

Article

Spatio-Temporal Evolution Characteristics of Multi-Scenario Land Use and Carbon Storage in Lhasa City Based on the PLUS-InVEST Model

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Abstract

As an important ecological security barrier, land use change on the Qinghai-Xizang Plateau has a profound impact on regional carbon storage functions. Exploring the impact of the spatiotemporal evolution of land use on carbon storage in Lhasa has significant reference value for improving regional carbon cycle theory and formulating differentiated low-carbon development strategies. This study takes Lhasa City as the research area, uses land use data from 2000 to 2020 as the benchmark, and couples the PLUS and InVEST models to simulate land use patterns under three different scenarios—natural development (NDS), urban development (UDS), and ecological protection (EPS)—in 2030, thereby revealing the spatiotemporal dynamic evolution differences of carbon storage under each scenario. The results show that: (1) From 2000 to 2020, the urbanization process in Lhasa was remarkable. Construction land, forest land, cultivated land, water area, and unused land all showed an increasing trend, with grassland being the main source of transformation. From 2000 to 2020, carbon storage in Lhasa showed a fluctuating trend of first rising and then falling, with the historical peak occurring in 2010 (207.70 Mt), declining to 206.53 Mt in 2020. The spatial pattern was high in the west and low in the east, with the west being the main high-carbon storage area. (2) The carbon storage of the three scenarios in 2030 differs: NDS is 205.80 Mt, UDS is 206.11 Mt, and EPS is 208.16 Mt. Among them, NDS and UDS are lower than the 2020 level (206.53 Mt), while EPS is not only higher than the 2020 level but also exceeds the historical peak of 2010 (207.70 Mt). The total carbon differences among the three scenarios are relatively small on a macro level, but the micro-level differentiation is significant. EPS performs best in grassland and forest land carbon storage, while NDS is relatively higher in cultivated land and unused land carbon storage. (3) Based on the 2020 baseline carbon storage, the Geodetector analysis shows that soil type ($q = 0.264$) and GDP ($q = 0.253$) have the strongest statistical associations with the spatial differentiation of carbon storage, followed by elevation ($q = 0.160$) and annual average temperature ($q = 0.115$). It should be noted that this analysis only reveals statistical associations and cannot be interpreted as an independent causal driving mechanism for carbon storage. Moreover, the results are subject to uncertainties in fixed carbon densities, data resampling, and scenario settings. This research can provide a scientific basis for ecological protection strategies under territorial spatial planning and carbon neutrality goals in Lhasa City.



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Keywords: land use; carbon storage; multi-scenario simulation; PLUS model; InVEST model; Lhasa City

1. Introduction

Global climate change is widely recognized as the most severe environmental challenge facing human society in the 21st century, and the carbon cycle of terrestrial ecosystems is a key scientific link in understanding the driving mechanisms of climate change [1]. Land use, as a core parameter characterizing the intensity of human activities' intervention in the natural environment, directly shapes the carbon sink function of the ecosystem by regulating the vegetation coverage pattern and the dynamics of the soil organic carbon pool [2]. In order to achieve the strategic goal of carbon neutrality, systematically assessing the impact of land use change on carbon storage and predicting the evolution trend of carbon sinks under multiple development paths have become core academic propositions in regional sustainable development research [3].

The Qinghai-Xizang Plateau is not only renowned for its lofty terrain as the “Roof of the World”, but also serves as a significant ecological security barrier globally due to its water conservation function as the “Asian Water Tower”. This high-altitude ecosystem is extremely sensitive to climate change and human activities, and the stability of its carbon sink function is related to the overall regional ecological security [4,5]. However, in recent years, with the acceleration of urbanization and population growth, the land use pattern in the river valleys of the Qinghai-Xizang Plateau has undergone profound changes. The expansion of construction land has encroachment on ecological space, and the reclamation of cultivated land has altered the original vegetation. These spatial occupation by human activities is having a non-negligible impact on the carbon storage function of the plateau ecosystem [6]. Lhasa, as a core city on the Qinghai-Xizang Plateau, is characterized by both ecological vulnerability and the demands of social development. The Lhasa River Valley is not only a major agricultural and population-concentrated area on the plateau, but also a region where the contradiction between ecological protection and urban development is concentrated. Xu et al. (2024) found that after the zonal vegetation in Chengguan District, Lhasa City was converted to construction land, the net primary productivity (NPP) decreased from 0.2–0.3 kg/m² to 0.16–0.26 kg/m², indicating a significant impairment of ecological productivity [7]. Hao et al. (2025) further simulated the carbon stock dynamics in the Lhasa River Basin from 2020 to 2040 under three development scenarios (BAU, cropland protection, and ecological priority) using the coupled PLUS-InVEST framework, revealing that carbon stocks would increase under most scenarios except the 2040 BAU [8]. At the broader plateau scale, Huang et al. (2024) employed the PLUS-InVEST-GeoDetector model to project carbon storage changes on the entire Qinghai-Xizang Plateau through 2030 under SSP-RCP scenarios, identifying NDVI as the most influential driver [9]. Despite these valuable contributions, three critical gaps remain in the existing literature. First, existing studies on the Lhasa River Basin primarily focus on decadal-scale simulations (e.g., 2040), while the 2030 time node—which aligns with both China's carbon peak target year and the territorial spatial planning horizon of Lhasa City—remains under-examined. Second, most studies either examine the entire Qinghai-Xizang Plateau at a coarse spatial resolution or focus narrowly on Chengguan District, leaving a scale gap at the city level where land use planning decisions are actually implemented. Third, while previous studies have documented the historical relationship between land use change and carbon storage, the differentiated responses of carbon storage to alternative urban devel-

opment pathways—particularly the trade-offs between urban expansion and ecological protection—have not been systematically compared for Lhasa City.

The PLUS model captures the complex relationship between land class transformation and driving factors through the random forest algorithm, and can achieve high-precision land use simulation at the patch scale [10–12]. The InVEST model has become the mainstream tool for carbon storage assessment due to its advantages of requiring fewer parameters and spatializing assessment results [13–15]. The integration of the two has been applied at different scales such as urban agglomerations, river basins, and agro-forestry intersections [16–18]. However, for city-level administrative units in high-altitude ecologically sensitive areas—where the tension between development demand and ecological constraint is most acute—the application of this coupled framework for policy-oriented carbon storage simulation remains insufficient.

Therefore, this study takes Lhasa City, Xizang Autonomous Region as the research area. By using the land use time series data from 2000 to 2020, a PLUS-InVEST coupling model is constructed to simulate the evolution trend of land use patterns and the accompanying changes in carbon storage under three development scenarios—natural development, urban development, and ecological protection—in 2030. The specific contributions of this study are threefold: (1) it fills the scale gap by providing city-level, patch-scale carbon storage simulations for Lhasa, complementing existing river-basin and plateau-scale assessments; (2) it targets the 2030 planning horizon, directly informing territorial spatial planning and carbon peak policy at the municipal level; (3) it systematically quantifies the carbon storage cost of urban expansion by contrasting the urban development scenario against the ecological protection scenario, thereby providing an empirical basis for the trade-off analysis between development and conservation in fragile plateau ecosystems. The aim is to reveal the differentiated impacts of different development paths on the carbon storage function of plateau ecosystems, and to provide scientific support for the ecological protection strategies under the territorial space planning and carbon neutrality goals of Lhasa City.

2. Materials and Methods

2.1. Research Area

Lhasa City is located in the middle reaches of the Lhasa River, a tributary of the Yarlung Zangbo River, in the central part of the Xizang Autonomous Region. Its geographical coordinates range from 89°45' to 92°37' east longitude and 29°14' to 31°03' north latitude. The average altitude is approximately 3650 m, and the total area is 29,600 square kilometers. Lhasa City is the political, economic and cultural center of the Xizang Autonomous Region, and it governs 8 counties and districts including Chengguan District, Damxung County and Chushul County. Lhasa City is located in the plateau temperate semi-arid monsoon climate zone, with distinct climate and environmental characteristics: strong solar radiation and long hours of sunshine. The distribution of precipitation is extremely uneven, with distinct dry and wet seasons. The precipitation from June to September accounts for over 90% of the annual total, and night rain occurs frequently. The daily temperature range is large and the annual average temperature is relatively low. The land use types in Lhasa City are mainly grassland and unused land. Cultivated land and construction land are mainly distributed in the Lhasa River Valley. Forest land is mainly distributed in the area at an altitude of 4000 to 5000 m, while tree forests and artificial forests are mainly distributed in the middle reaches of the Lhasa River and the Yarlung Zangbo River valley. As a typical river valley city on the Qinghai-Xizang Plateau, Lhasa is confronted with the dual pressures of ecological protection and urban development. On the one hand, its ecosystem is fragile and the recovery capacity of alpine vegetation is limited. On the other hand, the accelerated

urbanization process has led to the continuous expansion of construction land, exerting a squeeze on ecological space [19–23]. This contradiction makes Lhasa an ideal case for studying the response of land use change and carbon storage in plateau cities. The location of the study area is shown in Figure 1.

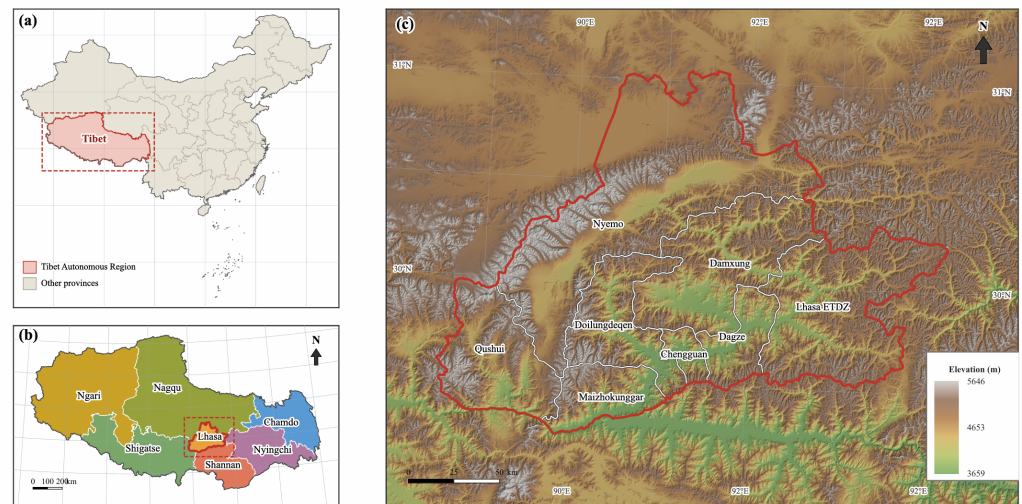


Figure 1. (a) The location of the Xizang Autonomous Region in China; (b) The administrative divisions of Xizang, with the red box indicating the location of Lhasa; (c) The topographic map of the study area, where the red lines indicate the boundary of Lhasa. The red dashed boxes and red lines are used to highlight the location and extent of the study area.

2.2. Data Sources and Processing

The land use data used in this study were obtained from the China Multi-Period Land Use Remote Sensing Monitoring Dataset (CNLUCC), published by Xu Xinliang et al. through the Resource and Environmental Science Data Center, Chinese Academy of Sciences (<http://www.resdc.cn>) [24]. The dataset was generated mainly from Landsat MSS/TM/ETM/OLI imagery through visual interpretation, with an original spatial resolution of 30 m. It covers 12 periods: 1980, 1990, 1995, 2000, 2005, 2008, 2010, 2013, 2015, 2018, 2020, and 2023. The land use classification adopts a two-level hierarchy: six first-level classes and 25 s-level classes. According to the accuracy assessment released with the dataset, the overall classification accuracy is 93% for the first-level classes and 91% for the second-level classes. In this study, data for [2000, 2010, 2020] were selected and reclassified into [farmland, woodland, grassland, water, built-up, and unused land] for subsequent analysis [25–28].

Elevation data were obtained from the SRTMDEM 30 m Resolution Original Elevation Data provided by the Geospatial Data Cloud (<http://www.gscloud.cn>). The data were jointly measured by the National Aeronautics and Space Administration (NASA) and the National Imagery and Mapping Agency (NIMA). The data acquisition time was February 2000, and the current version is V4.1. Slope data were calculated from this DEM in a GIS environment.

Temperature data were obtained from the National Tibetan Plateau Data Center (<https://data.tpdac.ac.cn>), using the Tibetan Plateau climate data (1901–2022) [29]. The original spatial resolution is approximately $1/30^\circ$ (about 3.3 km), and the temporal range is 1901–2022; the period used in this study is [2020]. <https://cstr.cn/18406.11.Atmos.tpdac.301081> (accessed on 20 October 2026). Precipitation data were obtained from the 1-km monthly precipitation dataset for China (1901–2025) published by Peng. The spatial resolution is 1 km, and the temporal range is 1901–2025; the period used in this study is [2000–2020] [30].

The soil type data were obtained from the China Soil Type Spatial Distribution Dataset provided by the Resource and Environmental Science Data Center, Chinese Academy of Sciences (<http://www.resdc.cn>). The dataset was compiled based on the 1:1,000,000 soil type map and the Second National Soil Survey.

GDP data were obtained from the China GDP Spatial Distribution Kilometer Grid Dataset (2020 version) published by Xu Xinliang through the Resource and Environmental Science Data Center, Chinese Academy of Sciences (<http://www.resdc.cn>). The spatial resolution is 1 km. Nighttime light data were obtained from the China Annual Nighttime Light Dataset, also published by Xu Xinliang through the Resource and Environmental Science Data Center, with a spatial resolution of 1 km. Population density data were obtained from the China Population Spatial Distribution Kilometer Grid Dataset from the same source, with a spatial resolution of 1 km. It should be noted that all socioeconomic datasets (GDP, nighttime light, and population density) used in this study are the native 2020 datasets. They were not extrapolated or interpolated from earlier base years, ensuring temporal consistency with the 2020 baseline land-use data and the subsequent Geodetector analysis.

In this study, some 1-km resolution data (e.g., GDP, population density, and precipitation) were resampled to 30 m to match the land use data. It should be explicitly noted that this operation was performed only to unify the raster cell size for spatial overlay analysis and does not add spatial detail that is absent from the original data. The information represented by a 30 m cell still originates from the original 1-km grid. This processing does not substantially improve the accuracy of spatial analysis; it only meets the need for data format matching. The detailed information and sources of these data are listed in Table 1.

Table 1. Simulated Drivers of Land Use Change.

Category	Data Name	Original Resolution	Time Period/Year	Source
Land Use (Dependent Variable)	Land Use/Land Cover (CNLUCC)	30 m	2000, 2010, 2020	RESDC (http://www.resdc.cn)
Natural factor	DEM	30 m	2020	http://www.gscloud.cn
	Slope	30 m	Derived from DEM	Derived from DEM
	Annual average temperature	~3.3 km (1/30°)	2000–2020	https://data.tpdac.ac.cn
	Annual average rainfall	1000 m	2000–2020	https://data.tpdac.ac.cn
	Soil type	1000 m	1995	http://www.resdc.cn
	Distance to river	30 m	2020	https://www.openstreetmap.org
Socioeconomic factor	GDP	1000 m	2020	http://www.resdc.cn
	Population density	1000 m	2020	http://www.resdc.cn
	Nighttime lighting	1000 m	2020	http://www.resdc.cn
	Distance to road	30 m	2020	https://www.openstreetmap.org
	Distance to railway	30 m	2020	https://www.openstreetmap.org
	Distance to county government	30 m	2020	https://www.openstreetmap.org

2.3. Research Methods

2.3.1. Multi-Scenario Dynamic Simulation of Future Land Use Based on PLUS Model

The PLUS (Patch-generating Land-use Simulation) model is a Land Use Simulation tool based on cellular automata, consisting of two core modules: Land Expansion Strategy Analysis (LEAS) and Multi-type Random Patch Seed CA (CARS). It can generate high-precision land use spatial patterns [31]. This model superimposes land use data from

different periods, analyzes the quantitative changes of each land use type, and uses the random forest algorithm to mine the nonlinear relationship between the transformation of different land use types and their driving factors, thereby calculating the development probabilities of each category. Based on this, by combining the random patch generation mechanism and the transfer transition matrix, the PLUS model can effectively predict the patch evolution process of various land uses under different scenarios [32,33].

This study takes the land use data of 2010 as the base period, combines parameters such as the probability of land use development, the number of pixels of future land use demand, the transfer cost matrix and the weight of neighborhood factors, and uses the PLUS model to simulate and obtain the land use prediction map of Lhasa City in 2020. To avoid information leakage, the neighborhood weights used in the PLUS model were derived exclusively from land-use expansion observed during 2000–2010, only from the period preceding the 2010 base year. The 2010–2020 observed land-use data were used only for validation and were not involved in calibrating the neighborhood weights or any other model parameter. The neighborhood weights of cultivated land, forest land, grassland, water area, construction land and unused land were finally determined to be 0.04, 0.25, 0.49, 0.03, 0.01 and 0.18 respectively. To verify the simulation accuracy of the model, the simulation results of 2020 were compared with the actual land use data, and the Kappa coefficient and overall accuracy (OA) were used for quantitative assessment. The results show that the Kappa coefficient is 0.918 and the overall accuracy is 94.75%, indicating that the PLUS model has a high simulation credibility in the study area. Based on the above verification results, this study further utilized this model to simulate and predict the spatial pattern of land use in Lhasa under three scenarios: natural development, urban development, and ecological protection in 2030.

2.3.2. Scenario Settings

This study establishes three land use change scenarios: the natural development scenario (NDS), the urban development scenario (UDS), and the ecological protection scenario (EPS). Policy-mandated constraints are directly derived from the planning documents approved by the State Council. These specifically include: the urban development boundary $\leq 230.55 \text{ km}^2$; the construction land expansion multiplier ≤ 1.3 times the 2020 scale; the ecological protection red line $\geq 9674.59 \text{ km}^2$; the permanent basic farmland area $\geq 366.14 \text{ km}^2$; and the cultivated land retention $\geq 510.73 \text{ km}^2$. The parameter settings for each scenario strictly follow the three principles of “policy anchoring—historical trends—total-volume truncation,” as detailed below [34,35]:

1. Natural Development Scenario (NDS): It is assumed that the land use change trends from 2000–2020 will continue completely through 2030, without any additional policy intervention. the Markov transition probability matrix directly adopts the historical 20-year cumulative transition probabilities from 2000 to 2020, without applying any policy adjustments (i.e., all transition coefficients are set to 1.0). The 10-year cumulative matrix ($P_{10} = P_{20}^{1/2}$) is then derived to forecast the 2030 demand.
2. Urban Development Scenario (UDS): Within the urban development boundaries approved by the State Council, urban development space is maximized, reflecting the “strong-center” strategy; the expansion multiple of urban development boundaries in the Tibet Autonomous Region is capped at no more than 1.3 times the 2020 urban construction land scale. The probabilities of forest land/grassland/cropland being converted to construction land are moderately increased relative to the historical trend ($\times 1.3$), but are controlled through total-volume truncation to ensure that construction land does not exceed 230.55 km^2 . The probability of grassland being converted to unused land is increased by 30%, while the probability of unused land being converted

to forest land/grassland is reduced by 30%, reflecting a relative reduction in ecological investment. The probability of construction land being converted out is reduced by 30%, reflecting the stickiness of construction land.

3. Ecological Protection Scenario (EPS): Ecological priority is adhered to, construction land expansion is strictly restricted, and territorial greening and ecological restoration are advanced on a large scale. The State Council's approval explicitly states that the ecological protection red line area in Lhasa shall be no less than 9674.59 km², accounting for approximately 32.6% of the city's total area; the plan requires advancing greening of the North and South Mountains and territorial greening in the Lhasa River Basin to enhance forest carbon sinks. By 2030, construction land should be controlled within the 2020 status quo of 186.69 km², or slightly increased to 200 km², achieving zero growth or negative growth. The probabilities of forest land/grassland/cropland being converted to construction land are reduced by 50% relative to the historical trend. The probability of grassland being converted to unused land is reduced by 50%, the probability of unused land being converted to forest land/grassland is increased by 50%, and the probability of cropland being converted to forest land/grassland is increased by 30%. The probability of construction land being converted out is increased by 30%, reflecting "revitalizing existing stock and strictly controlling total volume."

Among these, water and nature reserves are designated restricted areas. The rules of the transfer matrix are as follows: S1 to S3 represent three scenarios: natural development, urban development, and ecological protection. A to F represent six types of land (cultivated land, forest land, grassland, water area, construction land, and unused land). 1 indicates that conversion is allowed, and 0 indicates that conversion is prohibited (Table 2).

Table 2. Land use transfer matrix under different scenarios.

	S1						S2						S3					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
A	1	1	1	0	1	1	1	0	0	0	1	1	1	1	1	0	1	1
B	0	1	1	0	1	1	1	1	1	0	1	0	0	1	1	0	0	0
C	1	1	1	0	1	1	1	1	1	0	1	1	0	1	1	0	1	0
D	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0
E	0	1	1	0	1	0	0	0	0	0	1	0	0	1	1	0	1	0
F	0	0	1	0	0	1	1	1	1	0	1	1	0	1	1	0	0	1

2.3.3. Land Use Demand Prediction

In the PLUS model, land use demand (i.e., the total number of pixels for each land use type) is the basis for spatial allocation. This study employs a Markov Chain combined with policy constraint correction to predict the demand for each land use type in 2030. The specific steps are as follows:

First, based on the land use transition area matrix from 2000 to 2020, the 20-year cumulative transition probability matrix (P_{20}) is calculated. Then, according to the settings of the three scenarios, P_{20} is modified to obtain the scenario-specific 20-year cumulative matrix.

Since the forecast horizon from 2020 to 2030 is 10 years, the 10-year cumulative transition probability matrix (P_{10}) is derived by taking the square root of the 20-year matrix:

$$P_{10} = P_{20}^{1/2} \quad (1)$$

Finally, taking the current area of each land use type in 2020 as the initial state vector (S_{2020}), the initial demand for each land use type in 2030 (D_{initial}) is calculated as:

$$D_{\text{initial}} = S_{2020} \times P_{10} \quad (2)$$

(1) Natural Development Scenario (NDS): The area of each land use type in 2020 is directly multiplied by the 10-year cumulative transition probability matrix (P_{10}) derived from the 2000–2020 historical trend to obtain the demand for each land use type in 2030. Under this scenario, the demand for construction land will continue the historical expansion trend.

(2) Urban Development Scenario (UDS): After calculating the initial demand using the modified transition probability matrix, the probabilities of forest land, grassland, and cultivated land being converted to construction land are increased relative to the historical trend ($\times 1.3$). To strictly comply with the State Council-approved urban development boundary, a total-volume truncation is applied: the initial construction land demand is capped at 230.55 km² (approximately 256,161 pixels), and the truncated pixels are proportionally reallocated to the grassland category. The probability of construction land transfer out is reduced by 30%, and the probability of construction land retention is correspondingly increased. Finally, the modified total amount of each land use type is used as the Demand input for the PLUS model.

(3) Ecological Protection Scenario (EPS): The initial demand is similarly calculated based on the modified transition probability matrix. The probability of converting forest land/grassland to construction land is reduced by 50% based on the historical trend; the probability of converting cultivated land to construction land is reduced by 50%. The probability of converting cultivated land to forest land/grassland is increased by 30%. The probability of construction land being converted out is increased by 30%, reflecting “revitalizing existing stock and strictly controlling total volume.”

The land use requirements under each scenario for 2030 are shown in Table 3.

Table 3. Summary Table of Multi-Scenario Demand in 2030 (Number of Pixels).

Scenario	FarmLand	WoodLand	Grassland	Water	Built-Up	UnusedLand
2020	1,106,440	3,891,940	18,132,505	2,271,235	207,436	7,355,647
NDS	1,183,451	3,994,692	17,383,210	2,443,501	268,349	7,692,000
UDS	1,164,147	3,944,836	17,742,891	2,442,784	256,161	8,414,384
EPS	1,156,265	4,090,392	18,570,269	2,444,174	216,714	6,487,390

2.3.4. Carbon Storage Estimation Based on the InVEST Model

The InVEST model divides carbon storage into four carbon pools: above-ground biological carbon, underground biological carbon, soil organic carbon, and dead organic carbon [36–38]. The total carbon storage calculation formula is as follows:

$$C_{\text{total}} = \sum (C_{\text{above},i} \times A_i + C_{\text{below},i} \times A_i + C_{\text{soil},i} \times A_i + C_{\text{dead},i} \times A_i) \quad (3)$$

Among them, C_{total} represents the total carbon storage. $C_{\text{above},i}$, $C_{\text{below},i}$, $C_{\text{soil},i}$, and $C_{\text{dead},i}$ respectively represent the four carbon pool densities of the second type of land use. A_i represents the area of the first type of land use.

This study mainly employs the China Ecosystem Research Network (<http://www.cnern.org.cn/>), the “2010s China Terrestrial Ecosystem Carbon Density Dataset” as source data [39]. Given that the hydrothermal conditions in high-altitude regions differ significantly from the national average in China, directly adopting China’s average carbon density data would lead to substantial deviations in the estimation of carbon reserves in Lhasa. To this end, this study employs the correction factor formula proposed by Alam et al. [40] and introduces a localized correction model based on the mean annual temperature (MAT) and the mean annual precipitation (MAP) (Equations (4)–(10)). For China, the reference meteorological data were set as MAT = 10.9 °C and MAP = 668 mm; for Lhasa, the actual meteorological data were set as MAT = 9.0 °C and MAP = 472.9 mm, and the carbon

densities for grassland, forest land, and unused land were adjusted accordingly. Drawing on the findings of previous studies [8,41,42], we have supplemented the carbon density data for farmland, build-up, and water. Meanwhile, this analysis did not incorporate the carbon density of dead organic matter, as its contribution to the carbon pool is small. relatively small.

$$C_{SP} = 3.3968 \times MAP + 3996.1 \quad (4)$$

$$C_{BP} = 6.798 \times e^{(0.0054 \times MAP)} \quad (5)$$

$$C_{BT} = 28 \times MAT + 398 \quad (6)$$

$$K_{BP} = \frac{C_{BP}^a}{C_{BP}^b} \quad (7)$$

$$K_{BT} = \frac{C_{BT}^a}{C_{BT}^b} \quad (8)$$

$$K_B = K_{BP} \times K_{BT} \quad (9)$$

$$KS = \frac{C_{SP}^a}{C_{SP}^b} \quad (10)$$

where: MAP is the yearly average rainfall (mm), which is 668 mm in China and 472.9 mm in Lhasa; MAT is the average temperature of the whole country and Lhasa, which is determined to be 10.9 °C for the whole country and 9.0 °C for Lhasa. C_{SP} and C_{BP} are the soil carbon content and biological carbon concentration (kg/m²) modified for the annual average precipitation, respectively. C_{BT} stands for biological carbon concentration (kg/m²), which is adjusted for yearly mean temperature. In the equation for aboveground biological carbon concentration, K_{BT} represents the annual average precipitation element revision coefficient and K_{BP} represents the yearly average temperature component revision rate of aboveground biological carbon intensity. C_a represents the statistics generated from every year's average rainfall and temperature for Lhasa, C_b represents the data that is produced using the yearly averages of precipitation and temperature for China. K_B represents the correction coefficient of aboveground organisms K_S represents the revision coefficient of soil carbon density.

The final revised carbon density of Lhasa is presented in Table 4. The corrected carbon density parameters (Table 4) are significantly lower than the national averages. This result is consistent with the ecological characteristics of slow vegetation growth and low biomass accumulation in the cold and arid alpine environment of the Qinghai-Tibet Plateau.

Table 4. Carbon density of the study area (t · hm^{−2}).

Land Use Types	C_Above	C_Below	C_Soil	C_Dead
farmland	0.21	2.95	72.98	0.00
woodland	13.91	3.24	91.86	0.00
grassland	0.24	2.08	73.63	0.00
water	0.09	0.00	0.00	0.00
built-up	0.11	0.00	0.00	0.00
unused	0.31	1.68	53.59	0.00

2.3.5. Geographic Detector Analysis

A Geodetector is a statistical method used to detect the spatial heterogeneity of geographical phenomena and quantify the contribution of their driving factors [43,44]. The core assumption is that if a certain factor is a key factor influencing geographical phenomena, there should be a significant spatial coupling relationship between the spatial distribution of this factor and the spatial differentiation of the phenomena. Compared with

traditional statistical methods, geographic detectors have two major advantages: First, they do not assume linear relationships between variables; Secondly, it has lenient requirements for data types and is compatible with both continuous variables and categorical variables. Therefore, this method is widely applied in the driving force analysis in the fields of natural and human geography [45–47]. Its key statistic is the q value, and the calculation formula is:

$$q = 1 - \frac{\sum_{h=1}^L n_h \sigma_h^2}{N \sigma^2} \quad (11)$$

Here, L represents the number of classifications or partitions, n_h and σ_h^2 are respectively the number of samples in the h -th area and the variance of the dependent variable, and N and σ^2 are the total number of samples and the total variance of the entire study area. The range of q values is $[0, 1]$. The larger the q value is, the stronger the explanatory power of this factor for the spatial differentiation of the dependent variable is. In addition, this method can also be used to evaluate whether the explanatory power of the combined effect of two factors is significantly greater than the sum of the independent effects of each factor [29]. Based on the above principles, this study uses a geographic detector to conduct an attribution analysis of the spatial differentiation characteristics of carbon storage in Lhasa City, quantitatively revealing the influence intensity of land use change factors, socio-economic factors, and the interaction effects between the two on the distribution pattern of carbon storage.

This study used fishnet sampling to extract data. Specifically, based on a 30-m resolution land use raster, a fishnet with 50 rows and 50 columns was created and clipped to the study area. The dependent variable and all independent variables were extracted to the fishnet center points or polygon features. After data cleaning and matching, a total of 1276 valid samples were obtained. This scale can effectively reflect the spatial heterogeneity of carbon storage in Lhasa.

Before constructing the GeoDetector model, this paper conducted a collinearity diagnosis of the independent variables. Pearson correlation analysis showed that the correlation coefficient between population (pop) and GDP (gdp) was as high as 1.000, indicating extremely severe perfect collinearity; meanwhile, the correlation coefficients between net primary productivity (npp) and the above two factors were both greater than 0.77. To avoid variable redundancy leading to distorted model results and to follow the principle of “retaining variables with stronger explanatory power,” this paper removed population (pop) and net primary productivity (npp), and retained GDP (gdp) as the core driving factor of the socioeconomic dimension for subsequent analysis.

GeoDetector requires independent variables to be categorical. To eliminate bias caused by subjective grouping, this paper, referring to the framework of the optimal parameters-based geographical detector, systematically tested the K-means clustering method, equal interval method, geometric interval method, and quantile method. Preliminary tests found that socioeconomic data such as GDP exhibited an extremely skewed distribution; using K-means clustering or the equal interval method led to severe sample imbalance, with q values approaching 0 and p values not significant. Therefore, this paper ultimately adopted the quantile method for discretization. This method can ensure a balanced sample size across groups, thereby accurately capturing the spatial differentiation characteristics of skewed data.

3. Results

3.1. Spatio-Temporal Changes of Land Use in Lhasa City from 2000 to 2020

Table 5 shows the area changes of land use types in Lhasa City from 2000 to 2020. Grassland is the most dominant land use type in the study area, always accounting for

more than 50%. Unused land comes second. The proportion of construction land is the smallest but its growth is the most significant. From the perspective of changing trends, over the past 20 years, the grassland in Lhasa has decreased by 21.85%, the cultivated land has increased by 39.02%, the forest land has increased by 171.90%, the water area has increased by 18.07%, the construction land has increased by 214.14%, and the unused land has increased by 32.64%. Among them, the expansion of construction land is the most prominent, with a net increase of 127.26 square kilometers over the past 20 years, reflecting the accelerated urbanization process of Lhasa City.

Table 5. Changes in Land Use Area in Lhasa City from 2000 to 2020 (km²).

Land Use Types	2000	2010	2020
farmland	716.28	1077.48	995.80
woodland	1288.24	3531.48	3502.75
grassland	20,882.37	16,348.15	16,319.25
water	1731.32	2025.78	2044.11
built-up	59.43	62.42	186.69
unused	4991.03	6623.38	6620.08

In order to describe the transfer of land use more clearly, a Sankey diagram map of land use transfer in Lhasa City from 2000 to 2020 was drawn. As shown in Figure 2. During the period of 20 years, the transformation of the six land types was quite intense. 46.12% of cultivated land, 68.21% of forest land, 32.42% of grassland, 19.40% of water areas, 36.59% of construction land and 36.29% of unused land were converted to other land types. Grassland is the main source of supply for other land types. Among them, 497.83 square kilometers of cultivated land originated from the transformation of grassland. Among the forest land, 2821.07 square kilometers were converted from grassland, accounting for 80.54% of the total forest land area. The area of construction land has changed most drastically, and its main source is also the transfer of grassland and cultivated land. The net reduction in grassland area was 4563.12 km², but the transfer matrix analysis revealed a bidirectional transition between grassland and unused land, reflecting the instability of alpine ecosystems under the dual influence of climate change and human activities. The area of unused land increased by 1629.05 square kilometers, and 25.18% of the unused land was transformed into grassland, indicating that the ecological conditions in some local areas have improved. The area of forest land increased by 2214.50 square kilometers, mainly due to the implementation of ecological protection projects. The area of cultivated land has slightly increased, but the growth rate has slowed down, reflecting the limited development of cultivated land resources in the Lhasa River Valley.

3.2. Multi-Scenario Land Use Change Forecast for Lhasa City in 2030

This study takes the 2020 land use data as the base period and uses the PLUS model to simulate the changes in the land use pattern of Lhasa City in 2030 under three different scenarios. As shown in Figure 3a, under the natural development scenario (NDS), the land use change pattern in Lhasa City continues the historical evolution trend from 2000 to 2020, and the land use change exhibits the characteristic of low intervention. The expansion of construction land mainly relies on grassland: grassland-to-construction land conversion is 54.19 km², while farmland-to-construction land conversion is 1.88 km². There is no woodland-to-construction land or unused land-to-construction land conversion. Woodland remains almost undisturbed, with 3502.75 km² retained. Water area remains unchanged at 2044.11 km², and unused land is largely stable, with 6578.08 km² retained and 42.01 km² converted to grassland. This scenario indicates that in the absence of strong external intervention, urban expansion will prioritize the occupation of grassland with relatively

lower ecological costs, while farmland is largely retained due to its agricultural production function, with 986.06 km² retained.

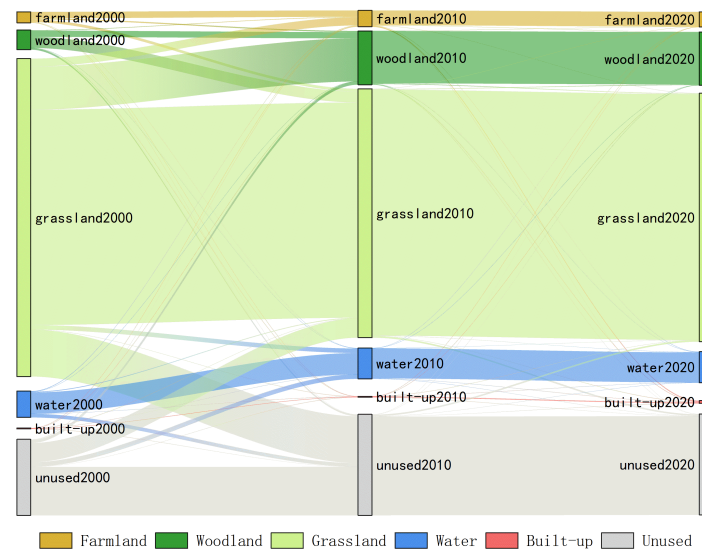


Figure 2. Sankey diagram of land transfer matrix in Lhasa City from 2000 to 2020.

As shown in Figure 3b, under the urban development scenario (UDS), land use change becomes more intense. Construction land expansion still mainly relies on grassland; grassland-to-construction land conversion changes to 3.65 km² from 54.19 km² under NDS. Unused land-to-construction land conversion is 0.33 km², while farmland-to-construction land conversion decreases to 1.73 km² from 1.88 km² under NDS. In contrast, grassland-to-woodland conversion decreases from 92.48 km² under NDS to 47.61 km². Grassland-to-unused land conversion decreases from 343.45 km² under NDS to 293.54 km², while unused land-to-grassland conversion decreases from 42.01 to 32.26 km². The water area remains 2044.11 km² with no conversion.

As shown in Figure 3c, under the ecological protection scenario (EPS), total construction land is the lowest among the three scenarios, at 195.05 km² (calculated as the sum of 181.19 km² retained plus 4.40 km² from farmland and 9.46 km² from grassland), compared with 241.57 km² under NDS (185.44 retained + 54.19 from grassland + 1.88 from farmland + 1.25 from unused land) and 190.67 km² under UDS (186.69 retained + 3.65 from grassland + 0.33 from unused land). Farmland-to-construction land is 4.40 km², higher than NDS (1.88 km²) and UDS (1.73 km²), while retained farmland is 958.47 km², lower than NDS (986.06 km²) and UDS (991.73 km²). A more prominent ecological signal is the increase in farmland-to-grassland conversion, from 6.59 km² under NDS to 23.46 km² under EPS. Although the net primary productivity of cultivated land may be higher than that of alpine grassland, from the perspective of soil carbon pools, returning farmland to grassland reduces the mineralization and decomposition of soil organic carbon caused by tillage disturbance, and the long-term carbon storage effect is more significant. In addition, unused land-to-grassland conversion increases from 42.01 km² under NDS to 492.05 km² under EPS, and grassland-to-woodland conversion increases from 92.48 to 129.73 km²; unused land-to-woodland conversion is 55.99 km². Built-up land converted to woodland and grassland is 2.99 km² and 2.52 km², respectively. The new construction land mainly comes from grassland (9.46 km²), followed by farmland (4.40 km²), with no woodland conversion, and the total amount is relatively controlled compared with NDS and UDS.

Overall, the evolution of land use patterns under different scenarios essentially reflects the gradual shift of development concepts from “natural occupation” to “growth priority” and then to “ecological priority.” The differences among scenarios are not accidental but

the result of the combined effects of policy orientation, development stage, and ecological awareness. In the Urban Development Scenario (UDS), cultivated land does not experience large-scale loss; rather, retained farmland is the highest among the three scenarios (991.73 km²), and farmland-to-construction land conversion is only 1.73 km². However, construction land expansion still mainly occupies grassland, and grassland-to-unused land conversion remains at 293.54 km², revealing the potential threat posed by rapid urbanization to grassland ecosystems and regional ecological security. In the Ecological Protection Scenario (EPS), the increase in grassland and forest land—driven mainly by unused land-to-grassland (492.05 km²), farmland-to-grassland (23.46 km²), and grassland-to-forest land (129.73 km²) conversions—highlights the crucial role of incremental restoration pathways in carbon storage management. The case of Lhasa City provides a typical research sample for an in-depth understanding of the formation mechanism and coordination mechanism of land use conflicts.

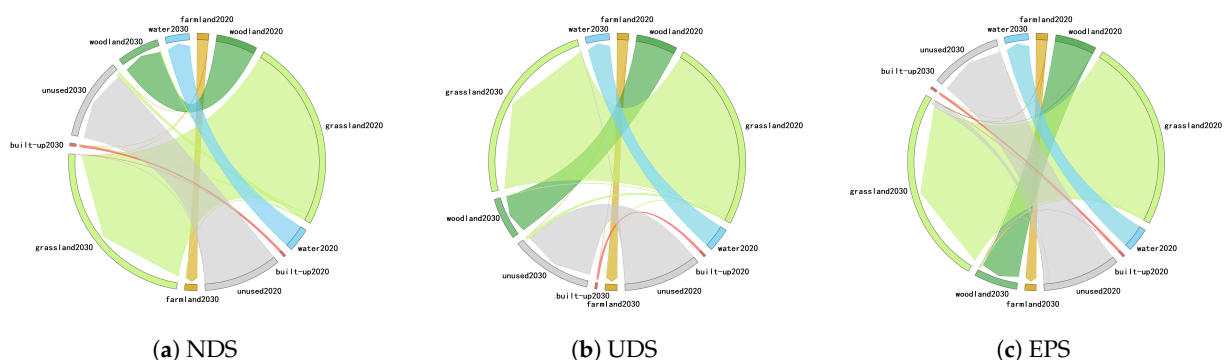


Figure 3. Chord diagram of land transfer matrix in Lhasa City under different development scenarios from 2020 to 2030.

3.3. Spatio-Temporal Evolution of Carbon Storage in Lhasa City from 2000 to 2020

The carbon storage changes in Lhasa City from 2000 to 2020 are shown in Table 6. From 2000 to 2020, the total carbon storage in Lhasa showed a fluctuating trajectory of “a slight increase first and then a slight decline at a high level”. It rose from 205.85 Mt in 2000 to 207.70 Mt in 2010, and then slightly dropped to 206.53 Mt in 2020. This evolution process is not a simple linear increase or decrease, but a comprehensive manifestation of the interplay between the rise and fall of carbon storage in different land types, ecological restoration projects and land use conversion losses. Grassland is the main body of regional carbon storage. In 2000, the carbon storage of grassland reached 158.60 Mt, accounting for 77.0% of the total carbon storage. It has continued to decline since then, dropping to 124.16 Mt in 2010 and slightly to 123.94 Mt in 2020. The continuous loss of grassland carbon storage is highly consistent with the previous results of the land use transfer matrix analysis. It is worth noting that the carbon storage of grassland decreased by 34.44 Mt between 2000 and 2010, while it only decreased by 0.22 Mt between 2010 and 2020. This indicates that grassland loss has been effectively curbed in the following decade, but the carbon loss that has already occurred is difficult to reverse. The carbon storage of forest land jumped from 14.04 Mt in 2000 to 38.50 Mt in 2010, with an increase of as high as 174%, which was the core driving force for the growth of total carbon storage during the same period. The carbon storage of unused land increased from 27.74 Mt in 2000 to 36.81 Mt in 2010 and remained at 36.79 Mt in 2020. However, by comparing the huge area base of unused land with its relatively low carbon storage, it can be found that the carbon density of unused land is very low, far lower than that of grassland and forest land. This means that unused land is the largest potential space for carbon storage increase in this region. If the unused land can

be gradually restored to grassland or forest land, the carbon storage will have the potential to increase significantly. The carbon storage of cultivated land increased from 5.45 Mt in 2000 to 8.20 Mt in 2010, and then dropped back to 7.58 Mt in 2020. The carbon storage of cultivated land is much lower than that of forest land and grassland, but also much higher than that of water areas and construction land, playing an “intermediate role” in regional carbon balance.

Table 6. Carbon storage changes in Lhasa City from 2000 to 2020 (Mt).

Year	Farmland	Woodland	Grassland	Water	Built-Up	Unused	Total Carbon Storage
2000	5.45	14.04	158.60	0.02	0.00	27.74	205.85
2010	8.20	38.50	124.16	0.02	0.00	36.81	207.70
2020	7.58	38.18	123.94	0.02	0.00	36.79	206.53

From 2000 to 2020, the carbon storage in this region underwent a process of “slight increase—slight decline at a high level”, which not only demonstrated the remarkable achievements of ecological restoration projects but also exposed deep-seated problems such as insufficient grassland protection, the carbon cost of water area expansion, and extremely low carbon storage in construction land. Future carbon storage management needs to shift from “emphasizing afforestation over protection” to “giving equal weight to afforestation and grassland protection”, from “single-objective ecological restoration” to “multi-objective collaborative optimization”, and expand from “natural land carbon storage” to “construction land carbon storage”, while fully tapping the carbon storage potential of unused land. Only in this way can the dual goals of sustained growth of regional carbon storage and ecological security be achieved in the context of increasingly complex land use changes.

3.4. Spatio-Temporal Dynamic Prediction of Carbon Storage in Lhasa City Under Different Development Scenarios in 2030

The distribution of multi-scenario carbon storage in Lhasa City in 2030 is shown in Figure 4. Overall, the total carbon storage under the three scenarios varies: NDS is 205.80 Mt, UDS is 206.11 Mt, and EPS is 208.16 Mt. Compared with the 2020 level (206.53 Mt), NDS and UDS are slightly lower, while EPS is slightly higher. This indicates that under NDS and UDS, the regional carbon storage capacity may enter a stage of hovering at a high level and slow decline, whereas EPS could still achieve a slight increase. The total carbon storage differences among scenarios are about 1.1%, but there are significant spatial differentiation and structural differences in the responses of various administrative regions and different categories. These micro-differences reveal the key directions for future carbon storage management.

At the land type level, grassland remains the absolute main body of carbon storage. The carbon storage of grassland is the highest under EPS (126.94 Mt), followed by UDS (121.28 Mt) and NDS (120.00 Mt). Compared with 2020 (123.94 Mt), NDS and UDS continued the declining trend, while EPS reversed the trend and achieved an increase. The carbon storage of forest land is the highest under EPS (40.13 Mt), followed by NDS (39.19 Mt), and the lowest under UDS (38.70 Mt); all three scenarios are higher than the 2020 level (38.18 Mt), indicating that after the explosive growth from 2000 to 2010, forest carbon storage has entered a plateau period at a high level. The carbon storage of cultivated land is the lowest under EPS (7.30 Mt), while NDS (8.11 Mt) and UDS (7.85 Mt) are higher than the 2020 level (7.58 Mt), whereas EPS falls slightly below the 2020 level. Overall, EPS performed better in grassland and forest land, but lower in cultivated land and unused land, while NDS and UDS showed the opposite trend. However, the differences between scenarios were moderate, indicating that the structural inertia left over from history, the saturation of

carbon storage growth, and the diminishing marginal benefits jointly led to the convergence of the paths.

At the administrative region level, spatial heterogeneity is extremely significant. The carbon storage changes in various districts of Lhasa City in 2030 under multiple scenarios are shown in Table 7. The carbon storage in Damxung County accounts for approximately 30.0% of the total regional volume across all scenarios, making it an absolute core carbon storage area. The proportion of Chengguan District is about 1.5%. Chengguan District is relatively sensitive to the development path, while Damxung County has the largest absolute carbon storage base and is a key node for carbon storage management in this region. The land use structure in Lhundrub County is extremely stable, with minimal differences among scenarios. The total carbon storage under NDS and UDS is lower than under EPS, with NDS being the lowest among the three scenarios, indicating that unconstrained development pathways are associated with lower regional carbon storage capacity, especially in areas with dense human activities. In terms of spatial layout, all three scenarios present a macroscopic pattern of being higher in the west and lower in the east, with only minor adjustments in the marginal areas. Under the EPS scenario, the range of high-value areas is slightly larger. Under the UDS scenario, the high-value area slightly contracted, consistent with the expansion of construction land. This indicates that by 2030, the spatial inertia of land use will be very strong, and short-term policy intervention can only produce marginal adjustment.

Table 7. Carbon storage changes in various districts of Lhasa City in 2030 under multiple scenarios (Mt).

County	NDS	UDS	EPS
Chengguan District	3.14	3.17	3.21
Dagze District	10.46	10.47	10.53
Damshung County	61.74	61.92	62.45
Doilungdechen District	18.62	18.68	18.85
Lhundrub County	33.26	33.26	33.55
Maldrogungkar County	43.68	43.69	44.32
Nyemo County	23.06	23.07	23.30
Chushul County	11.83	11.84	11.95
Total Carbon Storage	205.80	206.11	208.16

The predictions for the three scenarios in 2030 indicate a continuing challenge: after the golden period and plateau period of ecological afforestation, the region may enter a stage of slow decline in carbon storage capacity under NDS and UDS, while EPS could still achieve growth. Although the macro differences among different development paths are relatively small, the differences at the local and land category levels are significant. The EPS scenario retained 2.05 Mt more carbon storage than the UDS scenario, primarily associated with Maldrogungkar County (0.63 Mt) and Damxung County (0.53 Mt), followed by Lhundrub County (0.29 Mt) and Nyemo County (0.23 Mt). This disparity is associated with ecological protection policies enhancing the carbon density of forest and grassland, activating the carbon storage potential of unused land, and promoting the transformation of construction land into a “carbon storage friendly” type. These findings suggest that integrating refined carbon storage assessment and compensation mechanisms could help reverse the downward trend of carbon storage after 2030 and return to a path of carbon storage growth.

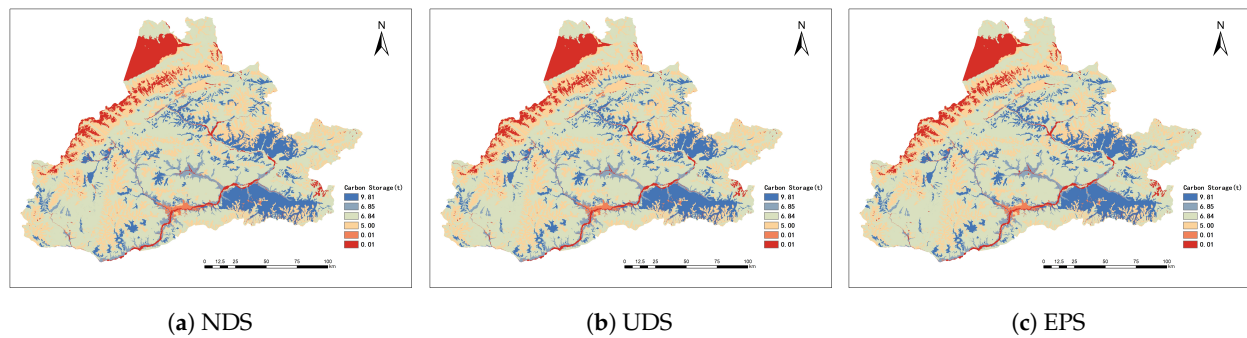


Figure 4. Spatial distribution of multi-scenario carbon storage in Lhasa City in 2030. (a) NDS scenario; (b) UDS scenario; (c) EPS scenario.

3.5. Statistical Associations of Carbon Storage Spatial Differentiation in Lhasa City

This study conducted a quantitative analysis of the statistical associations between the spatial differentiation of carbon storage in Lhasa in 2020 and ten explanatory variables from two dimensions—natural factors and socio-economic factors—namely: annual average temperature (X1), soil type (X2), slope (X3), distance from roads (X4), distance from rivers (X5), distance from railways (X6), annual average rainfall (X7), distance from government (X8), GDP (X9), and elevation (X10). All variables passed the significance test ($p < 0.001$).

The single-factor detection results (Table 8) show that soil type (X2) had the highest q value of 0.264, indicating the strongest statistical association with the spatial differentiation of carbon storage. GDP (X9) followed with a q value of 0.253, reflecting a significant spatial association between the intensity of socio-economic activities and carbon storage. Elevation (X10) and annual average temperature (X1) had q values of 0.160 and 0.115, respectively, also demonstrating relatively strong statistical associations. In contrast, the single-factor associations of distance from roads (X4, 0.079), distance from rivers (X5, 0.068), slope (X3, 0.055), annual average rainfall (X7, 0.040), distance from government (X8, 0.038), and distance from railways (X6, 0.032) were relatively weak. These results indicate that the spatial differentiation of carbon storage in Lhasa is not simply associated with a single natural or socio-economic factor, but with the combined effects of multiple factors.

In terms of interaction detection, the two-factor interactions significantly enhanced the explanatory power for the spatial heterogeneity of carbon storage, as shown in Figure 5. Among them, the interaction between GDP (X9) and elevation (X10) had the highest q value of 0.463, which is significantly higher than their individual q values (0.253 and 0.160), exhibiting the strongest enhancement effect. The interaction q value between soil type (X2) and elevation (X10) was 0.448, and the interaction q value between annual average temperature (X1) and soil type (X2) was 0.411, both far exceeding their individual q values. In addition, the interaction q value between GDP (X9) and distance from rivers (X5) was 0.313, and the interaction q value between GDP (X9) and distance from government (X8) was 0.307, also showing significant enhancement effects. These results objectively indicate that the synergistic effects of natural background conditions (such as soil, elevation, and temperature) and socio-economic factors (such as GDP) significantly amplify the explanatory power for the spatial differentiation of carbon storage.

Table 8. Single-factor statistical associations with carbon storage in Lhasa City.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
q	0.115	0.264	0.055	0.079	0.068	0.032	0.040	0.038	0.253	0.160
p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

In summary, the spatial differentiation of carbon storage in Lhasa is statistically associated with a combination of natural background and socio-economic factors. Single-factor detection shows that soil type and GDP exhibited the strongest statistical associations; interaction detection further reveals that the synergistic effects of natural factors such as elevation and temperature with socio-economic factors such as GDP and distance from government significantly enhance the explanatory power for the spatial heterogeneity of carbon storage. These results provide a statistical basis for understanding the spatial patterns of carbon storage in plateau cities.

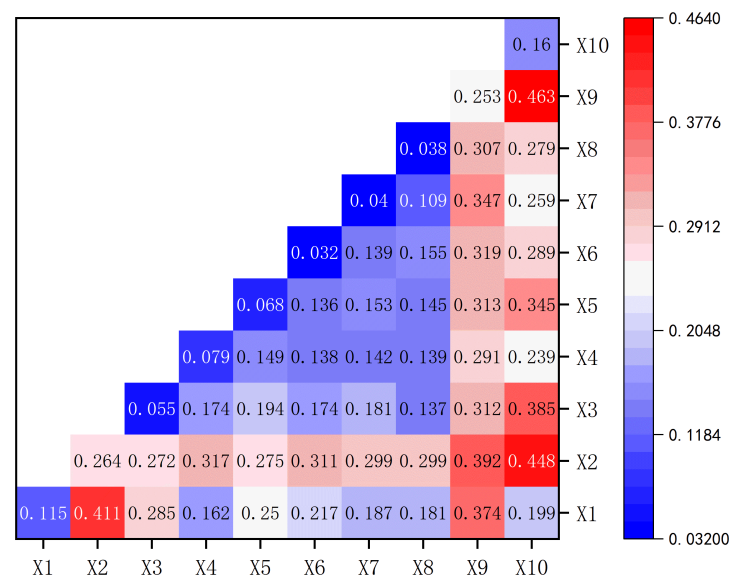


Figure 5. Interaction of influencing factors on the spatial distribution of carbon storage in Lhasa in 2020.

4. Discussion

4.1. Spatio-Temporal Response Characteristics of Land Use and Carbon Storage

The response relationship between land use and carbon storage in Lhasa City exhibits distinct spatiotemporal dynamics. Rather than merely reflecting changes in land area, this relationship is fundamentally governed by the differences in carbon density among land types and the bidirectional transitions between carbon accumulation and loss. Between 2000 and 2020, carbon storage showed a fluctuating trajectory of initial increase followed by a decline, rising from 205.85 Mt in 2000 to a peak of 207.70 Mt in 2010, and then slightly declining to 206.53 Mt in 2020. This trend is highly consistent with the ecological restoration policies and subsequent urbanization processes documented on the Tibetan Plateau. The initial increase can be largely attributed to ecological restoration projects, which enhanced vegetation and soil carbon storage. The subsequent decline coincided with rapid urban expansion, where high-carbon-density grasslands were converted into low-carbon-density construction land and cultivated land. This finding aligns with existing studies on the Tibetan Plateau, which report that ecological restoration can initially enhance carbon storage, but urbanization and agricultural expansion may subsequently offset these gains. Notably, the response exhibits significant time lags and path dependence: the carbon storage gains from afforestation are not immediate but require decades of vegetation growth and soil organic matter accumulation, while the carbon storage losses from construction land expansion have a cumulative and often irreversible effect.

4.2. Policy Implications of Different Development Paths

The three scenarios (NDS, UDS, and EPS) demonstrate differentiated trajectories for carbon storage functions under varying development paths. The Natural Development Scenario (NDS) indicates that without active ecological intervention, carbon storage levels may gradually decline as human activities expand; in fact, NDS yields the lowest total carbon storage (205.80 Mt) among the three scenarios. This pathway is relatively less aligned with the “dual carbon” goals and the ecological security barrier strategy of the Qinghai-Xizang Plateau. The Urban Development Scenario (UDS) results in a total carbon storage of 206.11 Mt, which is slightly higher than NDS but still lower than the 2020 level (206.53 Mt) and the historical peak (207.70 Mt). This path is dominated by urban expansion, where the conversion of cultivated land and grassland into construction land reduces the carbon storage of these land types, and infrastructure cutting may also exert systematic impacts on natural ecosystems. In contrast, the Ecological Protection Scenario (EPS) offers a reference pathway that balances development and protection. By strictly controlling construction land expansion and promoting territorial greening, EPS maintains carbon storage at 208.16 Mt, which exceeds both the 2020 level and the 2010 historical peak. The minor expansion of construction land under EPS is spatially scattered, avoiding concentrated impacts on carbon storage in sensitive areas. Therefore, EPS can be considered one of the preferred development directions for Lhasa and similar alpine urban areas, providing a reference for spatial planning that integrates ecological conservation with sustainable urban growth.

4.3. Statistical Associations of Carbon Storage Spatial Differentiation

The GeoDetector results reveal that soil type ($X_2, q = 0.264$) and GDP ($X_9, q = 0.253$) exhibited the strongest single-factor statistical associations with the spatial differentiation of carbon storage, followed by elevation ($X_{10}, q = 0.160$) and annual average temperature ($X_1, q = 0.115$). It should be emphasized that these results are based on the 2020 baseline data and represent statistical associations only; they cannot be interpreted as independent causal drivers of carbon storage.

The interaction detection further shows that the combined effects of these factors significantly enhanced the explanatory power for the spatial heterogeneity of carbon storage. The interaction between GDP and elevation ($X_9 \cap X_{10} = 0.463$) exhibited the strongest enhancement, followed by soil type and elevation ($X_2 \cap X_{10} = 0.448$) and temperature and soil type ($X_1 \cap X_2 = 0.411$). These results objectively indicate that natural background conditions (e.g., soil, elevation, temperature) and socio-economic factors (e.g., GDP) jointly explain the spatial heterogeneity of carbon storage. Elevation and temperature act as macro-scale constraints, while GDP reflects the intensity of human disturbance, which is mediated by the accessibility and resource conditions of the river valleys. This finding provides a statistical basis for understanding the spatial patterns of carbon storage in plateau cities.

4.4. Suggestions for Land Use Planning

Based on the above analysis of statistical associations, future land use planning can adopt a hierarchical and zonal strategy of “maintaining the overall pattern at the macro level, controlling interference at the meso level, and seizing hotspots at the micro level.” At the macro level, based on the dominant statistical associations identified—soil type and GDP, followed by elevation and temperature—the whole city can be divided into three functional zones: high-carbon-storage core areas characterized by specific soil types and high elevation with low human activity intensity, carbon storage improvement areas with moderate soil conditions and intermediate GDP levels, and carbon storage vulnerable areas

with lower elevation and higher GDP intensity. Differentiated ecological protection and restoration measures should be implemented accordingly. At the meso level, the focus should be on controlling the spatial transmission of human activity interference, particularly in areas where GDP interacts strongly with elevation ($X_9 \cap X_{10} = 0.463$) and where soil type interacts with elevation ($X_2 \cap X_{10} = 0.448$). Hierarchical control on both sides of roads and a carbon storage compensation mechanism for the urban radiation circle should be established. The carbon storage loss of newly added construction land can be offset through ecological restoration in other locations. Meanwhile, the construction of an ecological buffer zone along the Lhasa River Valley will be carried out to mitigate the direct impact of human activities on the carbon storage function of the river corridor. At the micro level, focus on the hotspots generated by the interaction of these factors for precise repair. High-value carbon storage patches associated with favorable soil types and high elevation should be identified and incorporated into a strict protection system, with development activities restricted. For areas with low carbon storage values, slot-type carbon storage increment projects should be implemented, including the construction of riverside ecological corridors, vertical greening in urban areas, and returning degraded farmland to grassland, to achieve positive growth of carbon storage functions on a low background.

4.5. Limitations and Uncertainties

There are still several deficiencies in this study that need to be improved in future work:

Uncertainties in carbon storage estimation and validation. The results of this study lack independent validation based on measured carbon flux or biomass data. InVEST is a linear estimation method based on land cover types. Future research should integrate eddy covariance flux tower observations or field sampling data for validation. Meanwhile, the use of fixed carbon density values (ignoring factors such as forest age and climate change) also introduces uncertainty. Sensitivity analysis shows that fluctuations in carbon density may affect the range of carbon storage estimates. Future research can construct high-precision carbon density maps through typical plot investigations and remote sensing inversion.

Uncertainties in land use data. This study discusses the inherent errors arising from data resampling (from 1000 m to 30 m), classification accuracy, and the simulation of future scenarios by the PLUS model. These uncertainties may propagate into the carbon storage estimates and should be interpreted with caution.

Uncertainties in scenario settings. Given the complex interactions among policy, economic, and natural factors, we acknowledge that several assumptions and biases inevitably exist in the PLUS model when setting different development scenarios (NDS/UDS/EPS). In the future, more macro policy variables and climate change scenarios can be introduced to refine the scenario design.

5. Conclusions

From 2000 to 2020, the land use structure in Lhasa City underwent significant changes. Grassland area decreased by 21.85%, while construction land experienced the most prominent growth. Forest land, cultivated land, water areas, and unused land all showed an increasing trend, with grassland serving as the primary source for these transformations. By 2030, the three scenarios display differentiated evolution trajectories. The natural development scenario (NDS) continues the low-intervention expansion model. Under the urban development scenario (UDS), construction land expands rapidly, primarily encroaching on grassland. In contrast, the ecological protection scenario (EPS) prioritizes the protection of cultivated land and water areas while promoting large-scale ecological restoration.

From 2000 to 2020, carbon storage in Lhasa City showed a fluctuating trajectory. It rose from 205.85 Mt in 2000 to a historical peak of 207.70 Mt in 2010, before slightly declining

to 206.53 Mt in 2020. The carbon storage of grassland has been continuously decreasing but slowed down in the later stage, while forest land carbon storage surged in the early stage and then entered a plateau period. Spatially, carbon storage is higher in the west and lower in the east, with the western region functioning as the main carbon storage area. Although ecological restoration projects have achieved remarkable results, future efforts must strengthen grassland protection and tap the carbon storage potential of unused land to achieve multi-goal coordination.

By 2030, the carbon storage trajectories diverge among scenarios. The total carbon storage is 205.80 Mt under NDS, 206.11 Mt under UDS, and 208.16 Mt under EPS. While NDS and UDS remain below both the 2010 historical peak (207.70 Mt) and the 2020 level (206.53 Mt), the EPS scenario surpasses both the 2020 level and the historical peak, achieving a net increase in carbon storage. At the macro level, differences among scenarios are relatively small, but micro-level spatial differentiation is significant. Damshung County accounts for the largest proportion (approximately 30.0%) of the total carbon storage, making it a critical node for carbon storage management. Maldrogungkar County exhibits the greatest absolute difference between the EPS and UDS scenarios (0.63 Mt), followed by Damshung County (0.53 Mt). Chengguan District, despite its small area, is relatively sensitive to policy pathways.

Based on the 2020 baseline carbon storage, the GeoDetector analysis indicates that soil type ($q = 0.264$) and GDP ($q = 0.253$) exhibited the strongest single-factor statistical associations with the spatial differentiation of carbon storage, followed by elevation ($q = 0.160$) and annual average temperature ($q = 0.115$). The interaction detection further reveals that the synergistic effects of GDP and elevation ($q = 0.463$), as well as soil type and elevation ($q = 0.448$), significantly enhanced the explanatory power for the spatial heterogeneity of carbon storage. It should be emphasized that this analysis is strictly based on the 2020 baseline data and only reveals statistical associations; it cannot be interpreted as an independent causal driving mechanism for carbon storage, nor does it apply to the 2030 scenarios. These results suggest that areas characterized by specific soil types, high elevation, and lower human activity intensity (as reflected by GDP) are crucial for maintaining high carbon storage. The research can provide a scientific basis for the ecological protection strategies under the territorial spatial planning and carbon neutrality goals of Lhasa City.

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