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Comprehensive Analysis of Land Use Change and Carbon Sequestration in Nepal from 2000 to 2050 Using Markov Chain and InVEST Models

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Abstract: The escalating pace of migration and urbanization in Nepal has triggered profound alterations in land use practices. This event has resulted in a considerable diminution of ecological diversity and a substantial decline in the potential for carbon sequestration and other ecosystem services, thereby impeding climate change mitigation efforts. To address this, a comprehensive assessment of land use change and carbon storage was conducted from 2000 to 2019 and forecasted to 2050 in Nepal. Employing the Markov chain and InVEST models, this study evaluated the loss and gain of carbon, elucidating its economic value and spatial distribution. The findings revealed that carbon storage in 2000 and 2019 were 1.237 and 1.271 billion tons, respectively, with a projected increase to 1.347 million tons by 2050. Carbon sequestration between 2000 and 2019 amounted to 34.141 million tons, which is anticipated to surge to 76.07 million tons from 2019 to 2050, translating to economic valuations of 110.909 and 378.645 million USD, respectively. Forests emerged as pivotal in carbon storage, exhibiting higher carbon pooling than other land use types, expanding from 37% to 42% of the total land area from 2000 to the predicted year 2050. Notably, carbon distribution was concentrated in parts of the terai and mountain regions, alongside significant portions of the hilly terrain. The findings from this study offer valuable insights for governing Nepal and REDD+ in developing and implementing forest management policies. The results emphasize the importance of providing incentives to local communities judiciously to promote effective conservation measures.

Keywords: carbon distribution; ecological diversity; ecosystem services; forest; local communities; mitigation

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1. Introduction

Carbon storage is about where and how carbon is retained in various reservoirs for long time periods, which can occur naturally or through human intervention, while carbon sequestration focuses on the process of actively capturing atmospheric CO_2 and storing it in these reservoirs [1]. Forest ecosystems, such as tropical, temperate, and boreal forests, are essential to the global carbon cycle. Collectively, they contain about 85% of the world's terrestrial aboveground biomass (AGB) [2]. These forests, rich in biodiversity, are substantial carbon reservoirs, contributing to approximately 40% of the global aboveground carbon pool. Research has indicated that tropical forests alone store between 250 and 300 gigatons of vegetation carbon, with a significant portion, approximately 200 gigatons, present in AGB [3,4]. Understanding the dynamics of biomass, which encompasses all organic matter above ground, is crucial for gauging how these ecosystems mitigate atmospheric carbon dioxide [5]. Effective management of these forests enhances their ability to absorb CO_2, incorporating it into the biomass and subsequently enriching the soil. In this context, the carbon cycle involves several key storage pools, including soil organic carbon (SOC), deadwood carbon, AGB, and belowground biomass (BGB), each of which plays a significant role in carbon sequestration and the overall health of the ecosystem [6–8]. Carbon released from these pools is reabsorbed by vegetation, highlighting the importance of efficient carbon management [9,10].

Initiatives such as the Green India Mission and REDD have been implemented globally to reduce CO_2 emissions. The Clean Development Mechanism under the UNFCCC promotes carbon sequestration through afforestation and reforestation. Meanwhile, REDD+ focuses on reducing emissions from deforestation and enhancing forest carbon stocks, demonstrating the critical role of forestry in mitigating climate change [11].

Recent studies have highlighted the viability of afforestation as a climate policy, indicating it as a highly effective alternative to combating the consequences of deforestation. Afforestation not only addresses the root cause but also offers a sustainable solution for carbon management [12,13]. The carbon cycle, which involves various storage pools, such as vegetation and firewood plantations, plays a critical role in this context. This cycle, detailed by researchers such as in [14,15] involves the release and reabsorption of carbon, which is influenced by land use changes. Hernández-Guzmán et al. in 2019 [15] analyzed land use and land cover (LULC) changes in a hydrologic basin in Mexico and their effects on carbon storage. We projected LULC changes up to 2050 and used the InVEST model for carbon storage estimation by employing unsupervised classification of Landsat images and cellular automata Markov (CA-Markov) chain modeling. They found significant landscape modifications, particularly an increase in exposed soils and a decrease in evergreen and tropical dry forests, leading to a reduction in carbon stock from 362.9 Tg C in 1986 to an expected 317.9 Tg C in 2050 [15]. Chen et al. [3] studied the dynamics of ecosystem services (ESs) in response to urbanization in China's Yangtze River Economic Belt. They used the future land use simulation (FLUS) model to simulate short-, medium-, and long-term land use changes and assessed six ESs under different land use scenarios. The study found intensive urban sprawl and a decrease in cropland, leading to declining trends in all ESs except a few under one scenario. This study highlights the impact of urbanization on ESs, including carbon storage, which is expected to decline by 1.95–6.781% [3]. These studies collectively showed the importance of strategic land management and afforestation in enhancing carbon sequestration and mitigating climate change.

In addition, Zhao et al. [16] evaluated the impact of ecological engineering on carbon storage in the semiarid northwestern region of China. They simulated land use/cover changes following ecological engineering programs and assessed their impact on carbon storage by linking the CA-Markov and InVEST models. The results indicated an increase in carbon storage by 10.27 Tg from 2015 to 2029, with a relative error of 0.22% in the linked model, indicating its high applicability in such assessments [16,17]. Focusing on the semiarid region of Sergipe, Brazil, the study highlights that deforestation and land degradation significantly reduced carbon stock, while restoration efforts can provide substantial carbon sequestration benefits. This research investigates the economic and environmental importance of preserving and restoring natural ecosystems [17]. Zhang et al. [18] investigated the effects of rapid urbanization in Shanghai, China, revealing a substantial decline in carbon stock due to the conversion of forested and agricultural lands into urban areas. The study outlines the critical role of urban green spaces and adaptative management in encountering the negative impacts of urban expansion on carbon emission. The investigation into wetland changes in China's coastal urban agglomerations demonstrates the fluctuating carbon storage trends and the effectiveness of ecological protection in enhancing carbon sequestration [19]. Hoque et al. analyzed forest plantations in coastal Bangladesh, revealing significant increases in regional carbon storage due to the expansion of mangrove areas under different land management strategies. The study also highlighted the trade-offs between carbon storage and food supply, emphasizing the need for balanced land use policies to address both climate adaptation and food security [20]. These studies employed the CLUE-S, CA-Markov, and InVEST models and collectively highlighted the critical need for sustainable land use planning and the adoption of multi-faceted strategies to improve carbon sequestration and achieve environmental goals using the CLUE-S, CA-Markov, and InVEST models.

A study in the Sariska Tiger Reserve highlights the necessity of integrating ecological and economic valuation in land management, with improved conservation scenarios significantly reducing carbon loss [21]. In addition, Saha et al. evaluated the biophysical and economic values of ESs in the Sundarbans Biosphere Region, India. They used Net Primary Productivity models, InVEST, and CA-Markov to assess the impact of climate change and land use dynamics from 1982 to 2045. The study observed significant variations in ES values, with the highest values in habitat service, nutrient cycling, and gas regulation. The study found that regulating services were most affected by land use and climate change [22]. Verma et al. assessed carbon sequestration mapping and its economic quantification in the Askot Wildlife Sanctuary, Western Himalayas. They employed a novel approach combining machine learning and spatial–temporal techniques for LULC simulation with the InVEST model. The study revealed significant economic losses owing to rapid forest cover decline, highlighting the importance of conservation strategies for forested landscapes [23].

Various methodologies exist to enhance the accuracy of carbon storage assessments, encompassing techniques such as biomass assessment, stock volume analysis, chamber measurements, and sampling methodologies. However, these methods face significant challenges in portraying carbon storage dynamics across large spatial areas over prolonged periods [24]. This study introduces a unique approach by combining the InVEST model with CA-Markov, offering an innovative technology for spatial representation, dynamic analysis, and quantitative evaluation of ESs [24]. Recent studies have witnessed the integration of various LULC simulation models, such as the multilayer perceptron (MLP) neural network-Markov chain [25], SD-CLUE-S [26], Logistic-CA-MC [27], FLUS [28], and the PLUS model [29], with the InVEST model. These integrated models are reliable techniques for assessing the impact of climate and LULC changes on ecosystem carbon storage. The InVEST model's carbon module primarily relies on land use data from key sources, making it well suited for large landscapes and extended time series. The precision of the InVEST model outcomes depends on the accuracy of the LULC maps used in the base and predicted years. CA-Markov in Terrset demonstrates a higher accuracy and is user-friendly in presenting LULC maps for current and projected years compared with other LULC simulation models.

Land use changes, along with forest and soil degradation, contribute to increased greenhouse gas emissions. Nepal, with its highly fragile ecosystem, faces significant challenges related to forest and soil degradation and carbon sequestration [30]. This issue warrants deep analysis due to its severity. Over the past few decades, both anthropogenic and natural impacts have continually altered land use and land cover in Nepal [31]. Agriculture is the primary economic activity, and rural populations heavily depend on forest resources for fuelwood and timber. The mountainous and hilly regions are particularly sensitive to land use and land cover changes, even with minimal human interference [31]. Since the 1970s, land use change trends in Nepal have accelerated due to population growth, leading to the conversion of significant forest areas into agricultural land and built-up area [32]. Recent studies indicate that forests accounted for 44.47% of total land area in 2018. Agricultural land expanded rapidly from 1910 to 2010 but has slightly declined since 2010 due to rapid urban expansion [33].

The application of the InVEST model integrated with CA-Markov in Nepal is limited. Rimal et al. [34] applied the InVEST model within a confined geographical area, specifically the Koshi River basin, incorporating a support vector machine approach. Similarly, Bastola et al. [35] employed the InVEST model in the Bagmati River basin for water yield analysis. However, these studies are unable to present a comprehensive overview of imminent land use change and carbon storage across the entire country, encompassing future predictions and economic valuation of sequestered carbon. To address this gap, the current study provides a holistic perspective by presenting total carbon storage and sequestration from 2000 to 2050, including economic values and the spatial distribution of carbon storage throughout the nation using the InVEST model coupled with CA-Markov of TerrSet for the prediction of land use change. This research segments the study area into three regions with alike features for higher accuracy and refines the results through averaging the carbon densities of similar studies of comparable regions. This technique both reinforces the findings and highlights the advanced methodology employed in this study. With Nepal setting ambitious net-zero emission targets for 2050, this research emerges as an informative tool for the government, assisting in the development of policies for effective land use management and the strategic allocation of incentives to local communities for sustainable forest management.

Furthermore, the comprehensive analysis of carbon sequestration, economic analysis, and presenting models of this study are beneficial for global policymakers in the realm of carbon trading. This study employs specific carbon and discount rates that are particularly relevant for countries with economies characteristics similar to Nepal, enabling them to assess their carbon outputs and thus facilitating their entry into international carbon markets. It proposes a plan for sustainable land management and climate change strategies that aim to strike a balance between environment protection and economic growth. This approach influences global environmental management policies and supports equitable economic development through engagement in international carbon markets.

2. Materials and Methods

The evaluation of carbon sequestration in Nepal encompassed the prediction of land use using CA-Markov of Terrset IDRISI, the tabulation of the carbon density of each land use type, and the measurement of carbon loss and sequestration through the application of the InVEST model. The research framework of this study is shown in Figure 1.

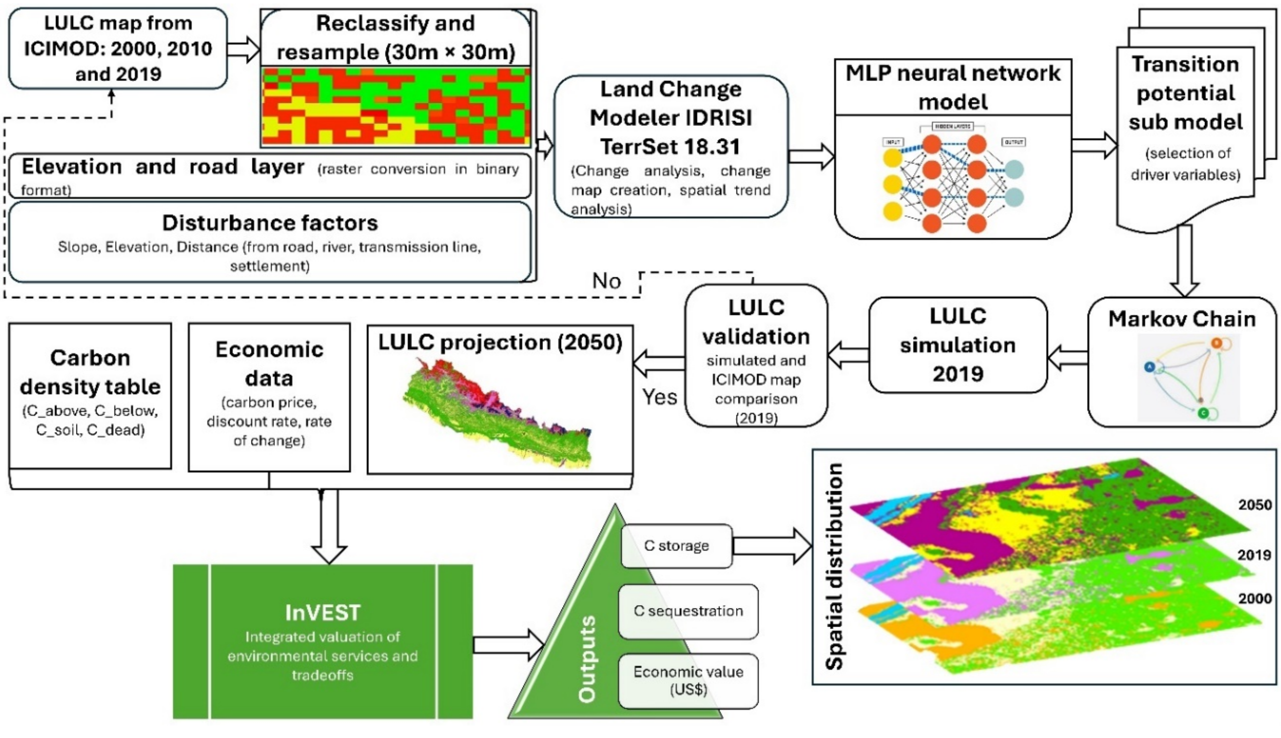

Figure 1. A conceptual framework showing the steps involved in this study.

2.1. Model Description

2.1.1. InVEST Model

Materials developed collaboratively by Stanford University, the University of Minnesota, the Nature Conservancy, and the Worldwide Fund for Nature (WWF), the InVEST model encompasses four modules for assessing terrestrial ESs. These modules focus on soil conservation, water retention, carbon storage, and biodiversity assessment, providing a comprehensive measurement of regional Ess [24]. Specifically, the carbon storage model within InVEST combines four distinct pools: aboveground biomass carbon, belowground biomass carbon, dead organic carbon, and SOC, each assigned to various LULC categories [36]. The formula for calculating the total carbon storage in Nepal is articulated as follows [8,24]:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead}, \tag{1}$$

where C_{total} is the total carbon storage, C_{above} is the aboveground carbon storage, C_{below} is the underground carbon storage, C_{soil} is the soil carbon storage, and C_{dead} is the dead organic matter carbon storage.

Based on the carbon pooling and land use data, the carbon storage of each land use type in Nepal is calculated as follows [24]:

$$C_{totali} = (C_{abovei} + C_{belowi} + C_{soili} + C_{deadi}) \times A_i, \tag{2}$$

where i is the average carbon density of each land use and A_i is the area of this land use.

2.1.2. CA-Markov Model

The CA-Markov chain model was used to forecast land use changes over different periods. This model stands out as a reliable method because of its efficient algorithm, which is particularly adept at eliminating any ambiguities in land use transfer [37]. This model comprises four integral components: cells and cell states, neighborhood, and conversion rules. The cell, which is the smallest computational unit, is instrumental in the model, with the cell state representing the category assigned to each cell. The neighborhood aspect pertains to the conversion state of the current cell, whereas the conversion denotes the specific rule in which the cell transforms. The general CA model formula is as follows [36]:

$$S_{(t+1)} = f\left(S_{(t)}, N\right), \tag{3}$$

where S is a finite and discrete state set of cells; N is the neighborhood of the cell; t and t + 1 represent two different moments; and f is the state transition rule.

Markov models perform matrix analysis within random time series through mathematical modeling, projecting the likelihood based on the existing state and evolving trends in LULC. The formulation of the Markov model can be articulated by the following formula [36]:

$$A_n = A_{n-1} \times P_{ij}, \tag{4}$$

where A_n and A_{n-1} are the spatial distribution states of land use at two moments, and P_{ij} is the state transition probability matrix, which is calculated as follows [38]:

$$P = P_{ij} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix}, \sum\nolimits_{i=1}^{n} P_{ij} = 1. \tag{5}$$

In the given formula, P represents the matrix of Markov transitions, where i and j denote the categories of LULC for the initial and successive timeframes, respectively. The variable "n" represents the number of LULC classes, and P_{ij} signifies the probability or likelihood of a specific type of land transitioning from one LULC category to another.

2.2. Study Area

Nepal is rich in a remarkable diversity of ecosystems, spanning from low-lying flatlands at 59 m above sea level (masl) to towering mountains reaching 8849 masl with geographical coordinates ranging from 26°20′53″ to 30°26′51″ N in latitude and from 80°03′30″ to 88°12′05″ E in longitude [39]. The predominant hilly and mountainous regions of Nepal play crucial roles as carbon sinks. Notably, community forests, extending from lowlands to high mountains, are exemplary models for carbon sequestration in South Asia. The study area was classified into three distinct parts [40]: terai (flat land), hill, and mountain, reflecting the highly heterogeneous environment and the significant variation in carbon density, particularly in forested areas across these regions. The major land use types in Nepal include forest, cropland, grassland, snow/glacier, wooded land (shrubland), barren land (sand, gravel, and rock), lakes and rivers, and built-up areas [31]. Among these land use types, forest covers approximately 39.1%, followed by cultivated lands at 29.83%, and grassland at 7.90%. The remaining land is covered by wooded land (shrub land), lakes, rivers, snow/glaciers, and built-up areas [41]. The common soils in the Tarai and Middle Mountain physiographic regions are Entisols, Inceptisols, Alfisols, and Mollisols. In contrast, the Siwaliks and High Mountain regions are predominantly covered with Entisols and Inceptisols. The High Himalayan region is characterized by the prevalence of Inceptisols and Spodosols, alongside rock outcrops [42]. The total population of Nepal is 29,164,578 [43]. A visual representation of the study area is shown in Figure 2.

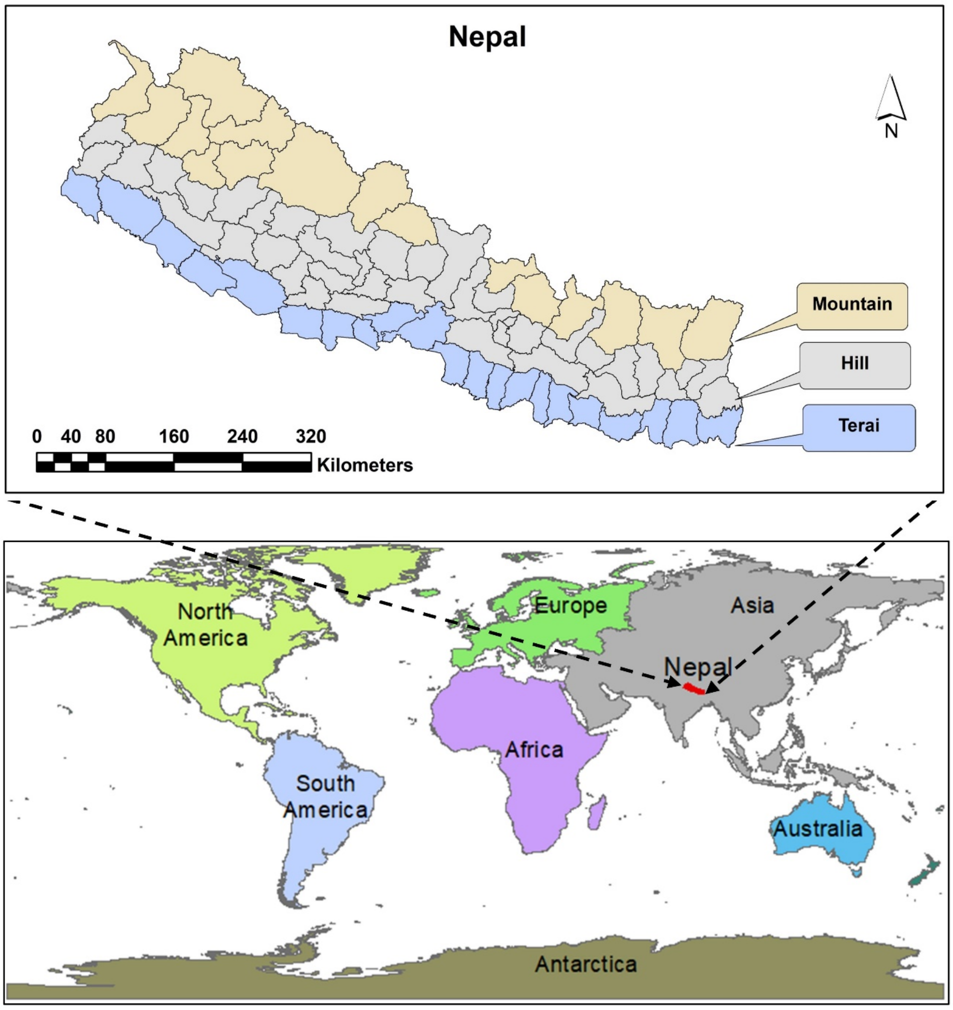

Figure 2. Geographical distribution of the study area.

2.3. LULC Map Preparation

This study employed the LULC map of Nepal created by ICIMOD, featuring a grid size of 30 m $\times$ 30 m. The ICIMOD map originally included 11 land use classes. In our research, we reclassified the map, merging snow and glaciers into a single category called snow/glacier and combining riverbed, bare soil, and bare rock into the category of bare land. The final map used in this study comprises the following land use types: wooded land (shrub land), waterbody, agricultural land, built-up area, forest, snow/glacier, grassland, and bare land.

The ICIMOD map is noted for its high accuracy, which is attributed to the use of a regional land cover monitoring system. This approach addresses challenges such as limited data accessibility, lack of transparency in data collection methodologies, and inconsistencies in land cover classification. The ICIMOD map stands out for its yearly generation of high-resolution land cover data for the Hindu Kush Himalaya region. Moreover, it employs a cloud-based machine learning system to generate the land cover map, validating its accuracy through extensive field monitoring [44].

2.4. LULC Map Prediction for 2050 Using CA-Markov in TerreSet

The prediction of future land use dynamics in Nepal was performed using the CA-Markov environmental simulation model, available in the Terrset 2020 version 19.0.8. This model's prediction process involved three fundamental steps: (1) change analysis and land use transition, (2) transition potentials, and (3) change demand modeling using the Markov chain.

Change analysis and land use transition were conducted using the Land Change Modeler within Terrset, using LULC maps, elevation maps, and road layers from 2000 to 2010 in the study area. The inputs were prepared in ArcGIS 10.5 and converted into the IDRISI format. A threshold of 5000 ha was set to ignore transitions below this value, resulting in a transition map illustrating 42 transitions from one land class to another between 2000 and 2010.

The study area, encompassing flat land, hills, and mountain regions, experienced LULC changes influenced by driver variables, such as slope, elevation, distance from the river [45], distance from the road [46], distance from settlement [47], and distance from transmission lines [48]. Cramer's V values were calculated for all variables, and those with low values were also included. The MLP neural network was employed for the transition sub-model, as it is an artificial neural network capable of handling nonlinear relationships without user intervention.

The final step in land use prediction involved the use of a Markov chain for change demand modeling. All sub-models, including the MLP neural network, were integrated to produce a single map for the predicted year. Initially, LULC maps for the years 2000 and 2010, prepared by ICIMOD, were employed to simulate the LULC map for 2019. This simulation was then compared with the ICIMOD-prepared map for 2019, which is known for its high accuracy, attained through comprehensive field survey validation. Once a high accuracy was achieved between the predicted and observed maps, the model was extended to predict the LULC map for 2050. The Markov chain method applied in this study relies on the conditional probability of past and present transitions, employing a soft prediction modeling approach with a logical "OR" aggregation type.

2.5. Assessment and Prediction of Carbon Sequestration Using the InVEST Model

In the assessment of carbon sequestration using the InVEST model, land use maps of Nepal were categorized into three regions—terai, hill, and mountain—using ArcGIS. The carbon pooling table for each land use type in these regions was constructed based on the IPCC guidelines [49] and relevant literature [21,34,35]. Table 1 presents carbon pools in AGB, BGB, SOC, and dead wood carbon across different classes of the LULC map.

Table 1. Carbon pool estimated (Mg/ha) for the InVEST model.

LULC Code	LULC_Name	C_Above	C_Below	C_Soil	C_Dead
1	Waterbody	0	0	0	0.01
2	Snow	0	0	0.01	0
	Forest (Terai)	77.88	26.12	33.66	6.95
3	Forest (Hill)	66.42	21.14	59.01	2.97
	Forest (Mountain)	114.27	38.09	114.03	2.97
4	Baresoil	3.6	4	10	0
5	Built-up	5	1	5	0
6	Agriculture	3.95	2	6.6	1
7	Grassland	0	0	84.9	0
8	Wooded land	13.3	5.15	27.24	2.54

The carbon trade agreement between the government of Nepal and the World Bank, which valued carbon at USD $5 per ton, was integrated into the study to incorporate economic considerations. The economic analysis employed a market discount rate of 3%, and the annual rate of change in the carbon price was assumed to be zero, drawing from the information obtained from [21].

This study spanned two-time intervals: 2000–2019 and 2019–2050. For the initial period (2000–2019), the LULC map for the base year 2000 was used, with the predicted year being 2019. Similarly, for the subsequent interval (2019–2050), the initial year was 2019, and the predicted year was set to 2050. After inputting all necessary information into the InVEST model, the simulation was executed, generating an output map that was then imported into ArcGIS to extract the required information. The model presents the carbon storage data for the years 2000, 2019, and 2050, utilizing information from the land use map and carbon pool table. Net carbon sequestration for the periods 2000–2019 and 2019–2050 was determined by calculating the difference in carbon storage between 2000 and 2019, and between 2019 and 2050, respectively, using the InVEST model.

2.6. Spatial Distribution and Cluster Characteristics of Carbon Storage

In ArcGIS, the carbon storage maps for Nepal's terai, hill, and mountain regions were merged to create a comprehensive raster map covering the entire country. This map delineates carbon storage for the years 2000, 2019, and 2050, employing a grid size of 30 m × 30 m. The map was subjected to natural breaks (Jenks) classification to enhance interpretability, resulting in six distinct classes. These classes are defined as follows: "no carbon" for areas with 0 tons, "very low" for those within the 0–1.16 tons range, "low" for 1.16–3.95 tons, "moderate" for 3.95–8 tons, "high" for 8–12.9 tons, and "very high" for 12.9–24 tons. This classification schema offers a detailed depiction of carbon storage dynamics across Nepal, facilitating a nuanced analysis of carbon distribution patterns for the specified years.

This study employed Global Moran's I to characterize the spatial differentiation of carbon storage in the study area, using the following formula [24]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2}, \tag{6}$$

where w_{ij} is the spatial weight, x is the attribute mean, x_{i} and x_{j} are the attribute values of elements i and j, respectively, and n is the number of cells. The correlation is considered significant when $|z| > 1.96$ corresponds to a 95% confidence level in hypothesis testing using the standard normal distribution. This statistical approach provides insights into the spatial patterns and characteristics of carbon storage, helping to discern significant correlations within the study area.

3. Results

3.1. LULC Mapping and Prediction

In Figure 3, the distribution of land classes is presented for the years 2000, 2019, and the projected year 2050. In 2000, forest land covered the largest area at 55,702.51 km^2 (37.54%), followed by agriculture land at 39,618.94 km^2 (26.7%) and grassland at 19,889.78 km^2 (13.4%). In 2019, the trend continued with forest covering 58,306.22 km^2 (39.3%), agriculture land covering 36,440.35 km^2 (24.56%), and grassland covering 18,979.76 km^2 (12.79%). Projected for 2050, forest land is expected to cover the largest portion at 62,062.05 km^2 (41.83%), followed by agriculture land at 38,371.04 km^2 (25.86%) and bare land at 18,898.57 km^2 (12.74%). Waterbodies consistently occupy the smallest area, less than 1%, whereas wooded land slightly decreases from 2.19% to 2.02%, as shown in Table 2. Similarly, the dynamics of land use changes during the 2000–2019 interval and the projected 2019–2050 interval are presented in Table 2. In the past time interval, the snow/glacier land use type experienced a 2.25% increase, followed by a 5.12% decrease in the projected time interval, showcasing a consistent trend. The built-up area demonstrated minimal change over both intervals. Conversely, bare land and agricultural land witnessed a decrease of 1.58% and 2.15% in the past, only to increase by 4.44% and 1.3%, respectively, in the projected period. Notably, the forest area exhibited growth in both time intervals, with a 1.75% increase in the past and a more substantial 2.53% increase in the projected period. These observations provide insights into the dynamic nature of land use changes, reflecting historical trends and anticipated shifts in the landscape over specified timeframes.

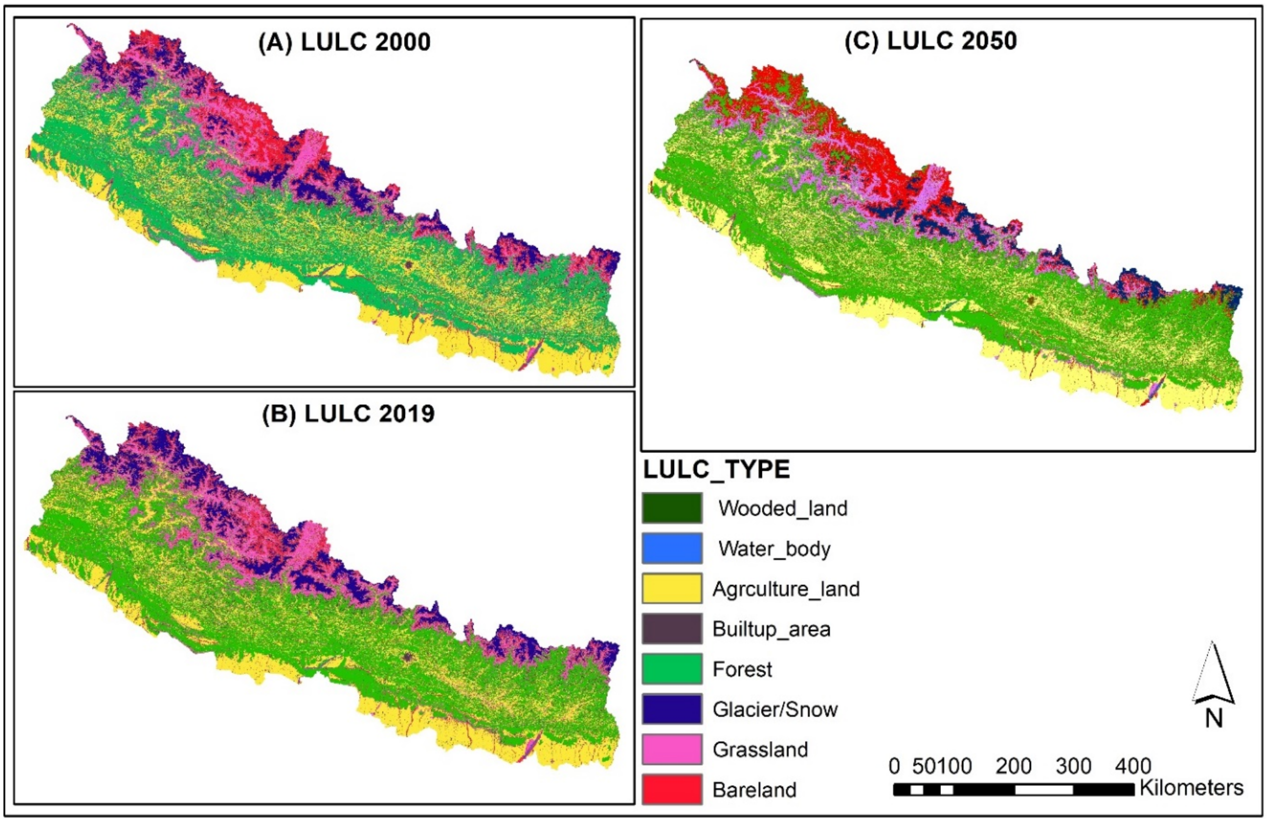

Figure 3. Historical and future projection maps of land use and land cover changes over time.

Table 2. Area-wise distribution of land use and land cover change over time intervals.

LULC Type	Year 2000		Year 2019		Year 2050		Change (%)	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	2000–2019	2019–2050
Waterbody	505.34	0.34	541.36	0.36	477.65	0.32	0.02	−0.04
Snow/Glacier	9793.64	6.6	13,134.41	8.85	5437.79	3.66	2.25	−5.19
Forest	55,702.51	37.54	58,306.22	39.3	62,062.05	41.83	1.76	2.53
Bare land	14,643.18	9.87	12,304.31	8.29	18,898.57	12.74	−1.58	4.45
Built-up area	4974.9	3.35	5471.52	3.69	5079.38	3.42	0.34	−0.27
Agriculture land	39,618.94	26.7	36,440.35	24.56	38,371.04	25.86	−2.14	1.3
Grass land	19,889.78	13.4	18,979.76	12.79	15,055.89	10.15	−0.61	−2.64
Wooded land	3251.26	2.19	3201.64	2.16	2997.2	2.02	−0.03	−0.14

3.2. Accuracy Assessment for Model Validation

The accuracy assessment involved a comparison between the predicted land use map and the LULC map prepared by ICIMOD, which is widely acknowledged for its high accuracy. Using the base year's LULC map of 2000 and the present year's map of 2010, the LULC map for 2019 was predicted through the integration of the MLP-Markov chain analysis (MLP-MCA) method. This projected map was then compared with the ICIMOD's validated map for 2019 for model validation, resulting in an overall average accuracy of 90.4%. The accuracy of the model for individual land use types was 98.7% for forest areas, 94.7% for agricultural land, 99.4% for grassland, and 71.3% for the snow/glacier land use type, as illustrated in Figure 4.

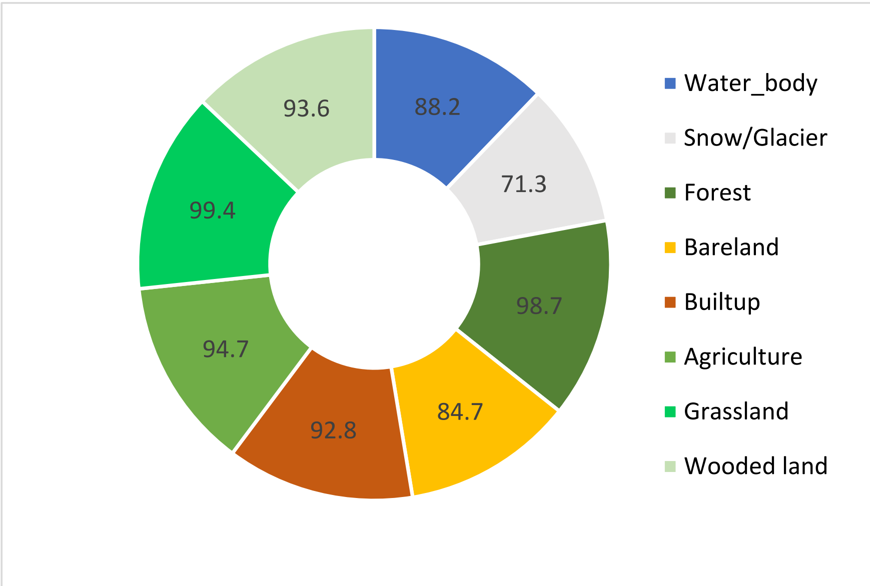

Figure 4. Accuracy of predicted model for individual land use types.

3.3. Carbon Storage and Sequestration in Nepal

Table 3 offers a comprehensive overview of carbon storage and sequestration in Nepal's diverse landscapes across different land use types for three distinct years. Figure 5 visually depicts the rate of change in carbon storage over specified time intervals. In 2000, the total carbon storage stood at 1.237 billion tons, increasing to 1.271 billion tons in 2019 with a projected rise to 1.347 billion tons in 2050. Forests play a crucial role, contributing significantly with carbon storage of 927 million tons in the initial year, 985 million tons in 2019, and an expected 1047 million tons in 2050. Grasslands follow suit, with approximately 149 million tons in 2000, 120 million tons in 2019, and an estimated 115 million tons in 2050. Agriculture land stored 69.4 million tons in 2000, 67.07 million tons in 2019, and an anticipated 73.05 million tons in 2050. Notably, carbon storage in forests increased by 6.3% from 2000 to 2019, whereas grasslands experienced a 19.9% decrease, and agricultural land witnessed a substantial 3.4% decrease in carbon storage during the same period. Looking ahead to the 2019–2050 period, forest and bare land storage are anticipated to grow by 6.2% and 50%, respectively. Waterbodies and snow/glacier land types exhibit low carbon storage, each holding less than 7.6 million tons of carbon. Waterbodies display a 5.7% increase from 2000 to 2019 but a 51% decrease for 2019 to 2050, whereas snow/glacier storage increases by 26.9% and decrease by 21.9% in the respective periods. Bare land and built-up areas had storage of 48.4 and 16.2 million tons, respectively, in 2000, and projected increases by 50% and decrease by 10.1% in 2019–2050, expected to reach 60 and 26.1 million tons, respectively.

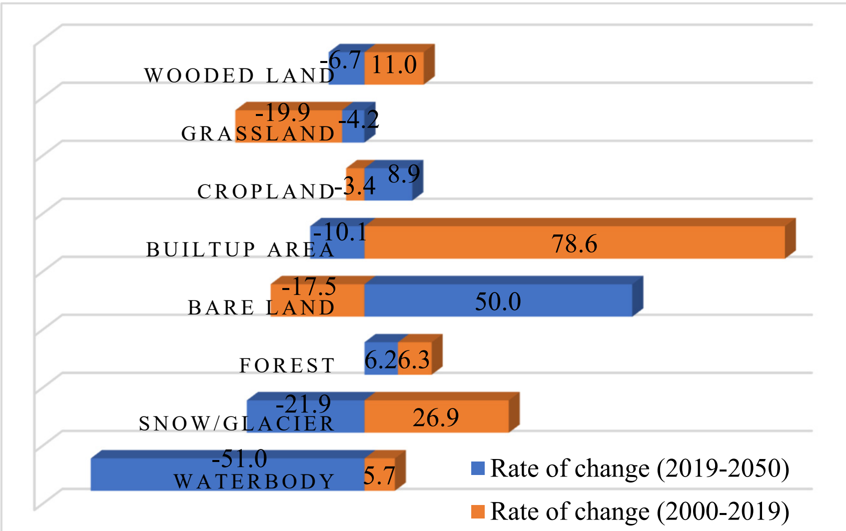

Figure 5. Proportion of change in carbon storage over different periods.

Between 2000 and 2019, total carbon sequestration was 34.141, which will be increased to 76 million tons in the projected 2019–2050 period, a remarkable increase. Bare land and cropland initially experienced decreases but are anticipated to rebound in 2019–2050. The carbon sequestration in both time intervals is positive at 58.2 million and 61.4 million tons in forest, which is major source of atmospheric carbon sequestration.

Table 3. Total carbon storage and sequestration in Nepal at different time intervals.

LULC Type	Carbon Storage_2050 (Tons)	Carbon Storage_2019 (Tons)	Carbon Storage_2000 (Tons)	Carbon Sequestration (2019–2050) (Tons)	Carbon Sequestration (2000–2019) (Tons)
Waterbody	338,242.8	690,891	653,862.6	−352,648.2	37,028.4
Snow/glacier	6,000,000	7,685,170.9	6,055,617.5	−1,685,170.9	1,629,553.4
Forest	1,047,090,863	985,614,088	927,336,647.4	61,476,774.5	58,277,440.6
Bare land	60,000,000	40,000,000	48,489,857.6	20,000,000	−8,489,857.6
Built-up area	26,112,506.3	29,049,802.2	16,266,090.9	−2,937,295.9	12,783,711.3
Cropland	73,052,858.3	67,079,110	69,452,611.8	5,973,748.3	−2,373,501.8
Grassland	115,000,000	120,000,000	149,822,066.6	−50,000,00	−29,822,066.6
Wooded land	19,710,590	21,115,590	19,016,129.4	−1,405,000	2,099,460.6
Total	**1,347,305,060**	**1,271,234,652**	**1,237,092,884**	**76,070,407.8**	**34,141,768.3**

3.4. Economic Loss and Gain from Carbon Sequestration

Figure 6 outlines the economic valuation of overall carbon sequestration in Nepal for two distinct periods, calculated by summing the loss and gain of carbon in three regions:

Terai, Hill, and Mountain. The total price of sequestered carbon in the 2000–2019 interval was 110.9 million US dollars, projected to increase more than threefold to 378.64 million US dollars in the 2019–2050 interval.

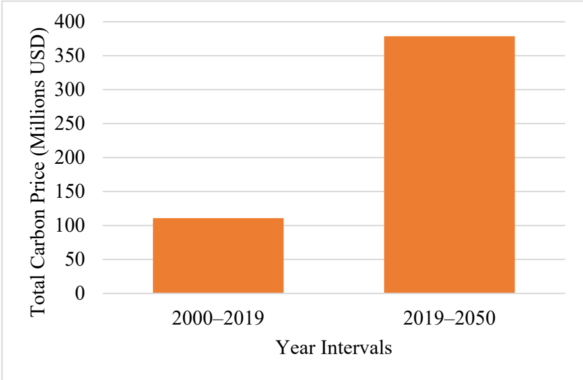

Figure 6. Economic valuation of sequestrated carbon over different periods.

3.5. Spatial Distribution of Carbon Storage in Different Years

A 30 m × 30 m grid was employed to create a carbon storage map in Nepal, ranging from 0 to 24 tons per grid cell. Carbon storage was categorized into classes ranging from "no carbon" to "very high carbon" using natural breaks (Jenk) classification in ArcGIS. Specifically, the classification scheme was as follows: 0 tons as no carbon, 0–1.16 tons as very low, 1.16–3.95 tons as low, 3.95–8 tons as moderate, 8–12.9 tons as high, and 12.9–24 tons as very high. Over the years 2000 to 2050, areas with very high carbon storage were prominent in the Chure range, hills, and mountains (excluding snow and glaciers). Land use changes were evident, with regions initially high in carbon storage shifting to moderate and low in 2019, projected to return to high in 2050. Notably, areas with very low carbon storage were predominantly found in agricultural lands in the terai and hilly regions, as shown in Figure 7.

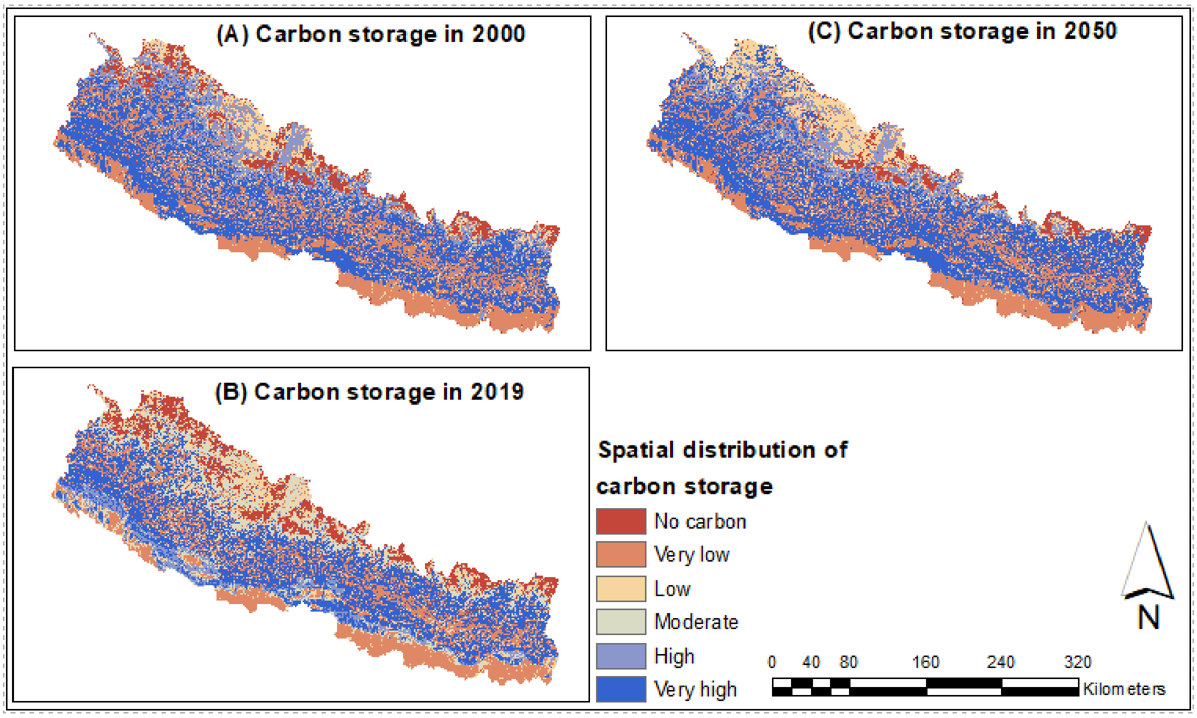

Figure 7. Spatial distribution of carbon storage in different years.

3.6. Spatial Cluster Characteristics of Carbon Storage

The carbon storage maps of 2000, 2019, and 2050 were gridded with a grid size of 30 m × 30 m, and the Moran's I index at the grid scale was calculated (Table 4). The Moran's value was greater than 0.4, $p < 0.001$ in all three years, indicating a significant spatial positive correlation and spatial cluster effect in the distribution of carbon storage in the study area. The significantly high Z-score of Z > 332, along with the low p value for study years, strongly supports the rejection of the null hypothesis of spatial randomness for carbon storage. In essence, the carbon storage map exhibits a robust and meaningful spatial structure, with carbon storage values displaying a notable tendency to spatially coalesce rather than being randomly dispersed across the landscape.

Table 4. Global Moran's I of carbon storage in different years.

Year	Moran's I	Z	p
2000	0.4444	336.19	0.00
2019	0.454	343.46	0.00
2050	0.4392	332.24	0.00

4. Discussions

Compared to prior research, our study observes a prevalent use of the CA-Markov chain for land use change prediction, coupled with InVEST models for carbon sequestration, as it consistently yields highly accurate results [16,20,23,50,51]. However, alternative studies [18,22] have employed CLUE-S and MOLUSCE for land use prediction. Notably, driver variables play a crucial role in predicting land use. For instance, ref. [21] incorporated elevation, slope, distance from roads, and distance from urban areas, whereas [17] considered factors such as distance from roads, water bodies, city headquarters, and conservation unit distances. In our study, we incorporated distance from roads, rivers, settlements, slope, elevation, and transmission lines, a factor particularly pertinent to Nepal. During disturbance factor selection, some studies [21] excluded factors with Cramer's V values below 0.15. We included disturbance factors with values higher and lower than 0.15 owing to our larger study area, aligning with the approach of others [23,52].

Investigating carbon sequestration within diverse land use types in the natural landscape represents a pivotal approach to conserving and managing natural resources, given its inherent role as a natural regulatory process [16,21]. The assessment of sequestered carbon, coupled with future projections, serves as a tangible indicator of national commitment to mitigating atmospheric carbon emissions. Studying the total carbon stock and projecting its future levels is crucial for the effective management of landscape based ESs and the development of strategies to achieve the government of Nepal's target of zero emissions by 2050. Additionally, spatial distribution and economic analyses play a crucial role in facilitating carbon trading and generating revenue, particularly for communities situated in areas with elevated carbon concentrations. Realizing the importance of sequestered carbon assessment and its trade potential, we utilized the InVEST model to predict carbon storage and sequestration across three distinct scenarios: 2000, 2019, and the projected LULC for 2050. Our findings highlight the significance of forested areas in Nepal as primary contributors to carbon storage and sequestration across all three periods, potentially aiding in global warming aligning with national commitment for emission reduction. Our projections suggest an upward trend in carbon sequestration compared to previous intervals, with economic gains anticipated to exceed threefold.

The terrestrial ecosystem's carbon cycle is directly or indirectly impacted by land use practices, given that it serves as a significant source and sink of carbon [53]. Accurate LULC mapping is a crucial input for measuring carbon sequestration using the InVEST model [15]. In this study, the predicted land use accuracy exceeded 90%, which was attributed to the use of a base year LULC map prepared by ICIMOD.

In our study, the observed increase in forest, bare land, and agriculture is attributed to anticipated land use transitions from snow/glaciers and grassland in the future. Despite forest land covering less than half of the total land, it consistently contributes to over three-quarters of the total carbon storage owing to its high atmospheric carbon sequestration capacity. Forests serve as effective carbon sinks through above- and below-ground biomass, as well as soil carbon, including decomposed organic matter.

The projected results of the study indicate that water bodies, snow/glaciers, built-up areas, wooded land (shrub land), and grasslands will decrease their carbon sequestration and carbon storage, whereas forests, croplands, and bare lands will potentially increase their carbon sequestration and carbon storage. This trend is positively correlated with changes in land use type over the projected timeframe [54]. The study [31] explains that in past decades in Nepal, grasslands have decreased due to harsh climatic conditions, poor management, and overgrazing. Several studies report that snow, glaciers, and water resources in the mountainous regions of Nepal are directly affected by climatic conditions and are highly sensitive to increases in global temperatures, which will likely accelerate the decline of these land types in the future [55,56]. There is a higher probability of converting shrubs into forests or agricultural land and built-up areas into bare lands due to high migration of people from rural to core city areas. The increase in forest land use in Nepal, both in the past and projected for the future, is attributed to the strict implementation of forest management policies during construction and development activities, as well as reduced intervention by local communities in the forests [57]. Studies in specific areas of Pakistan, Brazil, and China indicate that carbon storage will increase in forest and agricultural lands due to high carbon density and efforts to preserve natural resources [16,58,59] Conversely, the study in Iran presents that carbon loss occurs due to the shift from natural land cover to anthropogenic land cover and vice versa [60].

The distribution patterns of carbon storage, both historical and predicted, demonstrate significant clustering, with notably high carbon storage in specific parts of the terai and mountain regions, and most hilly regions, including the Chure. This concentration is attributed to extensive forest coverage, and our assumption regarding input values for carbon pooling remains consistent across all forest categories. This assumption aligns similarly with other land use types in the study area.

The findings of our study reveal exceptionally high carbon storage in forest landscapes, which is attributed to substantial carbon pooling values and extensive coverage. From 2000 to 2050, the total carbon storage in Nepal is projected from 1.237 to 1.347 billion tons, with forests making a significant contribution. Our study estimated the aggregate carbon storage in forest and wooded land in 2000 at 946.35 million tons, aligning closely with the 961 million tons calculated by [10]. Moreover, our study calculated the economic value of sequestered carbon using a carbon rate of US $5 per ton of CO_2 equivalent, following the agreement between the Nepal government and the World Bank for carbon trade [61]. We adopted a discount rate of 3% and an annual rate of change of price of zero, consistent with the approach taken by [21].

Numerous studies have underscored a significant transformation in land use across Nepal over the past two to three decades, driven by factors such as a high rate of migration, rural road construction, and escalating population density [62]. Although existing research in Nepal predominantly concentrates on carbon sequestration within forests in the current timeframe [10,30,63], a limited number of studies have delved into soil carbon measurement within specific geographic areas [64]. Notably, a research gap exists in presenting a comprehensive assessment of total carbon storage and sequestration across various land uses in Nepal, along with a lack of future predictions. In addition, essential information concerning the monetary value associated with carbon loss and sequestration, including the spatial distribution of carbon storage in Nepal's landscape, remains absent. This research aims to address such gaps in studies conducted in Nepal.

Managing carbon in the landscape involves essential details, such as the spatial distribution of carbon, annual carbon sequestration/loss, and the impact of land use changes on carbon sequestration [21]. This study provides necessary information for carbon management in Nepal's landscape, offering insights into the status of carbon distribution and the consequences of land use changes on carbon sequestration. Aligning with Nepal's commitment on emission reduction, this research aids in planning sustainable measures to mitigate human-induced development activities that lead to forest degradation. Additionally, this study encourages the adoption of sustainable alternative energy sources in local communities, thereby reducing reliance on fuelwood. In addition, quantifying ecosystem services in monetary terms and assessing their concentration in the landscape are important tools for the government and stakeholders engaged in carbon financing. This approach facilitates the provision of fair incentives to local communities, raising awareness among the populace about the importance of protecting forests and promoting plantation initiatives.

5. Conclusions

This study investigates the carbon storage dynamics in Nepal's landscape from 2000 to 2050 using the InVEST model. Despite its limitations, such as an oversimplified carbon cycle representation and the assumption of constant carbon pools, the model provided valuable insights into carbon storage trends across diverse land use types. This study utilized carbon pool data from similar studies and categorized the analysis into three distinct regions—Terai, Hill, and Mountain (Supplementary Materials)—each with unique features and varying carbon densities in forests and soil, thereby allowing for a more nuanced and accurate analysis of carbon storage across diverse landscapes of Nepal. Key findings reveal that by 2050, forests will cover 41.83% of Nepal's land, making them the primary contributor to carbon storage, followed by grasslands. The total carbon storage is projected to range from 1.237 to 1.347 billion tons, with annual sequestration ranging from 34.14 to 76 million tons. Significant carbon concentrations were identified in the Terai, hilly regions, and mountains. The economic valuation of carbon storage showed an increase from 110.909 million USD in 2000 to a projected 3.4-fold increase by 2050.

For future studies, it is recommended to expand the research including comparative analyses with similar ecosystems in other regions or countries. This will address the limitations of the InVEST model, validate the methodology, and enhance understanding of global carbon dynamics. Such expansion will increase the applicability of our findings, aiding policymakers and scientists in implementing effective strategies for sustainable land use and climate change mitigation.

Policy Recommendations

Based on the findings, the study proposes the following policy implications for governing bodies of Nepal to develop effective environmental, energy and forest management policies to achieve zero emission determination.

- Community-Based Conservation Incentives: In Nepal, forest management has evolved from primarily government-based practices to community-driven approaches since the implementation of the "*Panchayat Forest*" system in 1978 and the 1988 forest sector master plan. Recognized as a role model in Asia, this shift signifies the importance of local community involvement in forest conservation and carbon restoration. This study suggests the need for the Nepalese government to implement targeted incentive programs for local communities, which could include financial rewards for forest conservation, community development funds tied to conservation results, and initiatives focused on capacity building of local communities;
- Policy Framework for Sustainable Land Use: The study recommends the development of a comprehensive policy framework encompassing this finding to promote sustainable land use for both ecological sustainability and economic development;
- Carbon Credit Mechanisms: This study recommends the establishment of national carbon credit mechanisms encompassing all land use types strengthening to REDD$^+$ based on these findings on carbon sequestration. The mechanism would facilitate

Nepal's participation in international carbon markets, offering economic incentives for the preservation and improvement of carbon stocks;

- ❖ Public-Private Partnerships for Conservation: The study recommends the promotion of public-private partnerships that focus on conservation and sustainable land use (converting bare land into agroforestry). This approach can leverage private sector resources and expertise, augmenting governmental efforts in environmental stewardship;
- ❖ Expand Biogas Infrastructure: Promote the installation of biogas plants in rural communities, providing an eco-friendly alternative to traditional biomass fuels. This will reduce dependence on firewood and mitigate deforestation;
- ❖ Subsidies for Hydroelectricity Use in Rural Communities: Offer subsidies and declare free electricity of certain units to encourage the use of hydroelectricity for cooking and other household purposes in rural areas. This will decrease the frequency of forest visits for fuelwood, thus preserving forest resources;
- ❖ Implement Emission Charges: Impose emission charges on vehicles and industries that use petroleum products to incentivize the shift towards cleaner energy sources;
- ❖ Addressing GHG Emissions from Waste: In Nepal, greenhouse gas emissions from open dumping of waste pose a significant problem. Converting municipal waste to energy is an effective solution to reduce these emissions and manage waste sustainably.

The policy suggestions of this study, given their scalability and adaptability, could be effectively applied in other regions with similar ecological and socio-economic challenges. The study encourages governments in these areas to tailor and adopt these recommendations according to their unique circumstances.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16177377/s1, Carbon Pools in Terai, Hill, and Mountain.

Author Contributions: Methodology, software, conceptualization, data curation, formal analysis, investigation, writing—original draft, D.C.; conceptualization, editing, revision, R.L.R.; editing, A.O.Y. and J.P.; data analysis, N.N.S.; software, D.S. and J.-O.L.; investigation, supervision, funding acquisition, J.-S.H. All authors have read and agreed to the published version of the manuscript.

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