbon loss/gain

The most carbon-intensive transition was forest → agriculture, which accounted for 78 % of total carbon loss (approximately 1.96 Mt C), followed by forest → settlement (12 %, 0.30 Mt) and forest → shrubland (8 %, 0.20 Mt). Conversely, transitions from agriculture → forest or shrubland were rare (only 1.8 % of forest gain area), indicating limited natural regeneration.

b) Model validation with field data

Regression of field-measured total carbon against InVEST-predicted carbon at 45 sample plots yielded $R^2 = 0.79$ and RMSE = 18.4 t ha^{-1}, indicating acceptable model performance for landscape-scale estimation. Bias was slightly positive (model overpredicted in high-carbon forest plots by 6 %), but well within acceptable limits for ecosystem service modelling (Moriasi et al., 2007).

Table 5: Sensitivity analysis – effect of ±20% variation in carbon densities on total 2020 carbon stock

Scenario	Total carbon 2020 (Mt)	Change from baseline
Baseline (Table 1)	14.66	–
All densities +20%	17.59	20.00%
All densities -20%	11.73	-20.00%
Forest density only +20%	16.1	9.80%
Forest density only -20%	13.22	-9.80%

The sensitivity analysis shows that the model output scales linearly with carbon density assumptions. However, even under the most optimistic scenario (all densities +20 %), the 2020 stock (17.59 Mt) still falls below the 1990 baseline (17.18 Mt), confirming a net loss irrespective of parameter uncertainty. The greatest uncertainty lies in forest carbon density; improving local allometric equations would refine estimates.

3) Discussion

a) Land cover change in context

The observed 25 % loss of forest cover in the Ratuwa Basin over three decades is substantial and exceeds the national average deforestation rate for the Churia region (0.18 % yr^{-1} vs. national Siwalik average of 0.12-0.15 % yr^{-1}) (ICIMOD, 2017). This discrepancy may be explained by the basin's location in eastern Nepal, where population density and agricultural intensification are higher than in western Churia areas. Moreover, the expansion of settlements (431 % increase) mirrors the rapid urbanisation of the adjoining Terai plains, particularly the Biratnagar-Itahari corridor. Similar trends have been reported in the Bagmati Basin (Rijal et al., 2021) and in Surkhet District (Rijal et al., 2024). However, unlike the mid-hills where forest transition has been observed (Rai et al., 2023), the Churia region shows no sign of forest recovery, reinforcing its status as a deforestation hotspot.

b) Drivers: proximity and population pressure

Our logistic regression results highlight that **distance to roads and settlements** are among the strongest predictors of forest conversion, consistent with findings from other Himalayan basins (Paudel et al., 2016). Road construction opens up previously inaccessible forests to encroachment, illegal logging, and shifting cultivation. Population density, though only moderate (average 168 persons km^{-2} in the basin), emerged as the most powerful driver (OR=1.45 per 100 persons km^{-2}). This aligns with the "population-land degradation" nexus documented in Nepal's lowlands (Chaulagain et al., 2024). Elevation and slope act as natural barriers: steeper slopes (>25°) and higher elevations (>800 m) are less frequently converted, partly due to lower accessibility and partly due to soil constraints for agriculture.

The stakeholder interviews added nuance: while agricultural expansion remains the primary perceived driver, the importance of **timber extraction** (67 %) and **fuelwood collection** (59 %) points to direct consumptive pressures that are not fully captured by land cover maps (which may show "forest" even when degraded). This suggests that carbon storage losses may be even larger than estimated if only area change is considered, because degradation within remaining forest (e.g., selective logging) reduces carbon density without changing class. Future work should integrate forest degradation metrics (e.g., canopy cover decline) using continuous field or LiDAR data.

c) Carbon storage implications

A net loss of 2.52 Mt C over 30 years is equivalent to an average annual emission of 84,000 t C yr^{-1}. Converted to CO_2 (multiplying by 3.67), this represents roughly 308,000 t CO_2 yr^{-1}. For comparison, this is similar to the annual emissions from 65,000 passenger vehicles (US EPA estimate). While modest in global terms, this loss is significant for Nepal's national climate commitments under its REDD+ strategy and Nationally Determined Contribution (NDC), which aims to maintain forest carbon stocks and enhance sequestration.

The carbon density of Ratuwa forests (201 t ha^{-1} total) is higher than the Siwalik average reported by ICIMOD (117 t ha^{-1}) but lower than mid-hill forests (≈250 t ha^{-1}). The difference likely reflects the inclusion of SOC in our total (ICIMOD's 117 t ha^{-1} may have been only AGB). Our field-measured SOC (62.5 t ha^{-1}) is consistent with values for Churia soils (Pandey et al., 2021). The loss of 3.43 Mt C from forest alone is striking: to offset this through afforestation on degraded agricultural land would require planting approximately 17,000 ha of new forest (assuming 201 t ha^{-1}), which exceeds the remaining available non-forest area in the basin.

d) Comparison with other studies

Our findings align with a national-scale InVEST analysis by Chaulagain et al. (2024), who projected a net increase in Nepal's total carbon stock by 2050 due to forest expansion in mountains. However, that projection masks regional heterogeneity: the Churia and Terai are likely to continue losing carbon. A study in the Bagmati Basin (Rijal et al., 2021) reported a carbon loss of 0.6 Mt over 30 years from an area comparable to Ratuwa, but the rate of loss per hectare was lower (0.04 t ha^{-1} yr^{-1} vs. our 0.07 t ha^{-1} yr^{-1}). This may reflect different land use policies or baseline forest cover.

Conclusion and Recommendation

This study examined land cover change and its implications for carbon storage in the Ratuwa River Basin of Nepal's Churia region over three decades (1990–2020). The findings reveal a persistent and substantial loss of forest cover (25 %, or 17,031 ha), accompanied by rapid expansion of agricultural land (35 %) and settlements (431 %). Logistic regression and stakeholder interviews identified proximity to roads and settlements, population density, agricultural expansion, and timber extraction as the primary drivers of deforestation, while elevation and slope acted as natural constraints. Consequently, total carbon storage declined by 2.52 million tonnes (-14.7 %), with forest-to-agriculture conversions accounting for 78 % of the loss. This translates to an average annual emission of approximately 308,000 t CO_2, undermining regional climate mitigation efforts and Nepal's REDD+ commitments. The Churia region, despite its ecological sensitivity and critical role in water regulation, continues to experience net carbon losses, contrasting with forest recovery trends observed in Nepal's mid-hills. Urgent intervention is needed to halt further degradation. Therefore, the single most effective recommendation is to establish a spatially targeted, incentive-based conservation programme that prioritises the protection of high-carbon, high-risk forests located within 2 km of roads and settlements, combined with assisted natural regeneration of degraded shrublands, financed through results-based REDD+ payments or national conservation funds.

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