

Article

Spatiotemporal Evolution and Future of Carbon Storage in Resource-Based Chinese Province: A Case Study from Shanxi Using PLUS–InVEST Model Prediction

Yuhua Jiao , Yuhui Wang, Chenghong Tu, Xuenan Hou, Chunjuan Lyu *, Xiang Fan  and Lu Xia

School of Resources and Environment, Shanxi Agricultural University, Jinzhong 030801, China; z20223496@stu.sxau.edu.cn (Y.J.); 20233513@stu.sxau.edu.cn (Y.W.); 20233539@stu.sxau.edu.cn (C.T.); 20232287@stu.sxau.edu.cn (X.H.); xiangfan@sxau.edu.cn (X.F.); xialuxiaochen@163.com (L.X.)

* Correspondence: lcjcw@126.com

Abstract: Resource exploitation markedly alters land use and ecological carbon storage, posing risks to carbon sinks and food security. This study analyzes land-use change from 1990 to 2020 in the resource-based province of Shanxi, China. By introducing a mineral resource driver, the PLUS model was used to predict four scenarios: natural development (ND), cropland protection (CP), ecological protection (EP), and dual protection of ecology and cropland (DP). The spatial and temporal evolutions of carbon storage were then analyzed using the InVEST model. Forests were predominantly distributed in mountainous areas, with croplands in southerly and central flat areas, construction lands in and around cities, and mining lands sporadically distributed across Shanxi. From 1990 to 2020, croplands and grasslands decreased, while forest, construction, and mining lands increased. Carbon storage decreased continuously, with a total loss of 15.1×10^6 t. High-value carbon storage areas were in the Lüliang, Taihang, and Taiyue Mountains, and low-value areas were in the more populous central and southern regions. Carbon storage was predicted to decline by 2035 under the ND and CP scenarios and to exceed that of 2020 under the EP and DP scenarios. The DP scenario projected an increase of 4.93×10^6 t in carbon storage by 2035. The DP scenario realizes the protection of carbon sinks in resource-based areas and maintains food security, providing a theoretical reference for achieving carbon neutrality and high-quality sustainable development in Shanxi Province.

Keywords: land-use change; carbon storage; resource-based region; dual protection; PLUS–InVEST model



Citation: Jiao, Y.; Wang, Y.; Tu, C.; Hou, X.; Lyu, C.; Fan, X.; Xia, L. Spatiotemporal Evolution and Future of Carbon Storage in Resource-Based Chinese Province: A Case Study from Shanxi Using PLUS–InVEST Model Prediction. *Sustainability* **2024**, *16*, 4461. <https://doi.org/10.3390/su16114461>

Academic Editor: Hariklia D. Skilodimou

Received: 1 April 2024
Revised: 17 May 2024
Accepted: 21 May 2024
Published: 24 May 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In light of the negative impact elicited by the extensive burning of fossil fuels worldwide on global warming, the international community has adopted several agreements, including the Paris Agreement, aiming to combat global warming and encourage carbon emissions reduction [1–3]. These agreements seek to achieve carbon neutrality through combined measures, including emission reduction, improved energy efficiency, renewable energy development, carbon capture, storage technologies, carbon trading, and price setting. As the world’s second-largest economy, China is now a significant contributor to greenhouse gas emissions, accounting for more than 27% of global emissions. Accordingly, China has set ambitious environmental targets to achieve carbon peaking by 2030 and carbon neutrality by 2060 [4]. These targets, designated as the “Dual Carbon Goals”, represent a significant commitment to reducing greenhouse gas emissions [5]. Introducing the dual carbon target reflects China’s recognition of the urgency of combating climate change and mitigating environmental impacts [6]. The dual carbon target underscores China’s status as a significant global emitter while highlighting its pivotal role in global efforts to combat climate change [7]. By committing to reduce carbon emissions and ultimately becoming carbon neutral, China has set an exemplary precedent for other countries to

emulate [8]. The Dual Carbon Goals represent a transition to a more sustainable future and underscore China's commitment to a community of human destiny and a sustainable development strategy [9]. The Chinese government has proposed strategies to reduce CO₂ emissions and enhance carbon storage to achieve these goals [10]. Enhancing carbon sinks is a common strategy to fight climate change and reach carbon neutrality [11,12]. Land-use and land-cover (LULC) changes considerably affect terrestrial carbon pools [13], significantly impacting ecosystem carbon storage. Therefore, the design of successful management and conservation methods requires a complete understanding of how LULC influences carbon reservoirs. For example, carbon storage is affected by LULC changes such as deforestation and agricultural conversion. Given that different land uses store carbon differently, maintaining and improving terrestrial ecosystem carbon storage requires monitoring and regulating LULC changes. Indeed, effective sustainable land management and conservation measures can maintain carbon stores and reduce greenhouse gas emissions. However, understanding the relationship between LULC and carbon storage will help inform land-use decisions for carbon sequestration and ecosystem health.

Anthropogenic LULC affects plant and soil carbon storage capacity, degrading the environment and altering ecosystem services [14]. The 2016 IPCC report noted that intensive LULC emits 1.5 Pg/a of atmospheric carbon [15], demonstrating the considerable impact that LULC has on terrestrial ecosystems' global carbon cycle. Hence, sustainable development and ecosystem service value depend on measuring, forecasting, and understanding LULC and carbon storage. In recent decades, intensive research has been undertaken on LULC-related terrestrial carbon storage changes. Remote sensing data from 1973 to 2010 showed decreased carbon sinks in the US forest area [16]. Due to agricultural abandonment and restoration efforts that replaced drylands and pastures with trees, the carbon storage in rural Sierra Nevada increased from 28,961 t/a in 1921 to 60,635 t/a in 1995 [17]. Meanwhile, in 1999, the "Returning Farmland to Forest" initiative in China turned farmlands into forests, shrublands, and grasslands, markedly increasing carbon storage in the Loess Plateau [18]. In northern China, grassland degradation is reportedly the main cause of carbon storage loss [19]. However, urban trees can reduce CO₂ levels in cities, mitigating climate change [20]. Hence, forest, grass, agriculture, and building land changes are critical to terrestrial carbon storage and provide insights into LULC. Although there is a consensus that LULC affects the carbon cycle, its processes and mechanisms of carbon emissions remain unknown, warranting further investigation.

Regions in China that focus on natural resources have received relatively less attention than similar areas in global studies. The consequence has impeded the ability to predict changes in land use and carbon storage within these regions. Furthermore, it has hindered the implementation of specific methods for land administration and the achievement of carbon neutrality. It is particularly pertinent to note that regions focused on resources typically have an increased consumption of fossil fuels and higher carbon emissions compared to other places. A previous study demonstrated that resource-based regions in China have exhibited a significant rise in carbon emissions due to land use in Huainan City. Moreover, the carbon emissions resulting from land use have consistently exceeded carbon absorption. The primary factors contributing to the rise in carbon emissions from land use in Huainan are economic development and alterations in construction land use [21]. In a similar vein, between 2010 and 2020, the main contributors to carbon emissions in Yulin City were industry, mining, and transportation, accounting for most land-use-related emissions. Meanwhile, forest regions play a substantial role in storing carbon [22]. The region of North China, which relies heavily on natural resources, is at the forefront regarding carbon emissions from energy production and industrial activities. Assessing the possibility of attaining carbon-neutral growth in regions that rely on natural resources is crucial for sustainable development and for meeting China's carbon emissions reduction goals. For instance, Shanxi, situated in the middle reaches of the Yellow River Basin and serving as a significant coal energy production center, is vital in driving economic and social advancement. However, continuous economic expansion and insufficient governance have

transformed land utilization, creating tremendous ecological risk. Hence, analyses of the carbon storage fluctuations in Shanxi province and the projection of future characteristics can inform the design of reduction plans based on empirical information. The research can provide guidance for the Yellow River Basin in adopting low carbon practices and successfully attaining the Dual Carbon Goals.

Previous studies on carbon storage have primarily focused on determining forest carbon stocks by quantifying biomass. For example, in 1983, Cooper developed a model to estimate forest carbon stock based on the maximum biomass of the forest at maturity [23]. In 2005, Bunker et al. conducted a study to investigate the effect of species loss on carbon stock in tropical forests [24]. In 2006, Myeong et al. introduced a remote sensing technique for quantifying carbon storage in urban forests [25]. Subsequently, in 2015, Lange discovered that plant diversity increases the activity of soil microorganisms and the amount of carbon stored in the ecosystem [26].

The current study aims to investigate how carbon stocks are affected by changes in land use. In order to achieve this objective, the InVEST model was employed. This model is widely used to evaluate land-use changes and simulate different stages of the terrestrial carbon cycle. In fact, Jiang et al. conducted a 10-year study of three urban growth scenarios in the Chang–ZhuTan urban agglomeration to examine how urban expansion affects carbon sinks [27]. Similarly, Li et al. performed a study in Liaoning Province that used 16 elements and geographic techniques to predict LULC patterns and future carbon stocks [28]. The study also examined the regional and temporal distribution of carbon stocks and the effects of land-use changes. Moreover, Lahiji et al. analyzed the carbon storage potential of different LULC categories in Iran using the InVEST model. They reported significant differences in carbon sequestration under different scenarios [29]. Collectively, these previous studies demonstrate the effectiveness of the InVEST model for analyzing the carbon cycle in a specific location. Research on the response of carbon stock to land-use change should examine the spatial and temporal evolution characteristics of regional carbon stock and simulate and predict future land-use change and carbon stock. This will generate additional research findings that can inform the formulation of regional management policies and provide suggestions for future development [30]. The PLUS model is a versatile tool that can simulate and anticipate land use in many locations and land-use classifications, making it suitable for a wide range of environmental and geographic situations [31]. The PLUS model utilizes an analytical methodology for land scaling by combining a computational algorithm (CA) model with various forms of stochastic patch seeding. Moreover, this model offers a distinct methodology for modeling land-use change, distinguishing it from other widely used models such as CLUE-S, SLEUTH, Markov, and FL models [32]. The defining characteristic of the PLUS model is its capacity to precisely replicate the intricate progression of patches composed of numerous land-use categories [33]. It prioritizes the inclusion of patch dynamics in the analysis of land-use change, facilitating a more precise simulation and complete understanding of the complexities of land-cover change. Furthermore, this model can accurately reproduce land-use changes utilizing spatially explicit techniques. Hence, the PLUS model has exceptional versatility in adapting to various conditions and land-use categories.

The objective of the study is to enhance the precision of future land-use projections and provide theoretical guidance for policy formulation. To this end, a novel approach is proposed that considers mineral resource factors as significant influences on land-use change, in addition to the conventional physical, geographic, and economic drivers. This provides a more precise model for predicting land-use changes in regions that rely on natural resources. Moreover, mineral resource drivers are introduced to simulate future land-use changes. A dual-protection scenario of arable land and ecology is also established for resource-based areas. This scenario is based on the premise that the spatial and temporal evolution characteristics of carbon stocks in resource-based areas and their response to land-use changes can be explored in depth.

2. Study Area

Shanxi Province is located in northern China, bordering Hebei Province to the east, Shaanxi Province to the west, and Henan Province to the south (Figure 1). The province has abundant natural resources and diverse geographical features, including mountains, plateaus, and basins. Shanxi experiences a temperate continental climate characterized by four clearly demarcated seasons. Winters are frigid, summers are hot, while springs and autumns are moderate. The average yearly temperature (MAT) varies between 8 °C and 14 °C. The range of mean annual precipitation (MAP) is between 400 and 600 mm.

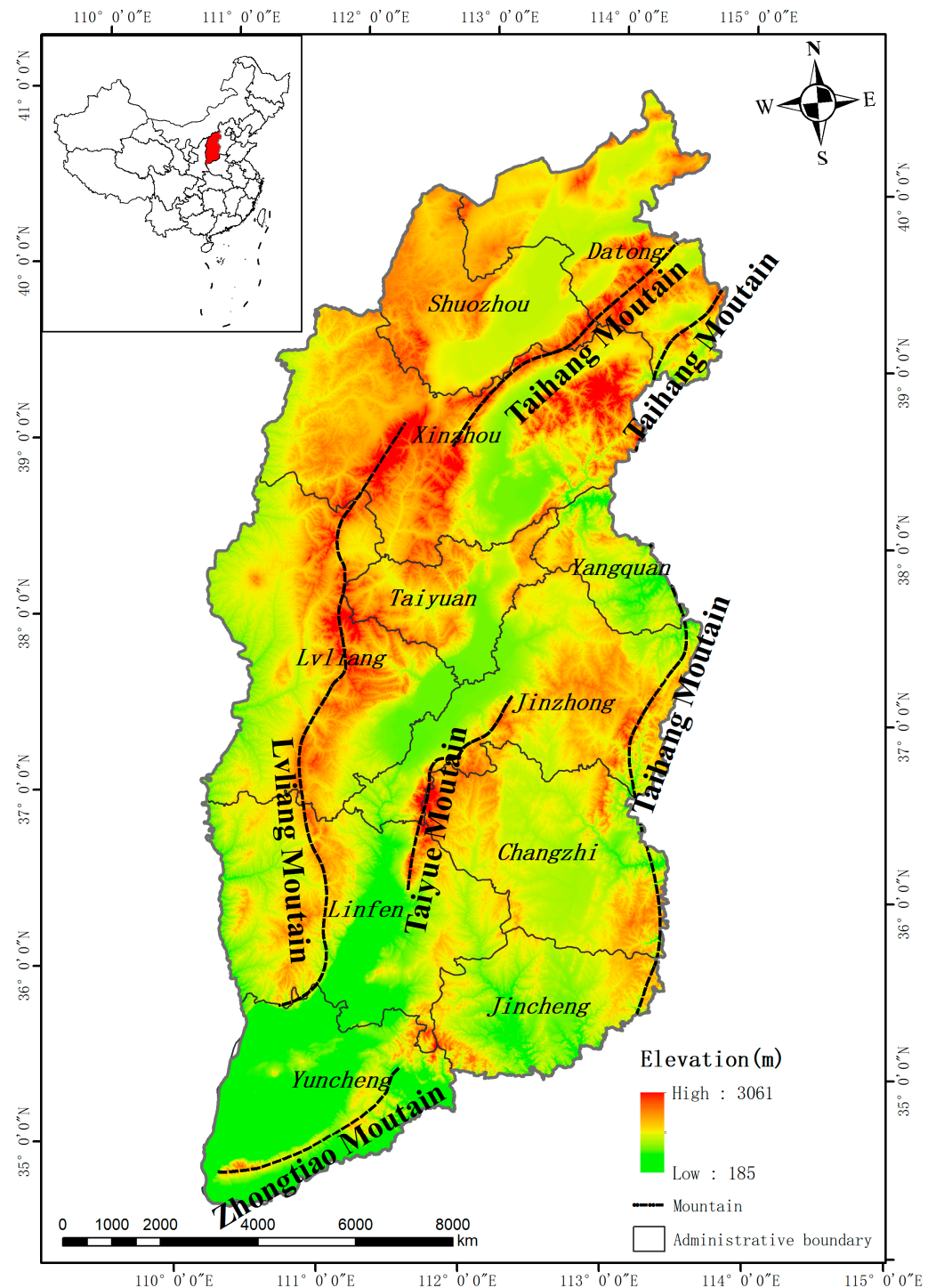


Figure 1. Map of Shanxi Province with elevation and administrative boundaries.

Shanxi is geomorphically complex, with mountains and hills accounting for ~80% of the land area and plains and terraces accounting for ~20%. The altitude difference is large, ranging from 176.7 to 3061 m. Overall, the terrain may be characterized by two mountain areas and a river, with a high north and low-lying south. The west is dominated by the Lüliang Mountains, the east by the Taihang Mountains, the central region by the Taiyue Mountains, and the southwest by the Zhongtiao Mountains; the Fen River Valley lies in the middle of the province. The soil types include yellow, sandy, brown, and mountain meadow soils. The land is suitable for agriculture and forestry, though it also contains abundant mineral resources, especially coal. Shanxi is the largest producer of coal in China; the coal industry contributes significantly to the provincial economy. However, extensive coal mining has led to serious environmental pollution and high carbon emissions.

3. Data and Methods

3.1. Data Sources

3.1.1. Land Use

Data on land use in Shanxi Province for the years 1990, 2000, 2010, 2015, and 2020 were obtained from the Chinese Academy of Sciences' Resource and Environmental Data Science Center (RESDESC-CAS) at a spatial resolution of 30 m × 30 m. Shanxi, being a province heavily reliant on natural resources, has seen the extensive extraction and consumption of these resources. To conduct a more accurate analysis of land-use change, our research classified land-use data into seven distinct types: cropland, forest land, grassland, water area, construction land, mining land, and unused land. This classification was determined based on the LULC classification standards set by the Ministry of Natural Resources of the People's Republic of China and our own observations. This method of classification allowed a detailed examination of how land was being utilized and changed over a specified period. By categorizing the data into specific types, we were able to better understand trends and patterns in land-use change. The inclusion of various land types, such as cropland, forest land, and mining land, provided a comprehensive overview of the diverse ways in which land was being utilized in the region. Overall, the use of these classification standards helped streamline the analysis process and provided a more structured approach to studying land-use change, ultimately leading to more precise conclusions regarding the dynamics of land use in the study area.

From the results of previous studies [19,31,33–39], it can be seen that land-use change is affected by many factors; we believe that the natural environment, geographical location, socioeconomic context, and so on are the main factors affecting land-use change as well as urban expansion, and in the study area of Shanxi Province, due to the wider distribution of mineral resources, the resource environment factor is also a key factor influencing the change of land use in Shanxi Province. We selected 15 driving factors, based on their accessibility, timeliness, and significance, to predict the future LULC distribution in Shanxi Province under four different scenarios (see Section 3.4). We further considered the natural, social, and economic characteristics of the region, especially the unique mineral resource conditions (Table 1).

3.1.2. Carbon Density

A carbon density database was established using measured data from the literature, with priority given to densities obtained from field surveys in the study area. Data without references were supplemented with research from neighboring areas. If gaps remained, the data were corrected using the carbon density correction formula proposed by Alam and data for six land types in China obtained by Xie Xianli [40,41]. This process provided carbon densities for different land types and areas in the study region. Additionally, densities for various land-use types were determined based on correction coefficients for mean annual precipitation (MAP) and mean annual temperature (MAT; Table 2). Overall, through meticulous data screening and correction methods, the establishment of this carbon density database has provided valuable insights into carbon densities across different land

types and regions within the study area. The incorporation of correction formulas and coefficients has ensured the accuracy and reliability of the obtained data, enhancing the credibility of the database.

Table 1. Factors driving LULC in Shanxi Province with data types, resolutions, and sources.

Factors	Data Type	Resolution (m)	Data Source
Natural environmental	Digital elevation model (DEM)	30	RESDC–CAS ¹
	Slope	30	Generated from DEM data
	Slope direction	30	
	Mean annual temperature (MAT)	1000	RESDC–CAS
	Mean annual precipitation (MAP)	1000	
Geographic location	Distance to river	1000	Open Street Map
	Distance to primary roads	1000	
	Distance to secondary roads	1000	
	Distance to tertiary roads	1000	
	Distance to railroad	1000	
Socioeconomic	Populations	1000	RESDC–CAS
	Gross domestic product (GDP)	1000	
Mineral resources	Distance to mining site	1000	China National Mineral Resources Database
	Distance to priority mineral resource extraction areas	1000	China National Natural Resources and Geospatial Basic Database
	Distance to key mineral resource monitoring areas	1000	

¹ RESDC–CAS, Resource and Environmental Data Science Center, Chinese Academy of Sciences.

Table 2. Carbon densities of different land-use and ground-cover types.

Land-Use Type	Above-Ground Vegetation (t/km ²)	Below-Ground Vegetation (t/km ²)	Soil (t/km ²)	Dead Organic Matter (t/km ²)
Crop	2.59	41.24	74.21	0.74
Forest	29.58	59.22	106.58	1.95
Grass	9.47	44.2	68.6	0.46
Water	0.05	0	0	0
Construction	0.38	4.2	71.73	0
Mining	0.19	2.1	66.86	0
Unused	0.2	0	28.88	0

3.2. Analysis of Land-Use Change

A single land-use dynamic degree can represent the rate of change of a land-use type over a certain period, which is generally measured by the dynamic degree index [37]:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \quad (1)$$

where U_a and U_b are the initial and final areas of the land type within a certain period, T represents a year, and K represents the annual rate of change in land-use type.

3.3. Simulation of Future Land-Use Change

This study utilized the land-use data of Shanxi Province in 2020 to create the foundational map. The PLUS model was employed to forecast the land-use data, drawing

upon data from the years 2000 and 2010 [31]. The process of validating the model entailed assessing its accuracy through a comparison between the real land-cover map of Shanxi in 2020 and the map obtained from the program's predictions. The accuracy of the model was assessed using the Kappa coefficient (κ , where 0–1), and the simulation results were validated using the PLUS model to guarantee the model's applicability in the study area. As the value of κ increases, so too does the simulation accuracy. The simulation accuracy is deemed high when κ exceeds 0.75. In this investigation, the value of κ was determined to be 0.84, and the final simulation achieved an overall accuracy (OA coefficient) of 0.89. Therefore, the model was considered appropriate for the study area. The basis map for extracting the increased land use from 2010 to 2020 and predicting the LULC by 2035 was based on the data on land-use change in Shanxi Province from 2015.

3.4. Scenario Setting for Land-Use Change

The PLUS model was configured with various parameters and constraints to create four scenarios, simulating land use in the study area by 2035. The escalating pace of societal advancement and urban sprawl has brought about significant ecological disruptions and encroachment on arable land, posing concurrent challenges to carbon sink functionality and food security. To address the requirements of sustainable, high-quality development in Shanxi Province for the future, it is imperative to address these pressing issues. Consequently, four distinct scenarios were devised to accommodate the diverse directions of future regional development: the natural progression scenario (ND), the cropland preservation scenario (CP), the ecological conservation scenario (EP), and a dual focus on both cropland and ecological protection scenario (DP). The simulation was conducted in alignment with the Land Space Planning of Shanxi Province (2021–2035), Ecological Restoration Planning of Land Space of Shanxi Province (2021–2035), Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin, and Outline of the Plan for Creating a Beautiful Shanxi (2023–2035) [32].

The following four scenario settings address the development needs of different scenarios and limit the expansion of various types of sites (Table 3):

Table 3. Transfer matrix of land-use changes under different scenarios.

		Scenario																											
		ND							CP							EP							DP						
Land-use type 1		A	B	C	D	E	F	G	A	B	C	D	E	F	G	A	B	C	D	E	F	G	A	B	C	D	E	F	G
A		1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0
B		1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
C		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0
D		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0
E		1	1	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	1	1	1	0	0	1	1	0
F		1	1	1	1	1	1	1	1	0	0	0	0	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	0
G		1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	1	0	0	0	1

1 Notes: 0: restricted conversion; 1: permitted conversion; A: cropland; B: forest land; C: grassland; D: water area; E: construction land; F: mining land; G: unused land.

Scenario 1. *Natural development (ND) scenario:* We assumed that the probability of land-use change from 2020 to 2035 would naturally increase, following the trend from 2010 to 2020. Therefore, all land-use types are allowed to be converted to other land types.

Scenario 2. *Cropland protection scenario (CP):* Starting with the ND scenario, the probability of transferring croplands to other land types was reduced by 50%, and other land types maintained the existing developmental trend. Consequently, the conversion of arable land into other land types has been restricted, and the expansion of land for construction and mining has been similarly restricted.

Scenario 3. *Ecological protection scenario (EP):* Starting with the ND scenario, the odds of converting croplands, forest lands, grasslands, and water regions into building and mining lands

were decreased by 30%, 50%, 20%, and 20%, respectively, in the ND scenario. The likelihood of converting forest lands into grasslands underwent a 50% decrease. The likelihood of converting water regions and grasslands into forest lands, construction lands into forest lands, and mining lands into forest lands and grasslands had respective increases of 30%, 15%, and 30%. As a result, forest land is restricted from being converted to other land types.

Scenario 4. *Dual-protection scenario for croplands and ecology (DP):* Starting with the ND scenario, the probability of transferring croplands to other land types (except forest lands) was reduced by 50%, and the probabilities of transferring forest lands, grasslands, and water areas to construction and mining lands were reduced by 50%, 20%, and 20%, respectively. The probability of transferring forest lands to grasslands was reduced by 50%. The probabilities of transferring water areas and grasslands to forest lands, and construction and mining lands to forest lands were increased by 25% and 20%, respectively. As a result, the conversion of cropland and forest land to other land types has been limited.

3.5. Spatial and Temporal Analysis of Carbon Storage

The carbon storage module of the InVEST model uses the land-use type of a given surface as the evaluation unit (Figure 2). Estimating the carbon storage of the terrestrial ecosystem mainly includes four basic carbon pools: above-ground biomass (from residual surface vegetation), below-ground biomass (from plant roots), soil (inorganic and organic carbon), and litter (from fallen leaves and dead trees) (Table 2) [36,39]. The module assessed local ecosystem carbon sequestration using land-use data and carbon density measurements:

$$C = C_{\text{above}} + C_{\text{below}} + C_{\text{soil}} + C_{\text{dead}} \quad (2)$$

where C represents the total carbon storage of the study area, C_{above} is the aboveground carbon storage, C_{below} is the below-ground carbon storage, C_{soil} is the soil carbon storage, and C_{dead} represents the litter carbon storage, with all presented in tons per square kilometer.

3.6. Spatial Autocorrelation Analysis

This term, which serves as an indication of the degree to which certain characteristics are aggregated or scattered in space, is referred to as spatial autocorrelation. It describes the interconnectivity of the attribute values of geographic objects that are located in nearby areas. The Local Indicator of Spatial Association (LISA), which measures the relevance of local Moran's I , was used in order to examine the spatial connectedness and disparities that existed between the research region and its adjacent neighborhoods. An additional evaluation was performed utilizing local spatial autocorrelation to determine the correlations between the attribute values of each geographic unit and the spatial units that are next to it [42].

$$G_i^* = \frac{\sum_j^n W_{ij} x_j}{\sum_j^n x_j} \quad (3)$$

where W_{ij} is the spatial weight matrix between patches i and j , X_j is the attribute value of patch j , and n is the total number of patches.

Carbon storage values for each township in Shanxi were determined using ArcGIS10.8. The whole-area autocorrelation results were obtained through Moran's I computation. Five distinct structures for carbon storage spatial autocorrelation were identified using the LISA diagram. These structures include the HH (high–high), LL (low–low), HL (high–low), LH (low–high), and NN (not noted) types. A positive correlation was observed in the HH and LL variables, signifying the significant spatial clustering of carbon storage. Conversely, a negative correlation was found in the HL and LH types, indicating a heterogeneous spatial arrangement of carbon storage, with high storage areas surrounded by low storage regions, and vice versa. The NN type signifies the absence of significant aggregation or dispersion in carbon storage.

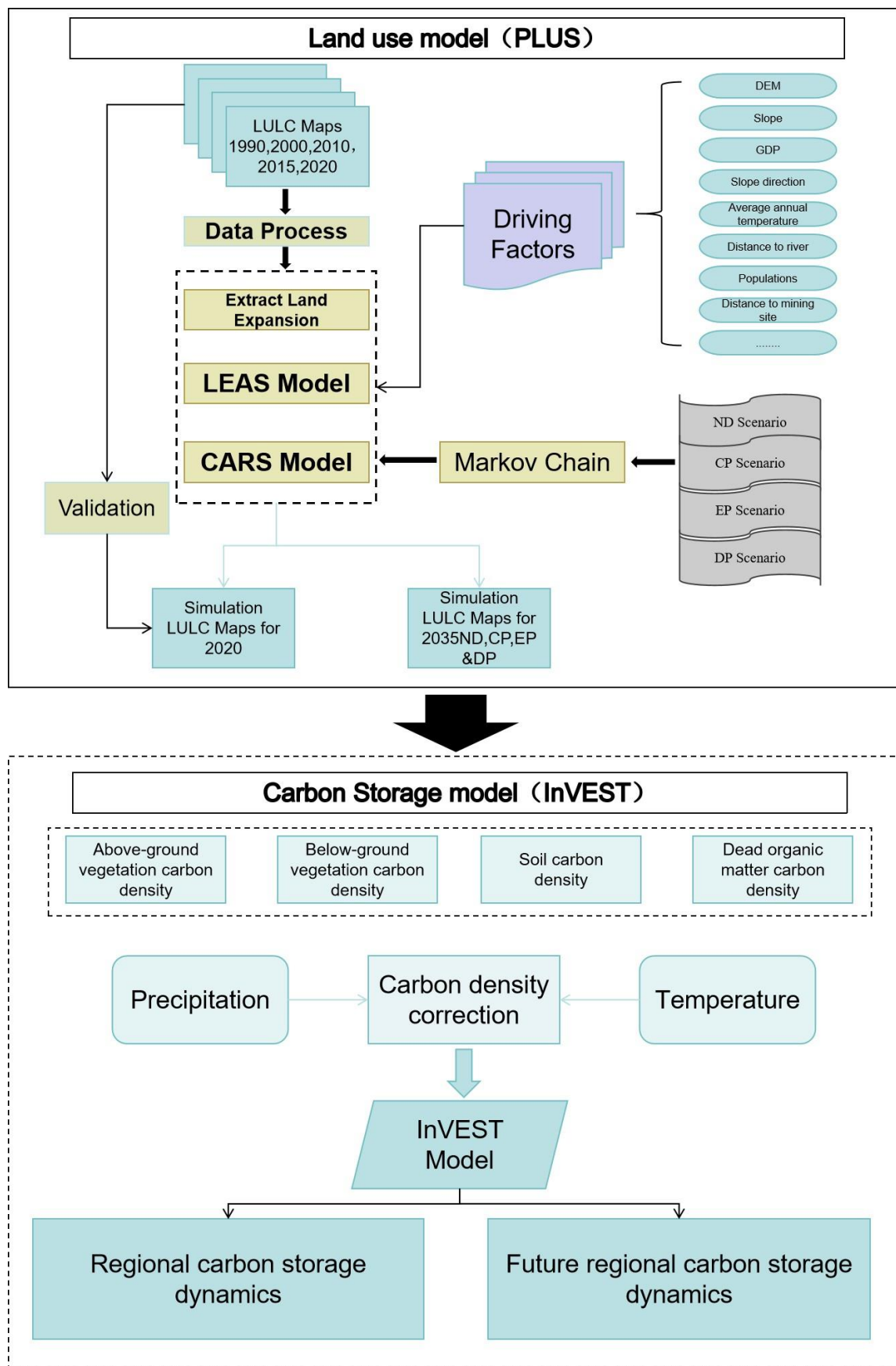


Figure 2. Research framework showing model inputs and outputs.

4. Results

4.1. Characteristics of LULC

The primary LULC in Shanxi during the study period mainly included forest lands, grasslands, and croplands, and presented overall as a matrix of forests and grasslands, with embedded patches of croplands and construction lands, dotted with mining lands. From 1990 to 2020, the proportion of the cropland area ranged from 39.09% to 36.86% (Figure 3 and Table 4) and croplands were mainly distributed in the central and southern plains of Taiyuan, Jinzhong, Lüliang, Yuncheng, and Jincheng. The cropland area decreased from 61,193.44 km² in 1990 to 57,779.07 km² in 2020, a decrease that was primarily caused by the constant expansion of construction lands across all cities in Shanxi. Meanwhile, the forest land area increased from 44,025.09 km² in 1990 to 44,469.29 km² in 2020, representing a relatively small increase from 28.09% to 28.37% that was mainly derived from the transformation of croplands and grasslands under the “Three-North Shelter Forestation Project” and the “Returning Farmland to Forest” project. Forest lands were mainly found in the mountainous and hilly areas of the Lüliang, Taihang, and Zhongtiao Mountains. Between 1990 and 2020, the proportion of grassland declined from 29.18% to 28.25%, having decreased from 45,731.58 km² to 44,278.01 km². Grasslands were patchily distributed throughout Shanxi, cross-distributed around forest lands and croplands, and mostly consisted of temperate scrub and semi-arid steppe vegetation. The water area of Shanxi Province is relatively small, mainly including part of the Yellow River, Fenhe River, and their tributaries. The construction land area increased from 3546.36 km² in 1990 to 6657.46 km² in 2020, representing a significant proportional increase from 2.26% to 4.25%. These lands were mainly distributed within all of the cities and their neighboring towns. From 1990 to 2020, the mining land area increased from 369.62 km² to 1950.30 km², with the proportion increasing from 0.24% to 1.24%, representing notable growth. Mining lands were scattered across Shuozhou, Yangquan, Taiyuan, and Yuncheng. Lastly, the unused land area decreased from 153.35 km² in 1990 to 106.60 km² in 2020 and was scattered around the water areas and mining lands.

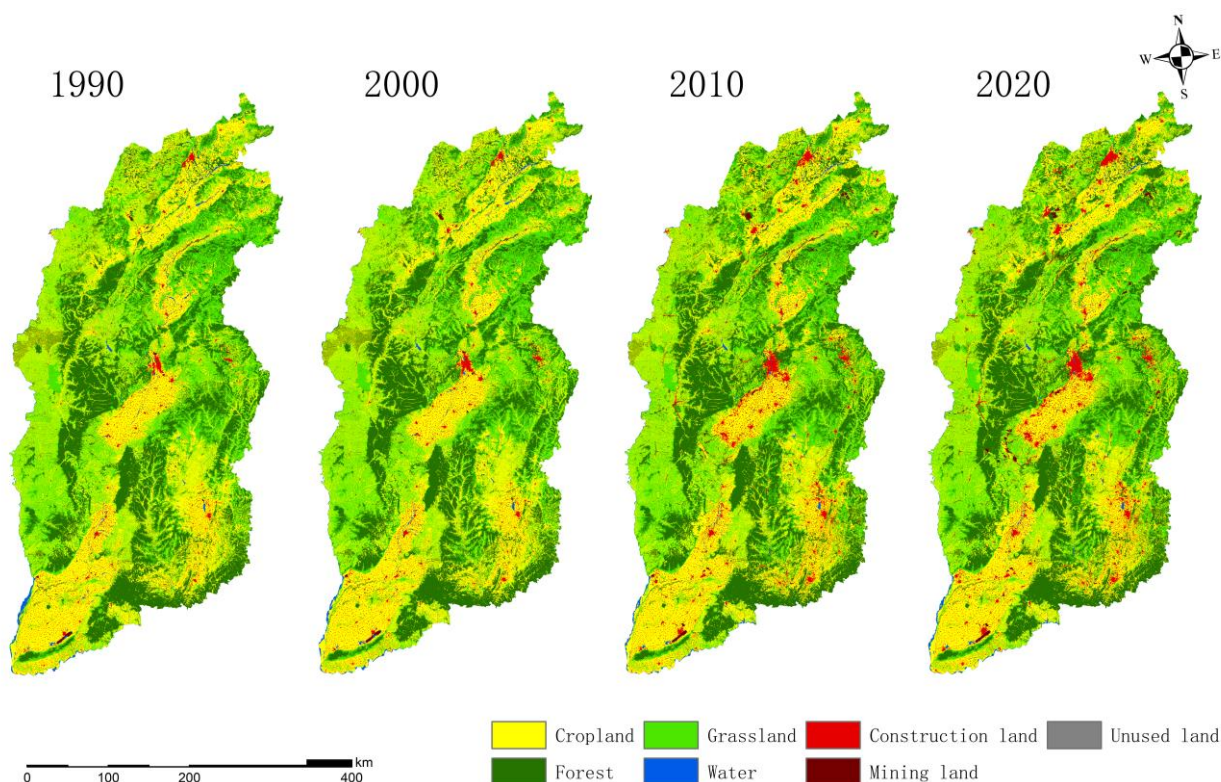


Figure 3. Distributions of land-use types in Shanxi from 1990 to 2020.

Table 4. Areas and proportions of different land-use types in Shanxi from 2000 to 2020.

Land-Use Type	1990		2000		2010		2020	
	Area (km ²)	Proportion (%)	Area (km ²)	Proportion (%)	Area (km ²)	Proportion (%)	Area (km ²)	Proportion (%)
Crop	61,193.44	39.04	61,272.28	39.09	58,040.89	37.03	57,779.07	36.86
Forest	44,025.09	28.09	43,743.17	27.91	44,595.60	28.45	44,469.29	28.37
Grass	45,731.58	29.18	45,699.04	29.16	44,844.52	28.61	44,278.01	28.25
Water	1717.95	1.10	1645.11	1.05	1475.35	0.94	1497.67	0.96
Construction	3546.36	2.26	3802.97	2.43	6027.54	3.85	6657.46	4.25
Mining	369.62	0.24	420.31	0.27	1644.55	1.05	1950.30	1.24
Unused	153.35	0.10	155.52	0.10	109.94	0.07	106.60	0.07

By calculating the single land-use dynamic degree (see Equation (1)), we assessed the effects of current socioeconomic activities on various land-use changes in Shanxi Province (Table 5). The results indicated a heterogeneous change rate across land-use types: croplands, grasslands, and water areas decreased by -0.19% , -0.11% , and -0.43% , respectively. Forest lands exhibited decreasing, increasing, and then decreasing trends from 1990 to 2020 but increased overall by 0.03% . This was mainly attributed to the implementation of the “Three-North Shelter Forestation Project” and the “Returning Farmland to Forest” project, which have effectively restored some forest lands. Construction and mining land areas saw increases of 2.92% and 14.96% , respectively, marking the most significant changes across all land-use types. Land-use change rates varied across different time periods, with 2000 and 2010 undergoing the most drastic changes, particularly in construction and mining lands. Between 1990 and 2000, the proportions of construction and mining lands increased from 0.72% and 1.37% to 5.85% and 29.13% , respectively, while that of forest lands increased by 0.19% . In contrast, croplands, grasslands, and water areas declined the most rapidly over the last three decades, decreasing by -0.53% , -0.19% , and -1.03% respectively. From 1990 to 2000 and 2010 to 2020, the trends in land-use change were similar, with croplands, grasslands, and water areas decreasing. However, in 2000 and 2020, the forest land also declined by -0.06% and -0.03% .

Table 5. Single land-use dynamic degrees from 1990 to 2020 (%).

Land-Use Type	1990–2000	2000–2010	2010–2020	1990–2020
Crop	0.01	−0.53	−0.05	−0.19
Forest	−0.06	0.19	−0.03	0.03
Grass	−0.01	−0.19	−0.13	−0.11
Water	−0.42	−1.03	0.15	−0.43
Construction	0.72	5.85	1.05	2.92
Mining	1.37	29.13	1.86	14.26
Unused	0.14	−2.93	−0.30	−1.02

From 1990 to 2020, the land-use change in Shanxi Province was remarkable, with a large number of LULC types changing (Figure 4 and Table 6). The areas exhibiting the greatest change were concentrated around all of the cities, indicating that with the constant acceleration of urbanization, the demand for land that is economically beneficial, such as construction and mining lands, increased to meet the needs of human society. Changes in land-use types were mainly reflected by the net increase in construction, mining, and forest lands, and the net decrease in croplands, grasslands, water areas, and unused lands. From 1990 to 2020, a large amount of cropland was converted into other types, among which the areas of croplands converted into forest lands, grasslands, construction lands, and mining lands reached 1235.09 km^2 , 2127.49 km^2 , 2857.42 km^2 , and 892.21 km^2 , respectively. From 1990 to 2020 and 2010 to 2020, the LULC was relatively small, due to a constant increase in construction and mining lands.

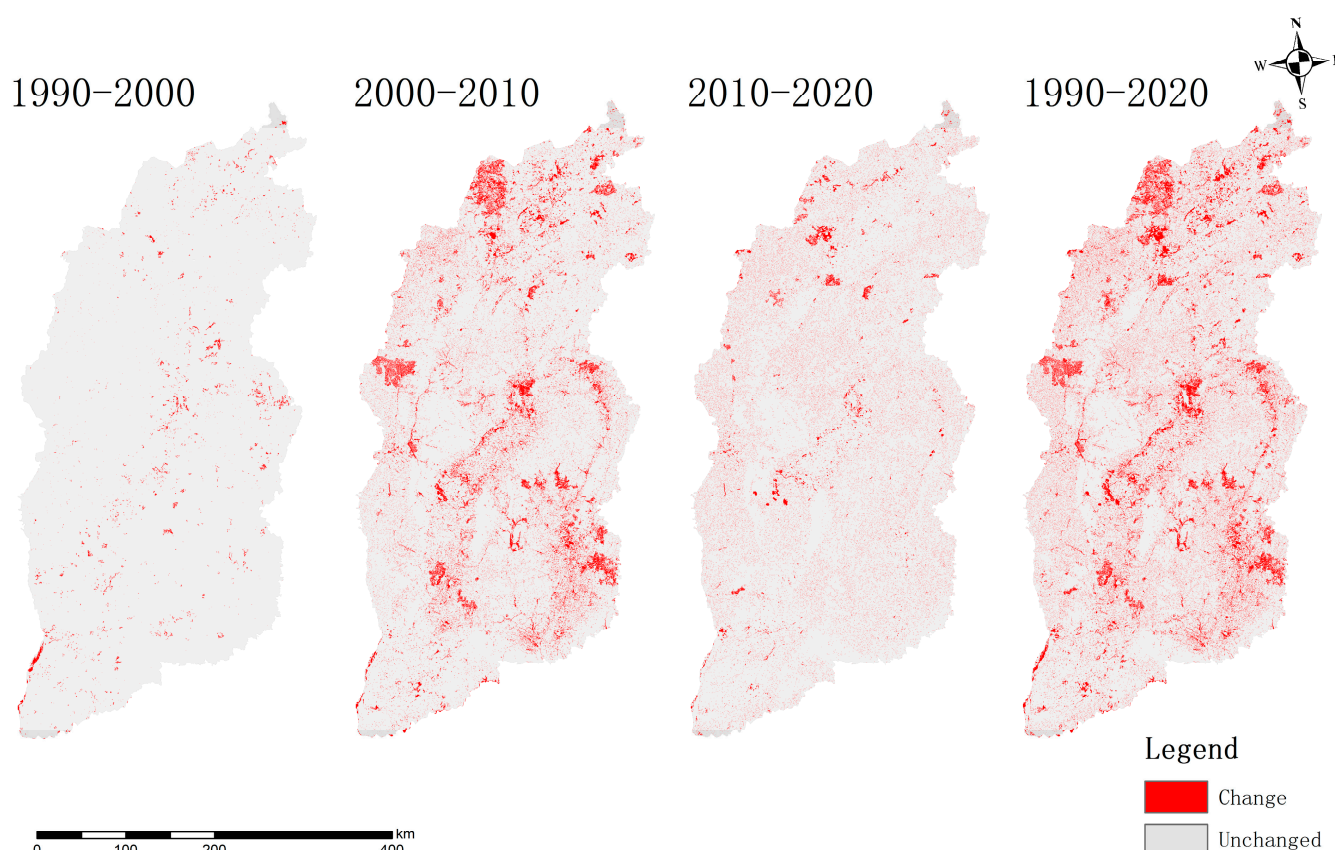


Figure 4. Spatial distributions of land-use change in Shanxi from 1990 to 2000.

4.2. Spatiotemporal Characteristics of Predicted Land-Use Change by 2035 in Different Scenarios

Predictions for 2035 under the ND scenario (refer to Figure 5 and Table 7) indicate a marginal increase in cropland area by 6.66 km² compared to 2020. The grassland area will decrease by 1297.29 km². The existing forest land area will be better protected and forest lands will increase slightly by 93.09 km² based on the existing ecological foundation. Construction and mining lands will expand rapidly, increasing by 1096.22 km² and 80.35 km², respectively. The newly added construction land will mainly be distributed among all cities and their neighboring towns, and mining lands will remain scattered across the study area. In the 2035 CP scenario, the cropland area is better than in the ND scenario. Compared with the situation in 2020, croplands will increase by 1089.18 km², while grasslands will decrease in area by 2204.71 km². Most of the forest lands will be well-protected, and the expansion of construction and mining lands will slow. Under the 2035 EP scenario, forest land area is projected to increase by 505.42 km² from 2020 levels. Additionally, compared to the CP scenario, an increase of 564.44 km² in forest lands is expected, with new areas primarily around the central Lüliang and southern Taihang Mountains. However, the grassland area will decrease by 1979.55 km². A slight decrease in mining lands (by 9 km²) is also predicted. Under the DP scenario for 2035, the cropland area will increase by 1089.07 km², which is consistent with the CP scenario. Grasslands will decrease in area by 2509.44 km², but there will be a significant increase in forest lands. Compared to 2020, the forest land area will increase by 325.48 km². The expansion of construction lands will be restricted, increasing by 1136.12 km², and compared with to 2020, the mining land area will decrease markedly (by 35.96 km²).

Table 6. Areal transfer matrix by land-use type in Shanxi Province from 1990 to 2020.

Phase	Land-Use Type	Crop (km ²)	Forest Land (km ²)	Grass (km ²)	Water (km ²)	Construction (km ²)	Mining (km ²)	Unused (km ²)
1990–2000	Crop	60,783.53	56.75	53.04	45.99	225.27	27.27	1.59
	Forest	98.00	43,621.17	293.72	4.91	3.45	3.83	0.00
	Grass	268.45	60.40	45,337.38	15.70	25.97	23.65	0.04
	Water	119.98	3.15	14.11	1578.47	1.39	0.00	0.84
	Construction	1.34	0.05	0.25	0.02	3543.76	0.94	0.00
	Mining	0.12	1.51	0.25	0.00	3.13	364.61	0.00
	Unused	0.28	0.01	0.02	0.00	0.00	0.00	153.04
2000–2010	Crop	55,586.59	1140.62	1536.95	168.14	2130.02	703.75	6.22
	Forest	408.83	42,236.23	808.99	30.74	102.58	154.02	1.79
	Grass	1374.29	1156.60	42,409.45	40.59	297.01	413.88	7.22
	Water	237.47	31.68	43.26	1214.63	41.69	64.26	12.12
	Construction	377.96	13.00	26.57	6.37	3348.53	30.28	0.25
	Mining	23.67	12.11	6.47	4.77	100.81	272.39	0.10
	Unused	32.09	5.36	12.84	10.11	6.90	5.96	82.25
2010–2020	Crop	56,022.08	267.81	813.75	65.33	607.06	263.28	1.57
	Forest	432.83	43,633.07	333.78	9.22	75.92	109.02	1.78
	Grass	1028.97	505.78	43,061.29	21.90	85.90	139.06	1.62
	Water	39.94	6.37	18.51	1392.56	15.80	2.00	0.16
	Construction	207.81	10.25	33.16	3.52	5751.25	21.49	0.06
	Mining	42.09	45.21	16.37	4.70	121.16	1414.90	0.10
	Unused	5.34	0.80	1.15	0.43	0.38	0.54	101.30
1990–2020	Crop	53,876.81	1235.09	2127.49	197.91	2857.42	892.21	6.51
	Forest	716.76	41,622.24	1290.85	38.56	143.54	209.37	3.77
	Grass	2400.91	1538.69	40,746.22	71.52	410.57	555.40	8.27
	Water	326.76	33.85	65.47	1171.13	51.80	56.51	12.42
	Construction	396.26	12.09	31.17	4.82	3070.78	30.95	0.28
	Mining	25.06	21.80	4.89	3.77	114.02	199.95	0.14
	Unused	35.98	5.38	11.62	9.97	9.30	5.90	75.21

4.3. Spatiotemporal Distribution of Carbon Storage

The carbon storage in Shanxi Province has seen substantial changes over the course of the last three decades. Specifically, the total carbon storage in 1990, 2000, 2010, and 2020 were recorded as 2186.94×10^6 t, 2184.23×10^6 t, 2177.49×10^6 t, and 2171.84×10^6 t, respectively, as indicated in Table 8. From 1990 to 2020, there was a decrease in carbon storage by 15.1×10^6 t. Regarding land-use and land-cover (LULC) types, there was an observed rise in carbon storage across forest, construction, and mining lands. Conversely, the carbon storage capacities of croplands, grasslands, and unused lands exhibited a significant drop. Specifically, the carbon storage capacities of croplands and grasslands underwent a decrease of 40.56×10^6 t and 17.84×10^6 t, respectively. In contrast, there was an observed increase in the carbon storage capabilities of forest, construction, and mining lands, with respective increments of 8.76×10^6 t, 23.74×10^6 t, and 10.93×10^6 t. Significant increases were seen in the carbon storage capabilities of construction and mining lands, while considerable decreases were observed in croplands and grasslands (by 40.56×10^6 t and 17.84×10^6 t, respectively). These changes were particularly pronounced during the period from 2000 to 2010. The carbon storage capacity of construction and mining lands underwent an increase of 16.98×10^6 t and 8.46×10^6 t, representing 0.78% and 0.39%, respectively. Similarly, the carbon storage capacity of forest areas witnessed an increase of 16.83×10^6 t, indicating a 0.89% increase.

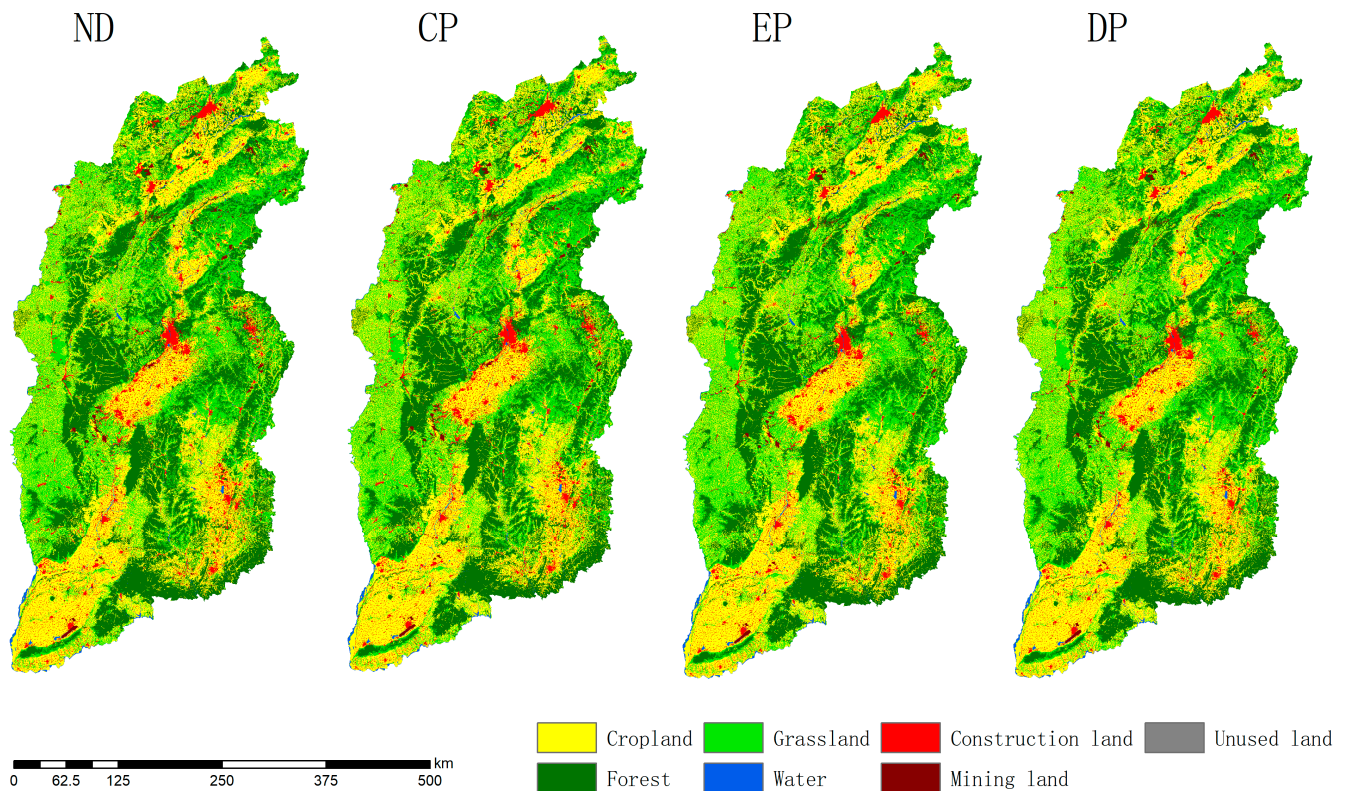


Figure 5. Spatial distributions of land-use types under four development scenarios predicted for Shanxi by 2035.

Table 7. Land areas of Shanxi Province predicted by 2035 per land-use type under each development scenario (km²).

Land-Use Type	2020	Scenario			
		ND	CP	EP	DP
Crop	57,779.07	57,785.73	58,868.25	57,997.53	58,868.15
Forest	44,469.29	44,562.38	44,410.27	44,974.71	44,794.77
Grass	44,278.01	42,980.72	42,073.3	42,298.46	41,768.57
Water	1497.67	1528.73	1505.3	1539.71	1506.77
Construction	6657.46	7753.68	7829.36	7893.78	7793.59
Mining	1950.3	2030.65	1959.71	1941.3	1914.34
Unused	106.6	93.61	89.31	90.01	89.32

Notes: ND, natural development; CP, cropland protection; EP, ecological protection; DP, dual protection of croplands and ecology.

Table 8. Carbon storage capacities of different land-use types in Shanxi from 1990 to 2020.

Land-Use Type	1990		2000		2010		2020	
	Storage (10 ⁶ t C)	Proportion (%)	Storage (10 ⁶ t C)	Proportion (%)	Storage (10 ⁶ t C)	Proportion (%)	Storage (10 ⁶ t C)	Proportion (%)
Crop	726.86	33.24	727.79	33.32	689.41	31.66	686.30	31.60
Forest	868.75	39.72	863.18	39.52	880.01	40.41	877.51	40.40
Grass	561.26	25.66	560.86	25.68	550.38	25.28	543.42	25.02
Water	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
Construction	27.06	1.24	29.02	1.33	46.00	2.11	50.80	2.34
Mining	2.56	0.12	2.91	0.13	11.37	0.52	13.49	0.62
Unused	0.45	0.02	0.45	0.02	0.32	0.01	0.31	0.01
Total	2186.94	100.00	2184.23	100.00	2177.49	100.00	2171.84	100.00

From the years 1990 and 2020, there was a consistent regional heterogeneity observed in the carbon storage patterns within Shanxi Province (Figures 6 and 7). The Lüliang and Taihang Mountains were the primary locations for high carbon storage zones, as shown by the distributions of vegetation and land-use and land-cover (LULC) types. Owing to their topographic and geomorphological conditions, these regions are mostly montane forest lands with high vegetation cover. Low carbon storage areas were mainly found across the Taiyuan Basin in central Shanxi, as well as around towns and cities. In terms of spatial change, areas with increased carbon storage were scattered across the province, mainly driven by increases in forest lands and croplands. The areas with decreased carbon storage were mainly found in Lüliang City in western Shanxi, central Taiyuan, central Shanxi, and in the Changzhi area of southeastern Jincheng, with sporadic distributions in other areas. Over the past three decades, the most significant change in carbon storage in Shanxi Province occurred between 2000 and 2010. Areas with decreased carbon storage in northern, central, and western Shanxi were patchily distributed, and those with increased storage were sporadically distributed across the study area.

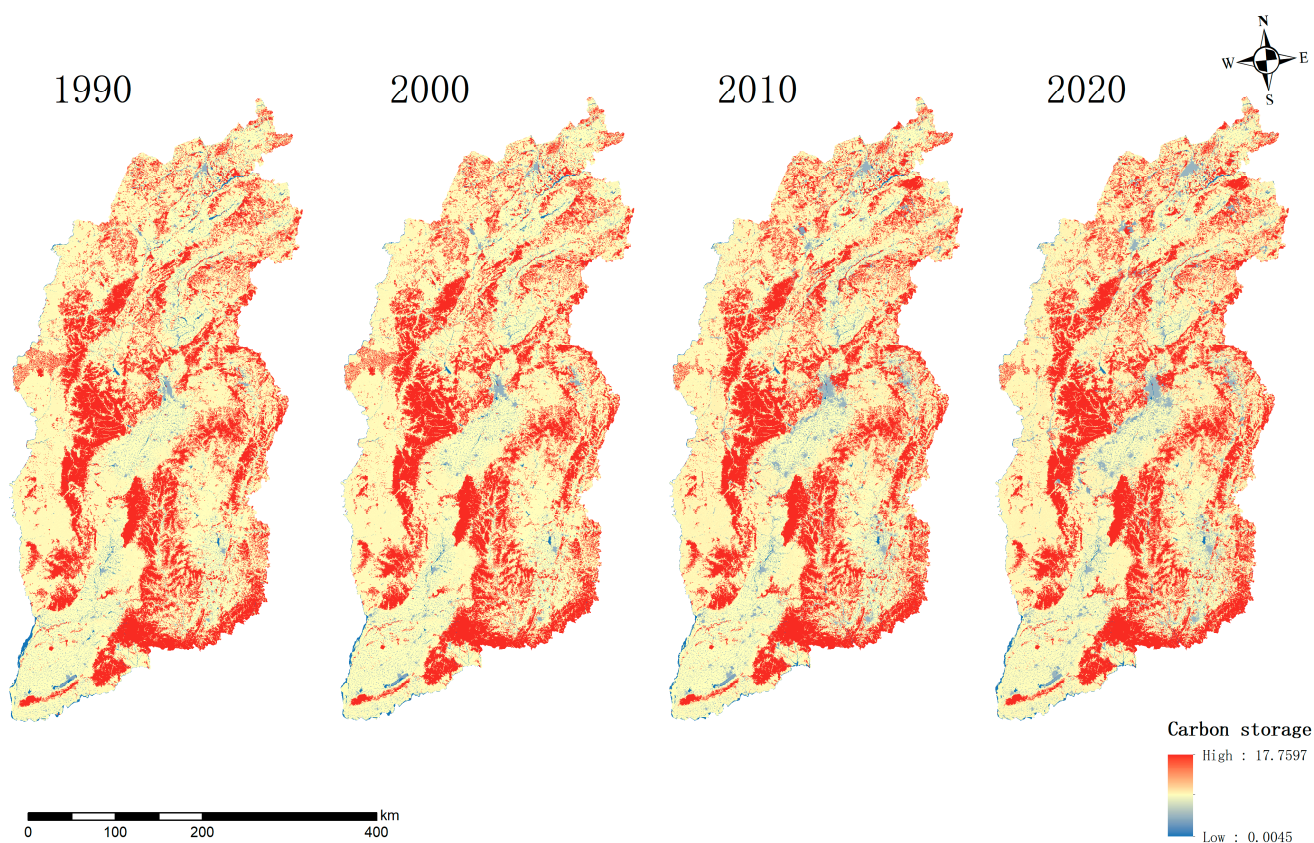


Figure 6. Spatial distribution of carbon storage in Shanxi from 1990 to 2020.

The spatial autocorrelation pattern of carbon storage in Shanxi Province showed a patchy distribution of HH-value areas, clustering of LL-value areas, and sporadic distribution of HL-value and LH-value areas (Figure 8). Areas of HH-value agglomeration were found in patches that were mainly concentrated in Xinzhou and Lüliang, whereas those of HL-values were rare and found in Datong, Jinzhong, and Lüliang. Low–high-value areas were sporadically distributed throughout the study area, while areas of LL-value agglomeration were present in the Taiyuan Basin, Yuncheng, and Linfen. In Shanxi, the spatial distribution of carbon storage significantly correlates with land-use types: high-value areas consist predominantly of forests and grasslands, whereas low-value areas include construction sites, mining areas, and unused lands.

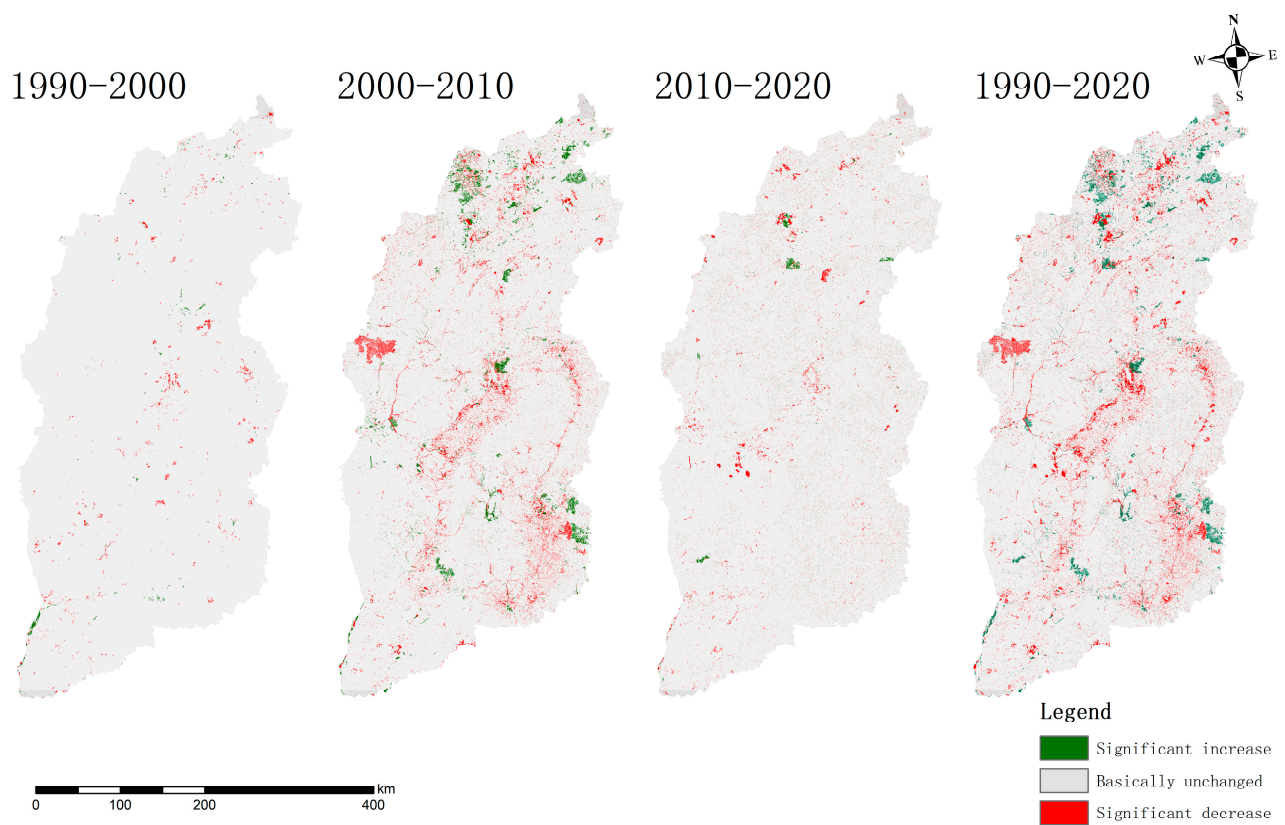


Figure 7. Changes in the spatial distribution of carbon storage in Shanxi from 1990 to 2020.

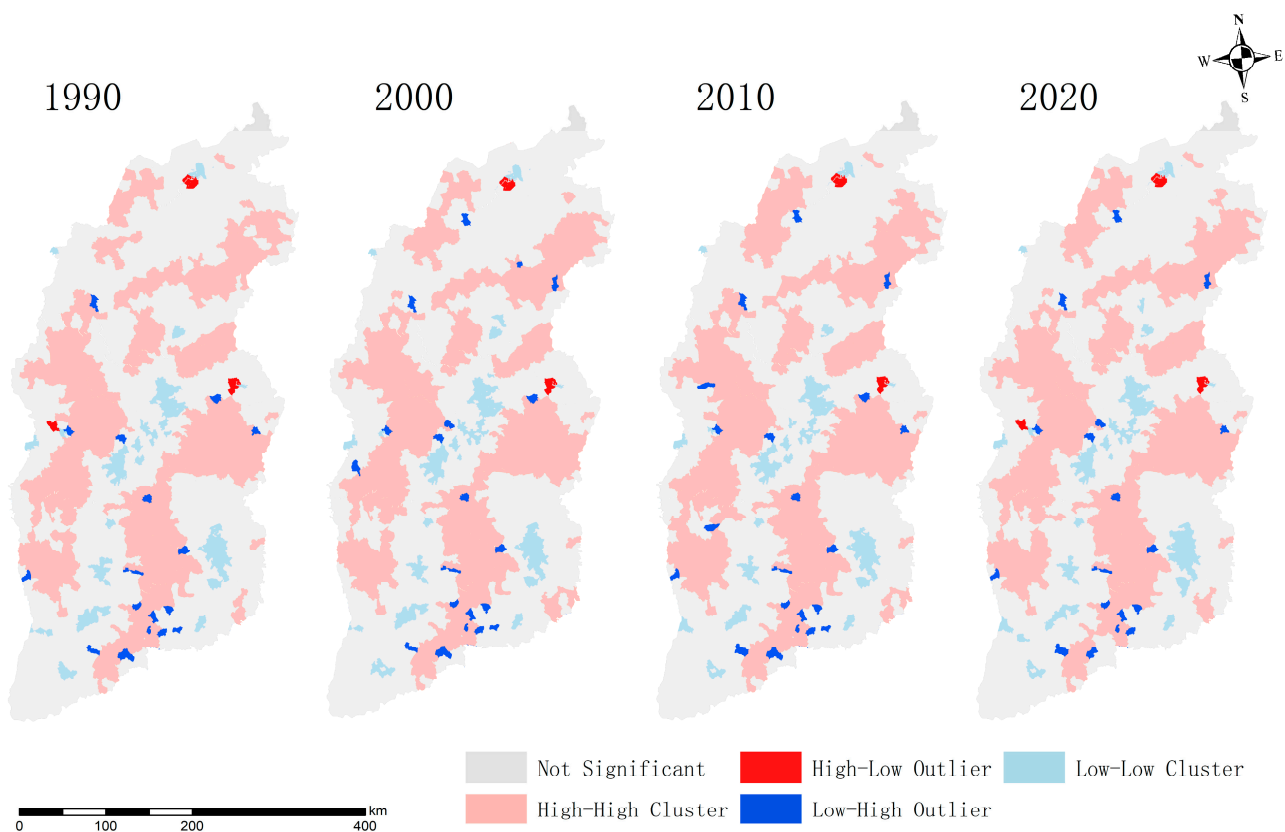


Figure 8. Spatial autocorrelation patterns for carbon storage in Shanxi from 1990 to 2020.

We input the future land-use simulation results into the InVEST model to assess carbon storage changes across four development scenarios from 2020 to 2035. The results indicated similar spatial distributions of carbon storage across scenarios (refer to Figure 9 and Table 9). Under the ND scenario, total carbon storage fell by 5.12×10^6 t, with grasslands and unused lands undergoing declines, whereas other land-use types saw increases. Specifically, carbon storage in construction and mining lands rose by 8.37×10^6 t and 0.55×10^6 t, respectively. The large gap in carbon production and storage due to decreased grasslands could not be compensated by increases in construction and mining lands. Under the CP scenario, croplands were effectively protected and restored compared to 2020, significantly increasing their carbon storage. However, the notable degradation of grasslands and forest lands reduced their carbon storage capacities by 1.16×10^6 t and 27.05×10^6 t, respectively. Consequently, a net decrease of 2.32×10^6 t in total carbon storage suggests that solely protecting croplands to maintain national food security is insufficient to boost the ecosystem's carbon storage in Shanxi Province. Thus, achieving the “dual carbon targets” requires adopting more comprehensive and systematic approaches.

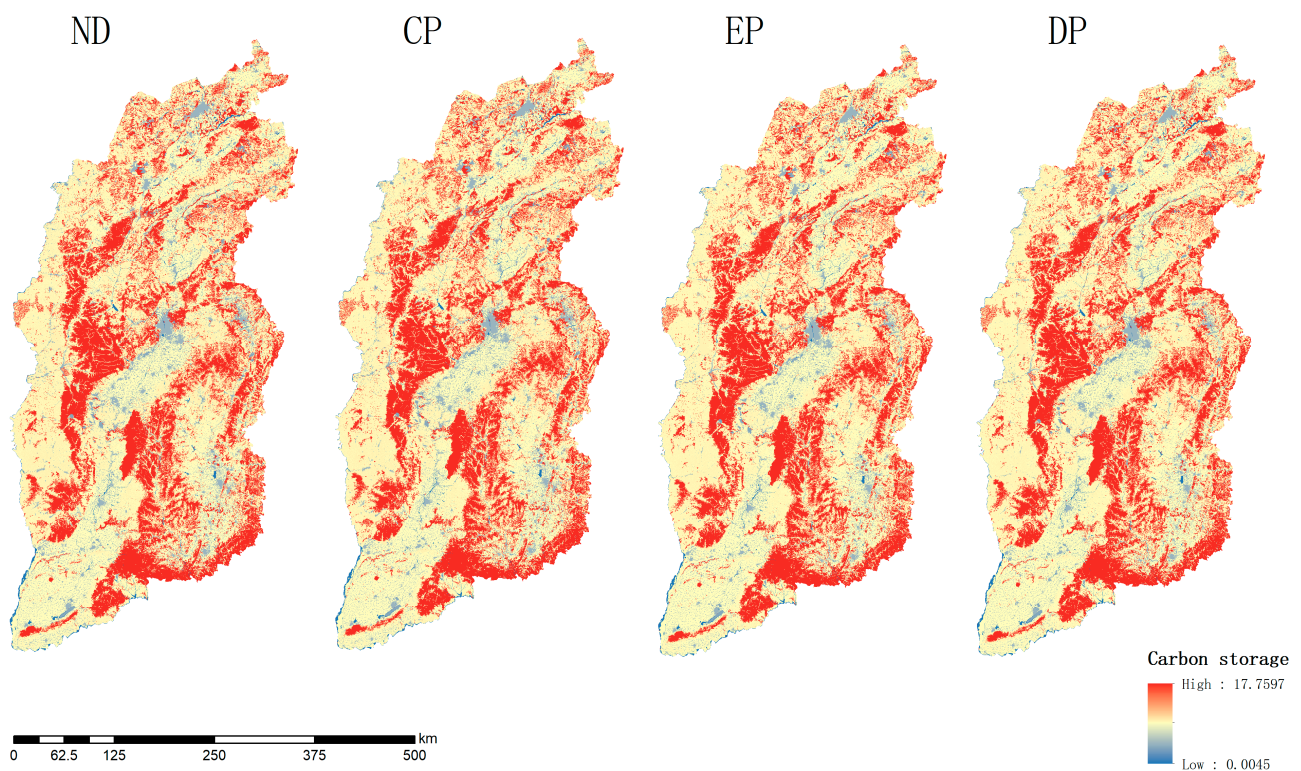


Figure 9. Spatial distribution of carbon storage predicted for Shanxi by 2035 under different land-use scenarios.

Table 9. Carbon storage capacities predicted for 2035 by land-use type under different scenarios.

Land-Use Type	Scenario			
	ND (10^6 t C)	CP (10^6 t C)	EP (10^6 t C)	DP (10^6 t C)
Crop	686.38	703.24	688.89	701.24
Forest	879.35	876.35	897.49	887.94
Grass	527.50	516.37	519.13	514.63
Water	0.01	0.01	0.01	0.01
Construction	59.17	59.75	60.24	59.47
Mining	14.04	13.55	13.42	13.24
Unused	0.27	0.26	0.26	0.26
Total	2166.72	2169.52	2179.44	2176.77

In the EP scenario, Shanxi Province's carbon storage exceeded that of other scenarios, increasing by 7.9×10^6 t. Enhanced ecological protection significantly increased carbon storage in forest lands while effectively conserving grasslands. Despite a decline in grassland carbon storage, degradation slowed, with cropland and construction land carbon storage rising by 2.59×10^6 t and 19.98×10^6 t, respectively. In the DP scenario, the coordinated development of croplands and the Shanxi ecosystem led to a 4.93×10^6 t increase in total carbon storage, despite decreases in grassland, mining, and unused land carbon storage, with grasslands undergoing the largest decline (28.79×10^6 t). Nevertheless, carbon storage in other land-use types, particularly croplands and forest lands, rose by 14.94×10^6 t and 10.43×10^6 t, respectively (Figure 10). The dual-protection strategy ensures national food security, meets daily life needs, enhances ecosystem carbon storage, and serves as a model for Shanxi's low carbon sustainable development.

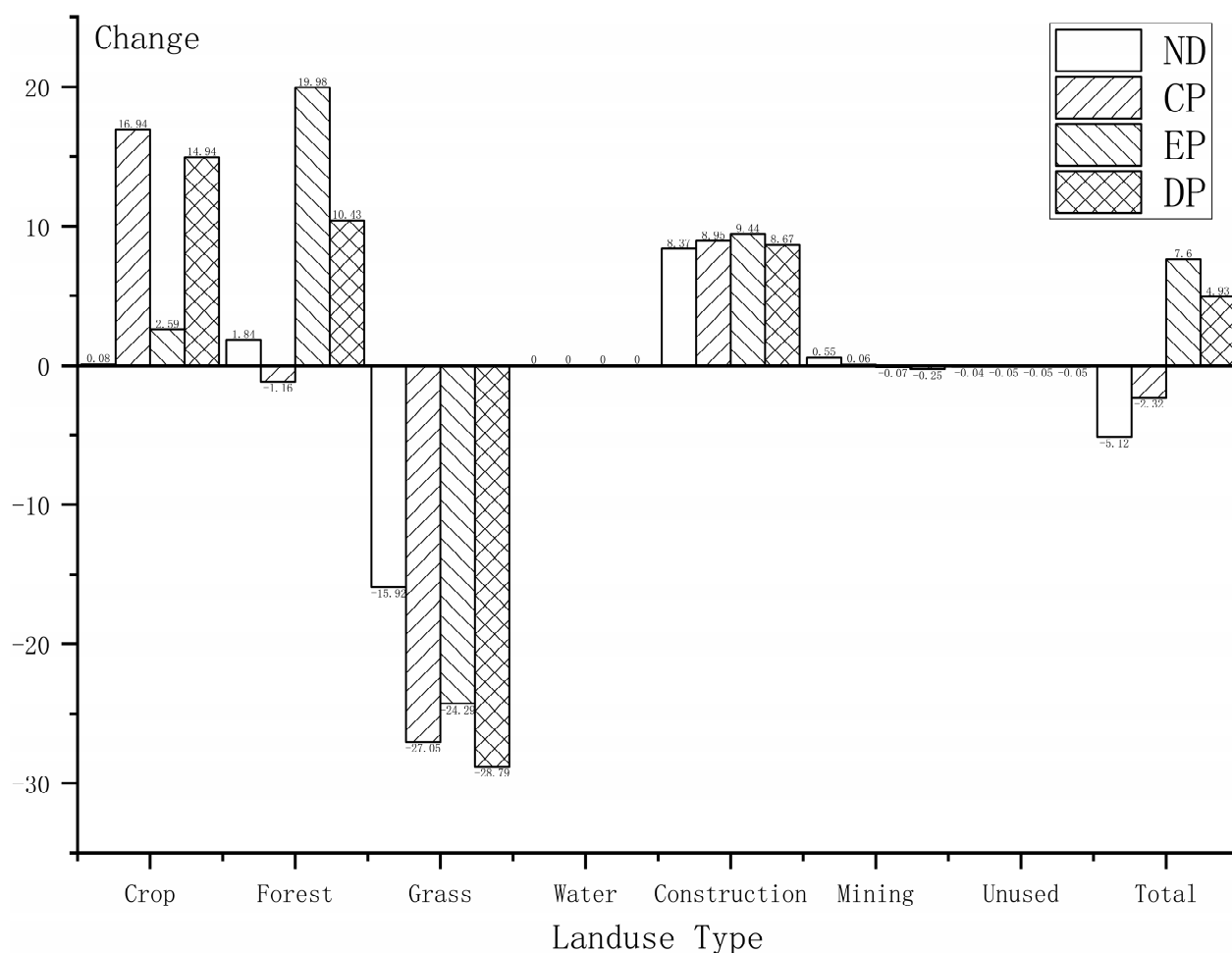


Figure 10. Changes in the carbon storage capacities of all land-use types in Shanxi by 2035 predicted under different development scenarios.

5. Discussion

5.1. Response of Carbon Storage to Land-Use Change

This study's findings reveal a significant correlation between land-use changes and variations in the spatial patterns and quantities of carbon storage in Shanxi Province. Previous research has indicated that land-use change plays a significant role in influencing carbon storage in terrestrial environments [43]. To conduct a more comprehensive examination of the variations in the influence of land area transfer on carbon storage across various land-use categories, we computed a distinct carbon storage transfer matrix by considering the transfer areas of said land-use categories (Table 10) [44].

Table 10. Changes in carbon storage by land-use type from 1990 to 2020.

Phase	Land-Use Type	Crop (10 ⁶ t C)	Forest (10 ⁶ t C)	Grass (10 ⁶ t C)	Water (10 ⁶ t C)	Construction (10 ⁶ t C)	Mining (10 ⁶ t C)	Unused (10 ⁶ t C)
1990–2000	Crop		0.4457	0.0210	−0.5460	−0.9567	−0.1353	−0.0143
	Forest	−0.7698		−2.1912	−0.0969	−0.0417	−0.0492	−0.0001
	Grass	−0.1060	0.4506		−0.1926	−0.1205	−0.1267	−0.0003
	Water	1.4245	0.0621	0.1731		0.0106	0.0000	0.0024
	Construction	0.0057	0.0006	0.0012	−0.0002		−0.0007	0.0000
	Mining	0.0006	0.0194	0.0013	0.0000	0.0022		0.0000
	Unused	0.0025	0.0001	0.0002	0.0000	0.0000	0.0000	
2000–2010	Crop		8.9595	0.6071	−1.9964	−9.0462	−3.4927	−0.0558
	Forest	−3.2113		−6.0350	−0.6064	−1.2414	−1.9743	−0.0301
	Grass	−0.5428	8.6282		−0.4980	−1.3787	−2.2176	−0.0676
	Water	2.8195	0.6251	0.5307		0.3179	0.4440	0.0352
	Construction	1.6052	0.1573	0.1233	−0.0486		−0.0217	−0.0012
	Mining	0.1175	0.1552	0.0347	−0.0330	0.0722		−0.0004
	Unused	0.2879	0.0903	0.1202	−0.0294	0.0326	0.0239	
2010–2020	Crop		2.1036	0.3214	−0.7757	−2.5782	−1.3067	−0.0141
	Forest	−3.3998		−2.4900	−0.1819	−0.9188	−1.3974	−0.0299
	Grass	−0.4064	3.7731		−0.2687	−0.3987	−0.7451	−0.0151
	Water	0.4743	0.1257	0.2270		0.1205	0.0138	0.0005
	Construction	0.8826	0.1240	0.1539	−0.0268		−0.0154	−0.0003
	Mining	0.2089	0.5795	0.0877	−0.0325	0.0867		−0.0004
	Unused	0.0479	0.0134	0.0108	−0.0013	0.0018	0.0022	
1990–2020	Crop		9.7016	0.8404	−2.3497	−12.1354	−4.4280	−0.0584
	Forest	−5.6301		−9.6297	−0.7608	−1.7371	−2.6837	−0.0635
	Grass	−0.9484	11.4786		−0.8774	−1.9059	−2.9759	−0.0774
	Water	3.8796	0.6678	0.8032		0.3951	0.3905	0.0361
	Construction	1.6829	0.1463	0.1447	−0.0368		−0.0222	−0.0013
	Mining	0.1244	0.2794	0.0262	−0.0260	0.0816		−0.0005
	Unused	0.3227	0.0905	0.1088	−0.0289	0.0439	0.0236	

From 1990 and 2020, the primary factor contributing to the decline in overall carbon storage was the conversion of croplands into construction and mining areas, forest lands into croplands and grasslands, and grasslands into construction and mining areas. These conversions resulted in losses of 12.1354×10^6 t, 4.428×10^6 t, 5.6301×10^6 t, 9.6297×10^6 t, 1.9059×10^6 t, and 2.9759×10^6 t, respectively. In the interim, the primary driver of carbon storage growth can be attributed to the conversion of croplands and grasslands into forest lands, resulting in respective increments of 9.7016×10^6 t and 11.4786×10^6 t. The land-use change pattern observed in the Loess Plateau of northern Shaanxi from 1995 to 2010 is attributable to the “Three-North Shelter Forestation Project” and the “Returning Farmland to Forest” project. Forest areas, being the primary terrestrial carbon reservoirs, have somewhat offset the recent decline in carbon storage resulting from the depletion of croplands and grasslands. Between 2000 and 2010, the conversion of croplands into construction and mining lands, as well as the conversion of forest areas into grasslands, resulted in a decrease in carbon storage by 9.04×10^6 t, 3.49×10^6 t, and 6.04×10^6 t, respectively. The conversion of croplands and grasslands into forest lands resulted in an increase in carbon storage by 8.96×10^6 t and 8.63×10^6 t, respectively. Between 2010 and 2020, the observed alterations were relatively minor and attributed primarily to the conversion of agricultural lands into construction and mining areas, as well as the conversion of forest lands into croplands and grasslands. Consequently, these transformations led to a decrease in carbon storage of 2.58×10^6 t, 1.31×10^6 t, 3.4×10^6 t, and 2.49×10^6 t, respectively. Therefore, the preservation of croplands is imperative to foster a regional carbon equilibrium and guarantee food security.

Through a comparative analysis of carbon storage capacities across various land-use types (Table 10), it becomes evident that the decline in carbon storage resulting from the conversion of forest lands, grasslands, and croplands to alternative land-use types primarily stems from the significantly higher carbon intensities associated with these heavily vegetated types in comparison to built land-use types [45]. Carbon storage is further enhanced by the transfer of other LULC categories. Forest lands, as the greatest carbon reservoir in the ecosystem, are crucial in ensuring environment security and stability. They are also essential for enhancing ecological carbon sinks and achieving regional “dual carbon targets.” Hence, to achieve ecological security and foster a regional carbon balance, the future ecological restoration and high-quality development of Shanxi Province must be founded upon a logical arrangement of land-use patterns.

Changes in land use impact carbon storage in the environment. Transitioning from high to low carbon density areas reduces storage, while the opposite effect is observed [14]. The results from this study showed that carbon storage patterns were consistent across all model scenarios. Areas with high carbon storage were primarily identified within mountainous and hilly regions with conducive ecological conditions and minimal development [46]. Conversely, areas with poor carbon storage were predominantly in regions with higher land-use intensities and active human activities [44]. In regions reliant on natural resources, forest lands exhibit a significant carbon storage capacity [47]. The main path of carbon flow in the opposite direction involves converting natural ecosystems (e.g., grasslands and forests) and agricultural regions into mining and construction areas. Conversely, positive carbon flow primarily arises from the conversion of mining lands into ecological lands and croplands.

In this study, clear differences in carbon storage were observed under the four development scenarios modeled for Shanxi Province by 2035. The carbon storage in the ND scenario was 5.12×10^6 t lower than in 2020, indicating that, following the existing development path, the expansion of construction and mining lands will lead to a decline in carbon storage. Compared with 2020, the CP scenario also showed a decrease in carbon storage (by 2.32×10^6 t), indicating that the protection of croplands from transformation into low carbon density lands (i.e., mining or construction lands) can slow the decline in carbon storage; however, this is insufficient to improve regional carbon storage. Under the EP scenario, owing to the implementation of ecological protection measures to protect high carbon density forest lands, grasslands, and croplands, the total amount of carbon storage increased by 7.9×10^6 t; this scenario also yielded the greatest recovery of carbon storage for Shanxi. Hence, the protection of ecological lands by curbing the transfer of lands with high carbon densities, such as forest lands and grasslands around cities and towns, into lands with low carbon densities, such as construction and mining lands, can greatly increase regional terrestrial carbon storage. However, this scenario cannot guarantee regional food security due to losses in croplands. In the DP scenario, the total carbon storage increased by 4.93×10^6 t; this improvement in ecological carbon storage was accompanied by the retention of a sufficient number of croplands, guaranteeing the sustainable development and food security of the region. Thus, based on the DP scenario, Shanxi Province should continue to implement protection measures, such as the “Returning Farmland to Forest” project and restoring ecological lands. Urban expansion should also be reasonably curbed.

5.2. Suggestions for the Future Development of Shanxi Province

The ecological environment has become more fragile due to rapid socio-economic changes and land development [48]. The grasslands and forests in Shanxi are deteriorating, reducing soil fertility and carbon stocks [49]. Local governments have struggled to adjust development policies, optimize land-use structures, and improve sustainable development [50]. The primary outcomes of this study are as follows:

(1) Construction and mining land have increased due to rapid urbanization and resource exploitation. Consequently, arable land and grassland areas have markedly decreased, reducing carbon sequestration and ecosystem sustainability [51]. Multiple

model scenarios predict that maintaining current development patterns and implementing cropland protection measures (alone) will reduce ecological carbon stocks in Shanxi by 2035 [52]. Under the EP scenario, ecosystem carbon storage capacity increases, but cropland is destroyed, threatening regional food production [33]. To ensure national food security, China should prioritize arable land protection [53]. The DP scenario protects cropland and ecosystems and increases cropland and forested land, ensuring food security and improving ecological functions, especially carbon storage. Slowing economic growth, changing the development strategy from “high speed” to “high quality”, restricting coal mining, and shifting from an energy-based economy to a green economy can increase ecosystem services in the study area [54]. Given the negative effects of rapid climate change on plant growth, food security, and natural carbon storage, abundant solar and wind resources must be implemented for energy conversion and to reduce fossil fuel use. This would mitigate climate change and prevent further losses. Additionally, local governments in Shanxi Province can increase grassland and woodland, especially woodland, which stores carbon well. This can be achieved by intensifying planted forests and restoring farmland forest habitats. However, sufficient cropland must be secured for food security. Implementing these measures will preserve forest ecosystems, improve forest land quality, and increase the carbon storage capacity of forests in this heavily resource-dependent region.

(2) Due to their unique role in the ecosystem, ecological land like forest and grassland has a much higher carbon stock than construction, industrial, and mining land [55]. Woodlands and grasslands have a higher carbon density and natural carbon sink capacity than urban and industrial land [34]. Researchers found that vegetation-covered ecosystems can absorb atmospheric carbon dioxide through photosynthesis, slowing global greenhouse gas emissions [56]. According to the spatial and temporal analysis of carbon stocks in Shanxi Province, policies like returning farmland to forests have yielded some results in recent decades. To better address climate change, these measures must be optimized and adjusted. Forest land and grassland should be better protected, and non-essential land development should be reduced at the policy and practice levels to maintain and improve their carbon sink function. Shanxi Province can also learn from land-use efficiency successes abroad. Implementing stricter land management policies can boost agricultural productivity while preserving ecological functions [57]. Intensive land use is promoted to minimize environmental impact while meeting economic development needs. Further increasing forest and grassland carbon sink capacity will mitigate climate change, conserve biodiversity, and improve local communities’ quality of life. Considering Shanxi Province’s unique situation, a set of comprehensive measures, including technology promotion, financial support, and policy guidance, should be developed to achieve these goals. Increasing forest and grassland protection and use is a key strategy for sustainable development. Relevant departments should use scientific management and technology to improve Shanxi Province and the region’s ecological functions and carbon sink capacity.

(3) Shanxi Province’s carbon stocks are highly heterogeneous, especially in areas with better nature protection, such as the Taihang Mountains and Luliang Mountains, which have high vegetation, intact ecosystems, and high carbon storage capacity [58]. These distribution characteristics demonstrate the importance of nature reserves for regional carbon balance and the urgency of protecting them [59]. Strengthening nature reserve management is crucial to Shanxi Province’s carbon sink function. First, stricter environmental protection policies should be implemented to protect ecologically sensitive areas from human activity. Mining and industrial expansion should be limited to preserve the ecosystem’s ecological state. Second, urban expansion should avoid high carbon areas through rational planning. This includes clear urban boundaries, green buffer zone policies, and city green space optimization to reduce urbanization’s negative effects on natural areas. Vertical and rooftop greening are encouraged in modern eco-cities to increase carbon absorption. Public environmental education and community nature conservation awareness must also be improved to reach more people through environmental education and public participation days [60]. Promoting cooperation between scientific research institutions and

local governments to study carbon storage and carbon sink functions can also inform local policies. Shanxi Province can better protect and enhance its carbon sink function and fight global climate change by improving nature reserve management, rationally controlling urban expansion, and increasing public participation and scientific research support.

5.3. Limitations and Prospects

The PLUS model is a sophisticated land-use change simulation tool that utilizes advanced algorithms and technology to simulate and predict the dynamic process of land-use change [38]. Nevertheless, despite its exceptional performance in several research and application domains [35], the PLUS model has certain constraints [61]. The limits of the PLUS model are evident in three specific aspects [62]:

The quality of the input data significantly influences the output quality of the PLUS model. This implies that the model requires access to accurate and detailed information regarding land use, land cover, and other fundamental geographical data. Errors or delays in updating the input data might negatively impact the accuracy and dependability of the model's predictions.

While the PLUS model efficiently simulates land-use conversions, it may not be sufficiently precise in capturing intricate spatial dynamic changes, particularly the evolution of patches of natural land types. This could result in an inadequate forecast of land-cover change patterns, impacting the model's efficacy in ecological conservation and land management decision support.

The PLUS model may not sufficiently account for non-physical aspects, such as policy direction, economic development, and social issues, when conducting land-use change simulations. Ignoring these elements can substantially impact land-use patterns and trends. Consequently, the model may not fully and properly capture the dynamics of land use.

In the future, the PLUS model can be combined with other land-use models or ecosystem service assessment models to improve its performance and expand its range of applications [63]. Integrating these factors will enhance the precision of land-use change projections and broaden the model's applicability to ecosystem services and environmental management [64]. Enhancing the algorithms and parameter settings of the PLUS model can enhance the model's adaptability and flexibility to various geographical and environmental situations, which will be crucial for future advancements [65]. This involves enhancing the fundamental algorithms of the model to improve its ability to handle various scales and types of land-use data, as well as to replicate the spatial patterns of land-use changes more precisely [66]. During the creation and deployment of the model, incorporating and analyzing social, economic, and policy elements can improve the alignment of the PLUS model with real-world land management and planning requirements [67]. This may require collaboration across many disciplines, such as geography, urban planning, environmental science, and socio-economics, to enhance the model's applicability and ability to support decision-making [68]. Overall, the PLUS model is a robust land-use simulation tool with great potential for its use in global land-use planning and environmental management. Its prospects are promising, thanks to ongoing technical enhancements and interdisciplinary collaboration, although it is encountering certain hurdles [37].

6. Conclusions

This study utilized optimized PLUS-InVEST models to estimate Shanxi Province's carbon storage, analyze LULC evolution, and assess regional ecosystem carbon storage capacity under four development scenarios based on LULC and LULC patterns. The principal conclusions of this study are as follows:

- (1) From 1990 to 2020, croplands and grasslands decreased significantly, forest lands increased slightly, and construction and mining land increased significantly. Forest lands were mainly distributed in the mountainous and hilly areas of the Lüliang Mountains and Taihang Mountains, while croplands were mainly found in the flat

areas of southern and central Shanxi, and mining lands were scattered across the province.

- (2) Ecological carbon storage in Shanxi decreased from 1990 to 2020, with a total loss of 15.1×10^6 t C; this was primarily attributed to massive losses in grasslands and croplands, the rapid expansion of construction lands, and the intensive development of mining lands. The distribution of carbon storage was highly spatially heterogeneous. High-value carbon storage areas were predominantly located along the Lüliang, Taihang, and Taiyue Mountains, whereas low-value areas were found throughout central and southern Shanxi.
- (3) Carbon storage in Shanxi is predicted to increase compared to 2020 under the EP and DP scenarios. However, a decrease is expected under the ND and CP scenarios. Our models show a notable increase of 4.93 million tons in carbon storage under the DP scenario. This particular development approach can potentially ensure sufficient farmland area and ecological carbon sinks in Shanxi province. Optimizing LULC based on the DP scenario has provided valuable insights for future spatial arrangement and ecological quality enhancement to boost regional carbon storage. Following optimization, a noticeable increase was observed in construction, cropland, and forest areas. This transformation supports urbanization, economic growth, cropland and ecosystem protection, regional carbon balance maintenance, ecological stability promotion, and food production stability. These principles serve as a foundation for future planning in Shanxi. This study presents an optimal strategy for improving land-use change based on natural resources in the region. It also provides technical support for ecological restoration and carbon enhancement, which is crucial for advancing ecological carbon sequestration efforts in other areas and achieving China's Dual Carbon Goals.

Author Contributions: Conceptualization, Y.J. and C.L.; methodology, Y.J. and C.L.; software, Y.J. and Y.W.; validation, Y.J., X.H., Y.W., and C.T.; formal analysis, Y.J.; investigation, Y.J.; resources, X.H., C.T., and Y.W.; data curation, X.H.; writing—original draft preparation, Y.J.; writing—review and editing, C.L., X.F., and L.X.; visualization, Y.J.; supervision, C.L.; project administration, C.L.; funding acquisition, C.L. All authors have read and agreed to the published version of the manuscript.

Funding: Shanxi Provincial Natural Science Foundation of China “Spatial-temporal evolution and driving force analysis of ecological spatial pattern of soil and water conservation in coal resource counties in loess hilly and gully area of yellow river basin”.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors express their gratitude to Shanxi Agricultural University for its generous financial support. Additionally, we extend our sincere appreciation to the experts for their invaluable and constructive feedback on the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Duan, H.; Zhou, S.; Jiang, K.; Bertram, C.; Harmsen, M.; Kriegler, E.; van Vuuren, D.P.; Wang, S.; Fujimori, S.; Tavoni, M. Assessing China's efforts to pursue the 1.5 C warming limit. *Science* **2021**, *372*, 378–385. [[CrossRef](#)] [[PubMed](#)]
- Fawzy, S.; Osman, A.I.; Doran, J.; Rooney, D.W. Strategies for mitigation of climate change: A review. *Environ. Chem. Lett.* **2020**, *18*, 2069–2094. [[CrossRef](#)]
- Rogelj, J.; Huppmann, D.; Krey, V.; Riahi, K.; Clarke, L.; Gidden, M.; Nicholls, Z.; Meinshausen, M. A new scenario logic for the Paris Agreement long-term temperature goal. *Nature* **2019**, *573*, 357–363. [[CrossRef](#)] [[PubMed](#)]
- Dong, F.; Zhu, J.; Li, Y.; Chen, Y.; Gao, Y.; Hu, M.; Qin, C.; Sun, J. How green technology innovation affects carbon emission efficiency: Evidence from developed countries proposing carbon neutrality targets. *Environ. Sci. Pollut. Res.* **2022**, *29*, 35780–35799. [[CrossRef](#)] [[PubMed](#)]
- Xiao, H.; Zhou, Y.; Zhang, N.; Wang, D.; Shan, Y.; Ren, J. CO₂ emission reduction potential in China from combined effects of structural adjustment of economy and efficiency improvement. *Resour. Conserv. Recycl.* **2021**, *174*, 105760. [[CrossRef](#)]
- Liu, D.; Guo, X.; Xiao, B. What causes growth of global greenhouse gas emissions? Evidence from 40 countries. *Sci. Total Environ.* **2019**, *661*, 750–766. [[CrossRef](#)] [[PubMed](#)]

7. Qi, R.; Shi, C.; Wang, M.Y. Carbon emission rush in response to the carbon reduction policy in China. *China Inf.* **2023**, *37*, 100–122. [\[CrossRef\]](#)
8. Wang, D.; He, W.; Shi, R. How to achieve the dual-control targets of China's CO₂ emission reduction in 2030? Future trends and prospective decomposition. *J. Clean. Prod.* **2019**, *213*, 1251–1263. [\[CrossRef\]](#)
9. Ge, J.; Lin, B. Impact of public support and government's policy on climate change in China. *J. Environ. Manag.* **2021**, *294*, 112983. [\[CrossRef\]](#)
10. Wang, P.; Huang, G.; Li, Y.; Liu, Y.; Li, Y. An ecological input-output CGE model for unveiling CO₂ emission metabolism under China's dual carbon goals. *Appl. Energy* **2024**, *365*, 123277. [\[CrossRef\]](#)
11. Sun, L.-L.; Cui, H.-J.; Ge, Q.-S. Will China achieve its 2060 carbon neutral commitment from the provincial perspective? *Adv. Clim. Chang. Res.* **2022**, *13*, 169–178. [\[CrossRef\]](#)
12. Chen, L.; Msigwa, G.; Yang, M.; Osman, A.I.; Fawzy, S.; Rooney, D.W.; Yap, P.-S. Strategies to achieve a carbon neutral society: A review. *Environ. Chem. Lett.* **2022**, *20*, 2277–2310. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Wang, C.; Liu, P.; Ibrahim, H.; Yuan, R. The temporal and spatial evolution of green finance and carbon emissions in the Pearl River Delta region: An analysis of impact pathways. *J. Clean. Prod.* **2024**, *446*, 141428. [\[CrossRef\]](#)
14. Zhu, G.; Qiu, D.; Zhang, Z.; Sang, L.; Liu, Y.; Wang, L.; Zhao, K.; Ma, H.; Xu, Y.; Wan, Q. Land-use changes lead to a decrease in carbon storage in arid region, China. *Ecol. Indic.* **2021**, *127*, 107770. [\[CrossRef\]](#)
15. Pan, Y.; Birdsey, R.A.; Phillips, O.L.; Jackson, R.B. The structure, distribution, and biomass of the world's forests. *Annu. Rev. Ecol. Evol. Syst.* **2013**, *44*, 593–622. [\[CrossRef\]](#)
16. Heimann, M.; Reichstein, M. Terrestrial ecosystem carbon dynamics and climate feedbacks. *Nature* **2008**, *451*, 289–292. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Canadell, J.G.; Raupach, M.R. Managing forests for climate change mitigation. *Science* **2008**, *320*, 1456–1457. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Xi, F.; Lin, G.; Zhao, Y.; Li, X.; Chen, Z.; Cao, C. Land Use Optimization and Carbon Storage Estimation in the Yellow River Basin, China. *Sustainability* **2023**, *15*, 11278. [\[CrossRef\]](#)
19. Chen, N.; Xin, C.L.; Tang, D.B.; Zhang, L.; Xin, S.-J. Multi-scenario Land Use Optimization and Carbon Storage Assessment in Northwest China. *Environ. Sci.* **2023**, *44*, 4655–4665. [\[CrossRef\]](#)
20. Liu, C.; Li, X. Carbon storage and sequestration by urban forests in Shenyang, China. *Urban For. Urban Green.* **2012**, *11*, 121–128. [\[CrossRef\]](#)
21. Wu, H.; Deng, K.; Dong, Z.; Meng, X.; Zhang, L.; Jiang, S.; Yang, L.; Xu, Y. Comprehensive assessment of land use carbon emissions of a coal resource-based city, China. *J. Clean. Prod.* **2022**, *379*, 134706. [\[CrossRef\]](#)
22. Li, L.; Bai, Y.; Yang, X. A low-carbon land use management framework based on urban carbon metabolism: A case of a typical coal resource-based city in China. *Sustainability* **2022**, *14*, 13854. [\[CrossRef\]](#)
23. Cooper, C.F. Carbon storage in managed forests. *Can. J. For. Res.* **1983**, *13*, 155–166. [\[CrossRef\]](#)
24. Bunker, D.E.; DeClerck, F.; Bradford, J.C.; Colwell, R.K.; Perfecto, I.; Phillips, O.L.; Sankaran, M.; Naeem, S. Species loss and aboveground carbon storage in a tropical forest. *Science* **2005**, *310*, 1029–1031. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Myeong, S.; Nowak, D.J.; Duggin, M.J. A temporal analysis of urban forest carbon storage using remote sensing. *Remote Sens. Environ.* **2006**, *101*, 277–282. [\[CrossRef\]](#)
26. Doetterl, S.; Stevens, A.; Six, J.; Merckx, R.; Van Oost, K.; Casanova Pinto, M.; Casanova-Katny, A.; Muñoz, C.; Boudin, M.; Zagal Venegas, E. Soil carbon storage controlled by interactions between geochemistry and climate. *Nat. Geosci.* **2015**, *8*, 780–783. [\[CrossRef\]](#)
27. Jiang, W.; Deng, Y.; Tang, Z.; Lei, X.; Chen, Z. Modelling the potential impacts of urban ecosystem changes on carbon storage under different scenarios by linking the CLUE-S and the InVEST models. *Ecol. Model.* **2017**, *345*, 30–40. [\[CrossRef\]](#)
28. Li, P.; Chen, J.; Li, Y.; Wu, W. Using the InVEST-PLUS model to predict and analyze the pattern of ecosystem carbon storage in Liaoning Province, China. *Remote Sens.* **2023**, *15*, 4050. [\[CrossRef\]](#)
29. Lahiji, R.N.; Dinan, N.M.; Liaghati, H.; Ghaffarzadeh, H.; Vafaeinejad, A. Scenario-based estimation of catchment carbon storage: Linking multi-objective land allocation with InVEST model in a mixed agriculture-forest landscape. *Front. Earth Sci.* **2020**, *14*, 637–646. [\[CrossRef\]](#)
30. Liu, Q.; Yang, D.; Cao, L.; Anderson, B. Assessment and prediction of carbon storage based on land use/land cover dynamics in the tropics: A case study of hainan island, China. *Land* **2022**, *11*, 244. [\[CrossRef\]](#)
31. Liang, X.; Guan, Q.; Clarke, K.C.; Liu, S.; Wang, B.; Yao, Y. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, 101569. [\[CrossRef\]](#)
32. Huang, X.; Liu, J.; Peng, S.; Huang, B. The impact of multi-scenario land use change on the water conservation in central Yunnan urban agglomeration, China. *Ecol. Indic.* **2023**, *147*, 109922. [\[CrossRef\]](#)
33. Fan, L.; Cai, T.; Wen, Q.; Han, J.; Wang, S.; Wang, J.; Yin, C. Scenario simulation of land use change and carbon storage response in Henan Province, China: 1990–2050. *Ecol. Indic.* **2023**, *154*, 110660. [\[CrossRef\]](#)
34. Fan, Y.; Wei, F. Contributions of natural carbon sink capacity and carbon neutrality in the context of net-zero carbon cities: A case study of Hangzhou. *Sustainability* **2022**, *14*, 2680. [\[CrossRef\]](#)
35. Hu, N.; Xu, D.; Zou, N.; Fan, S.; Wang, P.; Li, Y. Multi-scenario simulations of land use and habitat quality based on a PLUS-InVEST model: A case study of baoding, China. *Sustainability* **2022**, *15*, 557. [\[CrossRef\]](#)

36. Li, Y.; Yao, S.; Jiang, H.; Wang, H.; Ran, Q.; Gao, X.; Ding, X.; Ge, D. Spatial-temporal evolution and prediction of carbon storage: An integrated framework based on the MOP-PLUS-InVEST model and an applied case study in Hangzhou, East China. *Land* **2022**, *11*, 2213. [[CrossRef](#)]
37. Luan, C.; Liu, R.; Zhang, Q.; Sun, J.; Liu, J. Multi-objective land use optimization based on integrated NSGA-II-PLUS model: Comprehensive consideration of economic development and ecosystem services value enhancement. *J. Clean. Prod.* **2024**, *434*, 140306. [[CrossRef](#)]
38. Ma, G.; Li, Q.; Zhang, J.; Zhang, L.; Cheng, H.; Ju, Z.; Sun, G. Simulation and Analysis of Land-Use Change Based on the PLUS Model in the Fuxian Lake Basin (Yunnan–Guizhou Plateau, China). *Land* **2022**, *12*, 120. [[CrossRef](#)]
39. Zhao, H.; Guo, B.; Wang, G. Spatial–Temporal Changes and Prediction of Carbon Storage in the Tibetan Plateau Based on PLUS-InVEST Model. *Forests* **2023**, *14*, 1352. [[CrossRef](#)]
40. Alam, S.A.; Starr, M.; Clark, B.J. Tree biomass and soil organic carbon densities across the Sudanese woodland savannah: A regional carbon sequestration study. *J. Arid Environ.* **2013**, *89*, 67–76. [[CrossRef](#)]
41. Xie, X. Organic carbon density and storage in soils of China and spatial analysis. *Acta Pedol. Sin.* **2004**, *41*, 35–43.
42. Zhang, M.; Wang, K.; Liu, H.; Zhang, C.; Duan, Y. Spatio-temporal variation of vegetation carbon storage and density in karst areas of Northwest Guangxi based on remote sensing images. *Chin. J. Eco-Agric.* **2013**, *21*, 1545–1553. [[CrossRef](#)]
43. Wei, X.; Zhang, S.; Luo, P.; Zhang, S.; Wang, H.; Kong, D.; Zhang, Y.; Tang, Y.; Sun, S. A Multi-Scenario Prediction and Spatiotemporal Analysis of the Land Use and Carbon Storage Response in Shaanxi. *Remote Sens.* **2023**, *15*, 5036. [[CrossRef](#)]
44. Zhang, M.; Huang, X.; Chuai, X.; Yang, H.; Lai, L.; Tan, J. Impact of land use type conversion on carbon storage in terrestrial ecosystems of China: A spatial-temporal perspective. *Sci. Rep.* **2015**, *5*, 10233. [[CrossRef](#)] [[PubMed](#)]
45. Paddhushan, R.; Kumar, U.; Sharma, S.; Rana, D.; Kumar, R.; Kohli, A.; Kumari, P.; Parmar, B.; Kaviraj, M.; Sinha, A.K. Impact of land-use changes on soil properties and carbon pools in India: A meta-analysis. *Front. Environ. Sci.* **2022**, *9*, 794866. [[CrossRef](#)]
46. Aitali, R.; Snoussi, M.; Kolker, A.S.; Oujidi, B.; Mhammdi, N. Effects of land use/land cover changes on carbon storage in North African Coastal Wetlands. *J. Mar. Sci. Eng.* **2022**, *10*, 364. [[CrossRef](#)]
47. Wang, L.; Zhu, R.; Yin, Z.; Chen, Z.; Fang, C.; Lu, R.; Zhou, J.; Feng, Y. Impacts of land-use change on the spatio-temporal patterns of terrestrial ecosystem carbon storage in the Gansu Province, Northwest China. *Remote Sens.* **2022**, *14*, 3164. [[CrossRef](#)]
48. Wang, H.; Feng, R.; Li, X.; Yang, Y.; Pan, Y. Land Use Change and Its Impact on Ecological Risk in the Huaihe River Eco-Economic Belt. *Land* **2023**, *12*, 1247. [[CrossRef](#)]
49. Yang, Y.; Liu, L.; Zhang, P.; Wu, F.; Wang, Y.; Xu, C.; Zhang, L.; An, S.; Kuzyakov, Y. Large-scale ecosystem carbon stocks and their driving factors across Loess Plateau. *Carbon Neutrality* **2023**, *2*, 5. [[CrossRef](#)]
50. Bruff, G.E.; Wood, A.P. Local sustainable development: Land-use planning’s contribution to modern local government. *J. Environ. Plan. Manag.* **2000**, *43*, 519–539. [[CrossRef](#)]
51. Liu, Y.; Luo, T.; Liu, Z.; Kong, X.; Li, J.; Tan, R. A comparative analysis of urban and rural construction land use change and driving forces: Implications for urban–rural coordination development in Wuhan, Central China. *Habitat Int.* **2015**, *47*, 113–125. [[CrossRef](#)]
52. Wang, L.; Anna, H.; Zhang, L.; Xiao, Y.; Wang, Y.; Xiao, Y.; Liu, J.; Ouyang, Z. Spatial and temporal changes of arable land driven by urbanization and ecological restoration in China. *Chin. Geogr. Sci.* **2019**, *29*, 809–819. [[CrossRef](#)]
53. Wang, Z.; Zeng, J.; Chen, W. Impact of urban expansion on carbon storage under multi-scenario simulations in Wuhan, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 45507–45526. [[CrossRef](#)] [[PubMed](#)]
54. Chen, A.; He, H.; Wang, J.; Li, M.; Guan, Q.; Hao, J. A study on the arable land demand for food security in China. *Sustainability* **2019**, *11*, 4769. [[CrossRef](#)]
55. Chen, D.; Deng, X.; Jin, G.; Samie, A.; Li, Z. Land-use-change induced dynamics of carbon stocks of the terrestrial ecosystem in Pakistan. *Phys. Chem. Earth Parts A/B/C* **2017**, *101*, 13–20. [[CrossRef](#)]
56. Song, W.; Chen, S.; Wu, B.; Zhu, Y.; Zhou, Y.; Li, Y.; Cao, Y.; Lu, Q.; Lin, G. Vegetation cover and rain timing co-regulate the responses of soil CO₂ efflux to rain increase in an arid desert ecosystem. *Soil Biol. Biochem.* **2012**, *49*, 114–123. [[CrossRef](#)]
57. Olesen, J.E.; Bindi, M. Consequences of climate change for European agricultural productivity, land use and policy. *Eur. J. Agron.* **2002**, *16*, 239–262. [[CrossRef](#)]
58. Yue, J.-W.; Guan, J.-H.; Deng, L.; Zhang, J.-G.; Li, G.; Du, S. Allocation pattern and accumulation potential of carbon stock in natural spruce forests in northwest China. *PeerJ* **2018**, *6*, e4859. [[CrossRef](#)] [[PubMed](#)]
59. Malhi, Y.; Baldocchi, D.; Jarvis, P. The carbon balance of tropical, temperate and boreal forests. *Plant Cell Environ.* **1999**, *22*, 715–740. [[CrossRef](#)]
60. Grodzińska-Jurczak, M.; Cent, J. Can public participation increase nature conservation effectiveness? *Innov. Eur. J. Soc. Sci. Res.* **2011**, *24*, 371–378. [[CrossRef](#)]
61. Yu, Z.; Zhao, M.; Gao, Y.; Wang, T.; Zhao, Z.; Wang, S. Multiscenario Simulation and Prediction of Land Use in Huaibei City Based on CLUE-S and PLUS Models. *Appl. Sci.* **2023**, *13*, 7142. [[CrossRef](#)]
62. Lin, Z.; Peng, S. Comparison of multimodel simulations of land use and land cover change considering integrated constraints-A case study of the Fuxian Lake basin. *Ecol. Indic.* **2022**, *142*, 109254. [[CrossRef](#)]
63. Luan, C.; Liu, R. A comparative study of various land use and land cover change models to predict ecosystem service value. *Int. J. Environ. Res. Public Health* **2022**, *19*, 16484. [[CrossRef](#)] [[PubMed](#)]

64. Wang, P.; Li, R.; Liu, D.; Wu, Y. Dynamic characteristics and responses of ecosystem services under land use/land cover change scenarios in the Huangshui River Basin, China. *Ecol. Indic.* **2022**, *144*, 109539. [[CrossRef](#)]
65. Shi, M.; Wu, H.; Fan, X.; Jia, H.; Dong, T.; He, P.; Baqa, M.F.; Jiang, P. Trade-offs and synergies of multiple ecosystem services for different land use scenarios in the yili river valley, China. *Sustainability* **2021**, *13*, 1577. [[CrossRef](#)]
66. Lou, Y.; Yang, D.; Zhang, P.; Zhang, Y.; Song, M.; Huang, Y.; Jing, W. Multi-scenario simulation of land use changes with ecosystem service value in the Yellow River Basin. *Land* **2022**, *11*, 992. [[CrossRef](#)]
67. Xie, L.; Wang, H.; Liu, S. The ecosystem service values simulation and driving force analysis based on land use/land cover: A case study in inland rivers in arid areas of the Aksu River Basin, China. *Ecol. Indic.* **2022**, *138*, 108828. [[CrossRef](#)]
68. Arunyawat, S.; Shrestha, R.P. Assessing land use change and its impact on ecosystem services in Northern Thailand. *Sustainability* **2016**, *8*, 768. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.