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Spatial Optimization of Land Use Allocation Based on the Trade-Off of Carbon Mitigation and Economic Benefits: A Study in Tianshan North Slope Urban Agglomeration

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Abstract: The rational allocation of land use space is crucial to carbon emissions reductions and economic development. However, previous studies have either examined inter-objective trade-offs or intra-objective trade-offs within a single objective and lacked multilevel and comprehensive studies. Therefore, this paper integrates inter- and intra-objective carbon mitigation and economic efficiency trade-offs to comprehensively study the interaction between land pattern demand and space due to policies. The research methods were mainly multi-objective planning, a gray model, and patch-generating land use simulation model, and the study area was the less-developed urban agglomeration—the Tianshan north slope urban agglomeration. The results of the study show that the total change area of the study area from 2000 to 2020 was 5767.94 km^2, the grassland area was transferred out the most, 3582.59 km^2, accounting for 62.11%, and the cultivated land area was transferred in the most, 3741.01 km^2. Compared with 2020, the simulated land use pattern obtained for 2030 has significantly changed. In addition, the total economic benefits and total carbon emissions under the economic and low-carbon objectives changed in the opposite direction. The four landscape patterns under the three scenarios of economic and low-carbon objectives changed in the same direction, and the degree of landscape fragmentation, agglomeration, and regularity under the low-carbon objective was better than that under the economic objective. The study results are essential references for future land resource management, carbon mitigation, and sustainable development of urban agglomerations.

Keywords: carbon mitigation; economic benefits; scenario simulation; spatial optimization; Tianshan north slope urban agglomeration

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1. Introduction

The average temperature of the Earth's surface has risen in the last one hundred years above the highest levels of the previous few thousand years and is expected to continue to rise [1–3]. The increase in the average temperature has led to a series of climatic and ecological problems, such as the occurrence of extreme weather events (droughts and floods), the rise in sea level, and the decrease in biodiversity; global warming has become one of the severe challenges to the world's economic development [4–6]. In response to climate warming, the Paris Agreement proposes that global warming within the 21st century should be kept within 2 °C compared to pre-industrial levels, and efforts should be made to keep it within 1.5 °C. Otherwise, the ecological environment will continue to deteriorate [7,8]. Carbon emissions mainly originate from using energy sources such as coal, oil, electricity, etc.; land is an important carrier of these energy sources [9,10]. According to the way of use, land is divided into different types such as cultivated land, forest land, and construction land [11–13]. The amount of greenhouse gases emitted and the level of economic benefits vary according to the type of land use (e.g., construction land consumes a large amount of energy and thus emits a large amount of greenhouse gases but has a high economic level). In contrast, grassland, which is less affected by human activities, emits far fewer greenhouse gases than construction land but has a low economic level [12,14]). Therefore, the rational allocation of land use space is crucial to carbon emissions and economic development. In turn, optimizing land use space by the government's carbon reduction targets and the requirements of the level of economic growth can reflect the trade-offs between carbon reduction and economic development, as well as accurately controlling carbon emissions and economic level.

Land use spatial optimization is based on the human–land relationship [15], system theory [16], ecological economy [17], spatial equilibrium theory [18], etc. and adjusts the structure and layout of land use types by setting objectives and constraints to achieve the benign development of society, economy, and ecology [5,19,20]. Based on different conflicting goals, the early literature focused on the ecological service system and economic benefits as objectives to simulate land demand [21,22]; with the gradual maturation of social benefit measurement methods [23], social benefits were also introduced, such as Zhao et al. setting up the maximization of ecological, economic, and social benefits and adopting the principles of land use suitability and spatial compactness to optimize the land structure and space [24]. Subsequently influenced by national policies, cultivated land protection and carbon emission limitation have become new land optimization objectives [19]. In the existing research on the relationship between carbon emission and land use, the literature is often based on the energy perspective, with carbon emission efficiency and carbon neutrality as one-dimensional objectives, and economic benefits are only regarded as constraints [25–28]. Secondly, divided by the methodological purpose of the research in this field, scholars have already used the main tools such as the multi-objective programming model (MOP), gray linear programming (GM (1, 1)), system dynamics, etc. to optimize the land structure [29,30]. The ant colony algorithm [24], meta-cellular automata model [31], genetic algorithm [32], CLUE-S [33] (conversion of land use and its effects at small region extent) model, and other methods have been more frequently used in land spatial optimization studies [34].

Although the existing literature provides rich insights for us to understand the optimization of land patterns, as well as rich mathematical methods for us to carry out this research, there are still the following shortcomings: Firstly, in terms of research content, there are still not many current studies on the trade-offs between carbon mitigation and economic benefits through optimizing land structure and layout, and they are still in their infancy [27]. The existing literature mainly examines the trade-offs between objectives or trade-offs within a single goal. It lacks the study to further set up multiple scenarios under carbon mitigation and economic efficiency objectives to explore the land optimization problem within the objectives from various perspectives and at multiple levels. Secondly, regarding constraint setting, empirical constraints and land planning documents are often considered constraints, and mutual constraints between objectives are lacking. Thirdly, in terms of the research area, the past literature usually involves developed city groups, provinces, and regions, such as when Wu et al. analyzed the land optimization problem of Chengdu, a first-tier city in China [19]. There is a lack of land optimization problems under the objectives of carbon mitigation and economy trade-offs in less-developed regions. Conducting research with less-developed economic regions is conducive to obtaining different conclusions and also helps enrich the land optimization literature study area.

Aiming at the above deficiencies, this paper establishes two objectives of minimizing carbon emissions and maximizing economic benefits, analyzes the relationship between the two objectives by setting constraint thresholds between the objectives, and sets three scenarios of low-carbon development, economic development, and coordinated development under each objective to further study the deeper relationship between the two within the objectives. The underdeveloped urban agglomeration Tianshan north slope urban agglomeration was taken as a case study, and multi-objective planning and gray linear planning were used to predict the land pattern demand in 2030. The PLUS model was used to optimize the land spatial layout in 2030. In addition, the total carbon emissions and economic benefits of the land optimization results and the size of the landscape pattern index were calculated, and the land use structure and layout plan suitable for the study area were obtained by comparing the results and combining the actual situation.

China was selected as the country where the study area was located; it is not only the largest developing country in terms of economic output, but also one of the largest emitters of carbon [35,36]. In 2020, at the 75th session of the United Nations General Assembly, China, for the first time, put forward the goal of "carbon peaking and carbon neutrality" (hereinafter "the dual-carbon target") [37]. Establishing the "dual-carbon" goal indicates that China will go from carbon peak to carbon neutral in the shortest time in history. Currently, China is in the stage of new industrialization and urbanization, and there is still a great potential for future economic development. The trade-off between China's economy and carbon reduction in land use types is essential to the world economy and climate change [38,39]. The Tianshan north slope urban agglomeration was chosen because it is the resource-rich and most economically active region in Xinjiang, China, and has a radiation-driven role in the economy of the whole territory. It is also the westernmost point of the land-bridge corridor in the "two horizontal and three vertical" strategic urbanization pattern, which is also an essential impetus to China's economic development [40–42]. Because of the rich mineral resources of the urban agglomeration on the Tianshan north slope urban agglomeration, although the region accounts for only 5.7% of Xinjiang's land area, it concentrates 83% of the heavy industry in the whole of Xinjiang, which puts enormous pressure on the environment [43,44]. Exploring the trade-offs between economic development and carbon mitigation in this study area is strategically significant for China's climate governance.

The main objectives of this study were to (1) obtain the evolutionary pattern of land use changes in the Tianshan north slope urban agglomeration from 2000 to 2020; specifically, the land transfer matrix model was used to analyze the situation; (2) project the land demand in 2030 for each scenario; specifically, it was obtained by setting the objective function and constraints and using the LINGO platform; (3) optimize and simulate the land structure and allocation in 2030; specifically, based on the number of each land type under different scenarios, the results were obtained through the domain weights, transfer matrix, and restriction of conversion areas in the PLUS model; and (4) evaluate and compare the spatial optimization schemes; specifically, landscape pattern indices such as an aggregation index and average subdimension were used, and total carbon emission and economic value were calculated for evaluation and comparison. The study results are intended to provide a scientific reference and basis for the allocation of land structure and space in less-developed cities under the trade-off between carbon mitigation and economic efficiency.

2. Materials and Methods

2.1. Study Area

The Tianshan north slope urban agglomeration is located in the northern part of Xinjiang (83°24′~91°56′ E, 40°18′~46°11′ N), including the three prefectural-level cities of Urumqi, Karamay, and Turpan and five county-level cities of Wusu, Kuitun, Shawan, Shihezi, and Wujiaqu, as well as one autonomous prefecture, Changji, with about 193,900 km^2 (Figure 1) [43]. The region was formed in the flood–alluvial fan, in the hinterland of the Junggar Basin, with a unique and complex climate, including a temperate continental climate and plateau–alpine climate from south to north, with an average annual temperature of −15~15 °C, yearly precipitation of 0~1092 mm, and 53.98% of the land belonging to the arid and semi-arid areas [45]. Its economic status is critical, as it is the core area of the Silk Road Economic Belt, the westernmost point of the land-bridge corridor in the "two horizontal and three vertical" strategic pattern of urbanization, and the country's most resource-rich and economically active region. The urban agglomeration is one of the oasis city clusters in arid zones that the government will focus on cultivating in the future, and how to balance economic development and carbon emission reduction has become a vital issue for this city cluster to take shape and mature.

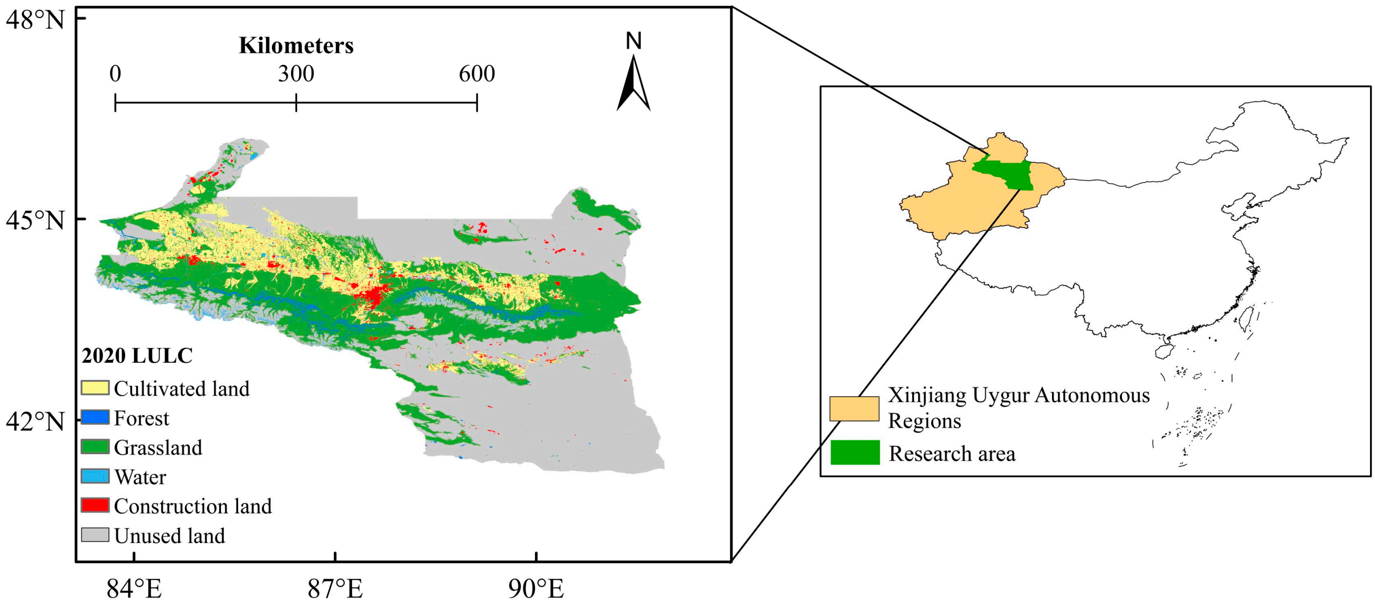

Figure 1. Overview map of the study area.

2.2. Data Sources

The data used in this study were divided into three types: base data, drivers, and socio-economic statistics, and the primary information on these data is summarized in Table 1. The basic data were land use remote sensing monitoring data, which were derived from the GlobeLand30 database; the pre-processing of these data was to classify the land use types and determine the object of land use spatial optimization. The GlobeLand30 database, an essential result for China, contains ten major surface cover types: cultivated land, forest, grassland, shrubland, wetland, water body, tundra, man-made surface, bare land, glacier and permanent snow. Combined with the current land use status of the region, the land use types were reclassified into cultivated land, forest, grassland, waters, construction land, and unused land (Table 2). The role of these data was threefold: Firstly, they were used to analyze trends in the spatial and temporal evolution of land use types from 2000 to 2020. Secondly, they were used to forecast land demand in 2030. Thirdly, it helped to simulate the spatial distribution of land patterns in 2030.

Table 1. Characteristics of dataset.

Data Type *	Data	Time Range	Resolution	Source	Description
Basic data	Land use	2000, 2010, 2020	30 m	https://www.webmap.cn/commres.do?method=globeIndex	Land use types, area
Driver data	DEM	2019	90 m	https://www.gscloud.cn/	Spatial grid data describing the elevation and slope
	Slope	2019	90 m	Calculated by DEM	
	Annual precipitation	2020	1 km	https://worldclim.org/data/index.html	Spatially interpolated datasets describing annual precipitation, annual mean temperature, and annual mean wind speed in the study area
	Average annual temperature	2020	1 km		
	Average annual wind speed	2020	1 km		
	Population density	2020	1 km	https://www.resdc.cn/	Spatial distributed grid datasets describing the population and GDP
	Average land GDP	2019	1 km		
	Highway	2020	-	https://www.webmap.cn/main.do?method=index	Spatial distributed datasets describing highway, railway, and water system
	Railroads	2020	-		
	Water system	2020			
Statistical data	Agriculture, forestry, animal husbandry and fishery output, etc.	2000–2020	-	https://tjj.xinjiang.gov.cn/tjj/zhhvgh/list_nj1.shtml	Temporal datasets describing the socio-economic level of the study area

* Basic and statistical data were accessed on 15 January 2024; driver data were accessed on 25 January 2024.

Table 2. Land use classification system.

Research Target	Type	Definition
Cultivated land	Cultivated land	The land is used for agriculture, horticulture, and gardens.
Forest	Forest	Land with tree cover and more than 30% canopy cover, and open forest land with 10–30% canopy cover.
	Shrub land	Land with shrub cover and more than 30% scrub cover, and desert scrub with more than 10% cover in desert areas.
Grassland	Grassland	Land with natural herbaceous vegetation covers more than 10% of the land.
Water	Water bodies	Areas covered by land-wide liquid water, including rivers, lakes, etc.
Construction land	Artificial surfaces	Surfaces formed by man-made construction activities.
Unused land	Bare land	Land with a natural cover of less than 10% vegetation.
	Tundra	Land covered by lichens, mosses, perennial hardy herbaceous and shrubby vegetation in boreal and alpine environments.
	Wetland	It is located in the boundary zone between land and water.
	Permanent snow and ice	Land covered by permanent snow, glaciers, and ice caps.

Socio-economic statistics were mainly used for determining the economic value and carbon emission coefficient in the objective function, including the output value of agriculture, forestry, animal husbandry, and fishery, the output value of secondary and tertiary industries, the input value of agricultural materials, the energy consumption for life and production of industrial enterprises and urban residents, the sown area of agricultural crops, etc. They were obtained from the Statistical Bureau of Xinjiang Uygur Autonomous Region, the Xinjiang Production and Construction Corps, etc. Further explanation: this dataset was mainly used to obtain the economic benefits and carbon emissions per unit area of cultivated land, forest, grassland, waters, and construction land from 2000 to 2020, and based on this result, the economic benefits and carbon emissions per unit area of cultivated land, forest, grassland, waters, construction land were forecasted for 2030.

The driver data were principally the development potential of land use types in the PLUS model, in which the digital elevation model is obtained from the geospatial data cloud and the slope data are obtained by extracting the digital elevation model through ArcGIS. The spatial distribution data of annual precipitation and annual average temperature were obtained from the Global Climate and Weather Database; the spatial distribution data of the yearly average wind speed, the population, GDP, and the vector of nature reserve range were derived from the Chinese Academy of Sciences. The road, railroad, and water system data were obtained from the National Geographic Information Resource Catalog Service System; the distance from the grid image of each land use type to the nearest road, railway, and water was obtained by the Euclidean distance processing in ArcGIS. These data were primarily used to help simulate the spatial distribution of land patterns in 2030.

We harmonized the projected coordinate system and the number of rows and columns of the above spatial data, and we harmonized the resolution to 30 m.

2.3. Research Design and Methods

The technical roadmap of the research is shown in Figure 2. The methods used in the research were classified into four types: land use transfer matrix, land use quantitative demand method, land use spatial optimization method, and landscape pattern index evaluation. Among them, in the land use quantity demand acquisition method, multi-objective planning breaks through the limitations of linear planning that can only list one-dimensional objective functions and has the advantages of positive and negative feedback of system dynamics. Still, it is easier to operate than system dynamics [21]. Meanwhile, to predict the future economic efficiency and carbon emission coefficients, this paper integrates GM (1, 1) and MOP models to determine the land use demand. Among the land use spatial optimization methods, the PLUS model was developed based on the FLUS model (future land use simulation), which solves the problem of land use simulation on the patch scale that could not be achieved in the past [46]; so, according to the PLUS model, this paper tries to complete spatial and structural optimization. Detailed descriptions and specific practices of the methods are shown in Section 2.3.1, Section 2.3.2, Section 2.3.3, Section 2.3.4.

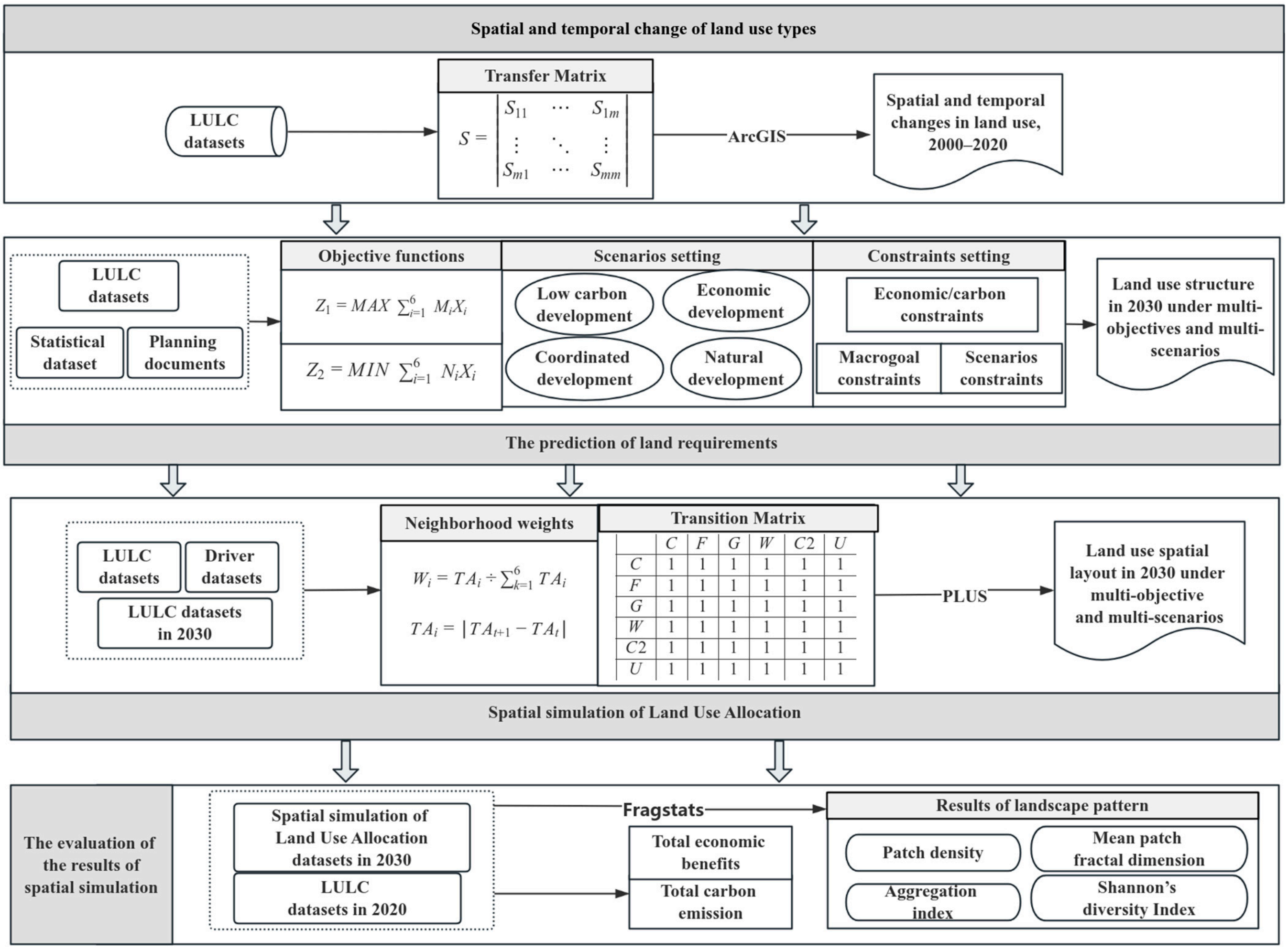

Figure 2. Technical route. Notes: Z_1, Z_2 are the economic objective function and carbon emissions objective function, respectively. A detailed explanation is shown below, in Section 2.3.2.

2.3.1. Transfer Matrix Modeling

The land use transfer matrix is mainly used to describe the structural characteristics of land use change, which can reflect the mutual conversion of land use types in different periods, and the result is expressed by a two-dimensional matrix [47]. Through the superposition analysis in ArcGIS 10.7, the transfer matrices between 2000 and 2020 were obtained, from which the direction of inflow and outflow of each land use type could be analyzed to obtain the land use evolution pattern. The generalized form is:

$$S_{ij} = \begin{vmatrix} S_{11} & S_{12} & \cdots & S_{1m} \\ S_{21} & S_{22} & \cdots & S_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ S_{m1} & S_{m1} & \cdots & S_{mm} \end{vmatrix} \tag{1}$$

where S represents the area, m represents the number of land use types before and after the transfer, $i, j(i, j = 1, 2, \ldots\ldots, m)$ represents the land use types before and after the transfer, respectively, and S_{ij} represents the area of land type i before the transfer that is converted to land type j.

2.3.2. Land Use Quantity Demand Approach

The land use quantity demand needs to determine the objective function according to the research content and then determine the constraints according to the national macro plan. This study used the GMMOP model to solve the land use quantity demand results under different objectives and scenarios. GMMOP is an integration of gray linear programming and multi-objective linear programming models. Among them, GM (1, 1) was used to predict the economic value and carbon emission coefficient of the research area in 2030. The MOP model can realize the constraints to solve the optimal value of the land use quantity under different scenarios with multiple objectives.

- Coefficients for the economic value and carbon emissions of land use

Economic value and carbon emission coefficients are mainly used to establish the objective function. The economic value coefficient refers to the existing studies [21,48]. The output value of agriculture, forestry, animal husbandry, and fishery per unit area from 2000 to 2020 was taken as the economic value coefficient of cultivated land, forest, grassland, and waters, respectively. The output value of the agriculture, forestry, animal husbandry, and fishery service industries and the secondary and tertiary industries was taken as the economic value coefficient of construction land; the unused land was set as 0.1. The carbon emission coefficient is each land use type's carbon emission per unit area. Among them, the cultivated land was calculated from the use of agricultural materials such as chemical fertilizers, compound fertilizers, agricultural films, and agricultural diesel in agriculture, as well as the plowing of agricultural land [49–51]; grassland was obtained from the CH_4 and N_2O gases released from the intestinal fermentation of livestock and poultry and fecal emissions in animal husbandry by converting them into CO_2 [49,50]; construction land was obtained from the energy consumption of urban land, industrial land, and rural settlement [25]; forest and water carbon emissions were set as 0.03 and 0.72, respectively, concerning the existing literature [25]; and unused land was set to 0.1. The carbon emission calculation method mainly adopts the source strength estimation method based on inventory analysis, and the detailed calculation will not be expanded here due to space limitations. Based on the above data, the economic values and carbon emission coefficients of each category in the study area in 2030 were predicted by GM (1, 1) (Table 3).

Table 3. Economic value and carbon emission coefficients of each land use type in 2030.

	Cultivated Land	Forest	Grassland	Water	Construction Land	Unused Land
Economic value coefficient (10^4 ¥·hm^{-2})	3.82	1.10	0.39	0.51	265.67	0.1
Carbon emission coefficients (t·hm^{-2})	65.27	0.03	0.39	0.72	3501	0.1

- Objective function construction and scenarios' setting

Objective function construction. This paper constructs two objectives: maximizing economic development (economic objective) and minimizing carbon emissions (low-carbon objective). The formula is as follows:

$$Z_1 = MAX\sum_{i=1}^{6} M_i X_i \quad (2)$$

$$Z_2 = MIN\sum_{i=1}^{6} N_i X_i \quad (3)$$

where Z_1, Z_2 are the total economic benefits and total carbon emissions of regional land use, respectively; X is the research subject; X_i is the area of land use in category i; and M_i, N_i are the economic benefits and carbon emissions per unit area of land use in category i, i.e., the economic benefit coefficient and carbon emission coefficient, respectively.

Scenarios' setting. The Tianshan north slope urban agglomeration faces the trade-off between economic development and carbon emission reduction; so, this paper refers to the existing research and experts' experience. In order to emphasize the focus on the economic and low-carbon objectives, three different development scenarios were set up under each objective in addition to the natural development scenario; they are the low-carbon development scenario, the economic development scenario, and the coordinated development scenario, respectively. Among them, the natural development scenario is not subject to policy intervention and was obtained through the Markov chain in the PLUS model; the low-carbon development scenario emphasizes the increase in ecological land with high carbon sequestration capacity, i.e., forest, grassland, and waters; the economic development emphasizes appropriately liberalized economic policies and the expansion of the area of agricultural, urban, and industrial oases to promote economic efficiency; and the coordinated development scenario involves the rationalization of the area of low-carbon land and economic land to achieve the coordinated development of low-carbon and economy.

- Constraints' setting

In order to enhance the match between scenario simulation and relevant policies and development needs, the following constraints were set (Table 4). Three development scenarios were set up under both objectives, and the constraint on the total economic value was set based on the growth rate in 2030 compared with that in 2020 obtained from the regional GDP projections for the period 2000–2020 for the coordinated development scenario; the other two scenarios were adjusted up or down as appropriate. The total carbon emission constraint was set by the article "Strengthening Action to Combat Climate Change: China's Nationally Owned Contributions", which states that carbon emissions per unit of GDP should be reduced by 60–65% by 2030 compared with the 2005 level. Therefore, the coordinated development scenario was set to reduce carbon emissions per unit of regional GDP by 65%, with a 5% upward and downward fluctuation in low-carbon development and economic development. The macro target constraints and scenario constraints were based on the "14th Five-Year Plan for the Protection, Development, and Utilization of Land Resources in the Xinjiang Uygur Autonomous Region", the "Overall Territorial Spatial Plan of Urumqi City (2021–2035)", and other policies and plans.

Table 4. Constraint setting.

Target Type	Scenario Setting	Economic/Carbon Constraints	Macro-Goal Constraints	Situational Constraints
Economic target	Low-carbon development	70% reductionin carbon	(1) Total area constraints: the total area of each land use type is 19,394,160.03 ha; $\sum_{i=1}^{6} x_i = TA$	Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq$ CUAN; Construction land area: $X_5 \geq$ COAC; $X_5 \leq 1.2$*COAC; Unused land area: $X_6 \geq 0.95$*UAC
	Coordinated development	60% reductionin carbon		Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq 1.2$*CUAC; Construction land area: $X_5 \geq$ COAC; $X_5 \leq 1.2$*COAC; Unused land area: $X_6 \geq 0.925$*UAC
	Economic development	65% reductionin carbon		Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq 1.3$*CUAN; Construction land area: $X_5 \geq$ COAC; Unused land area: $X_6 \geq 0.90$*UAC

Table 4. *Cont.*

Target Type	Scenario Setting	Economic/Carbon Constraints	Macro-Goal Constraints	Situational Constraints
Low-carbon goal	Low-carbon development	20% increasein GDP	(2) Ecological protection: Forest, grasslands, and waters are not lower than the current values. ($X_2 \geq$ FAC; $X_3 \geq$ GAC; $X_4 \geq$ WAC)	Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq$ CUAN; Construction land area: $X_5 \geq$ COAC; $X_5 \leq$ 1.2*COAC; Unused land area: $X_6 \geq$ 0.95*UAC
	Coordinated development	25% increasein GDP		Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq$ 1.2*CUAC; Construction land area: $X_5 \geq$ COAC; $X_5 \leq$ 1.2*COAC; Unused land area: $X_6 \geq$ 0.925*UAC
	Economic development	22.5% increasein GDP		Cultivated land area: $X_1 \geq$ CUAC; $X_1 \leq$ 1.3*CUAN; Construction land area; $X_5 \geq$ COAC; Unused land area: $X_6 \geq$ 0.90*UAC

Notes: TA denotes total area; FAC denotes forest area of 2020 (259,542.9 ha); GAC denotes grassland area of 2020 (5,901,417.6 ha); WAC denotes water area of 2020 (175,399.2 ha); CUAC denotes cultivated land area of 2020 (2,248,494.6 ha); CUAN denotes cultivated land area in the natural development scenario (2,352,502.44 ha); COAC denotes construction land area in 2020 (339,688.4 ha); UAC denotes unused land area in 2020 (10,469,617.38 ha); X_1, X_2, X_3, X_4, X_5, and X_6 represent cultivated land, forest, grassland, waters, construction land, and unused land, respectively.

2.3.3. Spatial Optimization Models

On the basis of the quantitative land use demand under different objectives and scenarios obtained from the GMMOP model, the PLUS model was coupled to optimize the spatial layout of land use under different objectives and scenarios in 2030. In addition to the demand for land use quantity, the PLUS model must also set up the driving factors, domain weights, restricted conversion areas, and conversion rules. The main steps of the PLUS model were as follows: Firstly, we took the 2000 and 2010 land use data as the basic data, and, according to the driving factors, domain weights, restricted conversion areas, and conversion rules, obtained the 2020 land use data through the PLUS model prediction. Then, the predicted 2020 land use data and the actual 2020 land use data were verified for accuracy; when the Kappa value is more than 0.7, it indicates higher accuracy. Finally, using the 2010 and 2020 land use data as the base data, and according to the original set of drivers, domain weights, restriction of conversion areas, and rules, and then inputting the land use quantity demand of 3 different scenarios under the two objectives, six spatial optimization results of land use in 2030 were obtained.

(1) Driving factors' selection. Driving factors were mainly used to obtain the development potential data of each land use type, combining with the actual situation of the study area and referring to the existing literature [21,52]; selecting soil type, elevation, and slope as the geological and topographic driving factors; annual average wind speed and temperature and annual precipitation as the climatic driving factors; population density and land-averaged GDP as the socio-economic driving factors; and the distance to highway, distance to railway, and distance to water as the accessibility driving factors.

(2) Neighborhood weight setting. Domain weights mainly indicate the expansion ability of each land use type. The range is 0–1; closer to 1 means a more vital expansion ability of the land use type [46]. We found, through the following formula, combined with an expert opinion, the obtained domain weights of cultivated land, forest, grassland, water, construction, and unused land were, respectively, 0.21, 0.1, 0.28, 0.1, 0.1, and 0.21.

$$W_i = \frac{TA_i}{\sum_{i=1}^{6} TA_i} \tag{4}$$

$$TA_i = |TA_{t+1} - TA_t| \tag{5}$$

In Equation (4), W_i is the domain weight of land use in category i and TA_i is the area of expansion or contraction of land use in category i. In Equation (5), TA_{t+1} and TA_t indicate the area at the end and beginning of a land use type, respectively.

(3) Transition matrix setting. The transition matrix mainly stipulates whether a certain land use type can be converted to another one, with 0 representing that it cannot and 1 representing that it can. By analyzing the land use changes in 2000–2020, it was found that each category could be converted to another one; therefore, the values of the transition matrices were set to 1.

(4) Accuracy verification. To verify the accuracy of the above model construction, the land use results in 2020 were predicted from the basic data and driver data in 2000 and 2010. A Kappa value of 0.86 was obtained by comparing them with the real data, indicating that the model had high accuracy. It can be used for the simulation of the land use of the research area in 2030.

2.3.4. Landscape Pattern Index

This paper introduces the landscape pattern index to evaluate the land use spatial layout optimization results, including four indices: aggregation index, patch density, mean patch fractal dimension, and Shannon's diversity index. Among them, the aggregation index refers to the spatial agglomeration level of the landscape; the larger the value is, the higher the level is. Patch density refers to the fragmentation level of the landscape; the larger the value is, the higher the level is. Mean score dimension refers to the regularity of the landscape layout; the lower the value is, the more regular it is. Shannon's diversity refers to the level of landscape diversity; the higher the value is, the higher the level is.

3. Results and Analysis

3.1. Spatial and Temporal Characteristics of Land Use Change

The land use type of the Tianshan north slope urban agglomeration is dominated by unused land and grassland, followed by cultivated land, forest, and construction land (Figure 3). From 2000 to 2020, cultivated land, water, and construction land decreased by 3019.3 km^2, 18.13 km^2, and 1236.65 km^2, respectively. Forest, grassland, and unused land increased by 38.52 km^2, 3073.51 km^2, and 1162.05 km^2, respectively. The total transferred area was 5767.94 km^2, with grassland transferring the largest area, 3582.59 km^2, accounting for 62.1% of the total transferred area, of which 80% was transferred to grassland. The next largest area transferred out was unused land, at 1279.27 km^2, accounting for 22.2% of the total transferred area, of which 64.2% was transferred to cultivated land. Therefore, cultivated land was the most transferred area, with 3741.01 km^2 transferred, followed by construction land, with 1237.11 km^2 transferred (Table 5).

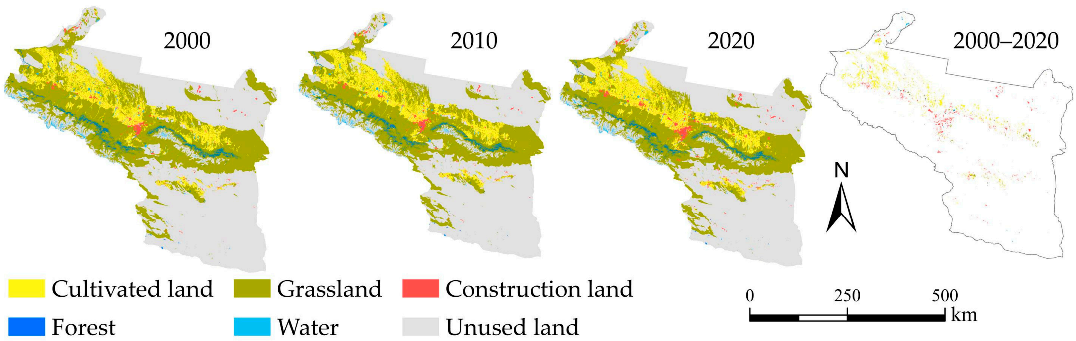

Figure 3. Land use change map.

Table 5. Transfer matrix (km^2).

2020 2010	Cultivated Land	Forest	Grassland	Water	Construction Land	Unused Land	Transfer Out
Cultivated land	18,743.94	0.03	344.39	2.93	371.69	2.67	721.71
Diversion rate	—	0.005%	47.7%	0.4%	51.5%	0.4%	100%
Forest	40.35	2582.21	6.13	1.70	2.34	1.21	51.72
Diversion rate	78.0%	—	11.9%	3.3%	4.5%	2.3%	100%
Grassland	2865.75	11.54	58,505.10	109.50	538.06	57.74	3582.59
Diversion rate	80.0%	0.3%	—	3.1%	15.0%	1.6%	100%
Water	12.98	—	43.89	1603.69	19.70	55.60	132.18
Diversion rate	9.8%	0%	33.2%	—	14.9%	42.1%	100%
Construction land	0.41	—	0.05	0.0009	2159.77	—	0.46
Diversion rate	88.4%	0%	11.4%	0.2%	—	0%	100%
Unused land	821.53	1.64	114.62	36.17	305.32	104,578.95	1279.27
Diversion rate	64.2%	0.13%	9.0%	2.8%	23.9%	—	100%

3.2. Quantitative Land Use Requirements under Different Objectives and Scenarios

According to the LINGO 18.0 platform, the land use quantity demand results for the low-carbon development, coordinated development, and economic development scenarios under macro-objectives, ecological protection, trade-offs, and scenario constraints were obtained for the economic and low-carbon objectives, respectively (Table 6).

Table 6. Quantitative land use needs in 2030 (thousand km^2).

Target	Scenario Setting	Cultivated Land	Forest	Grassland	Water	Construction Land	Unused Land
Economic target	Low-carbon development	23.53	6.11	59.01	1.75	4.08	99.46
	Economic development	28.23	2.60	59.01	1.75	8.12	94.23
	Coordinated development	26.98	3.96	59.01	1.75	5.38	96.84
Low-carbon goal	Low-carbon development	22.48	3.11	59.01	1.75	3.40	104.18
	Economic development	28.23	3.11	59.01	1.75	3.40	98.43
	Coordinated development	23.53	3.11	59.01	1.75	3.40	103.14

From 2020 to 2030, land patterns can change significantly. Under the natural development scenario, compared to 2020, cultivated land will increase by 4.6%, grassland will decrease by 3.1%, water will decrease by 1.4%, and construction land will change the most, rising by 32.1%. Under the economic maximization objective, cultivated land, forest, and construction land will increase significantly, with cultivated land rising by 4.6%, 20.6%, and 25.6% under the low-carbon, economic, and coordination scenarios, respectively, compared to 2020. Construction land will increase by 20%, 139.1%, and 58.5%, respectively. The increase in cultivated land, forest, and construction land will slow down under the carbon minimization objective compared to the economic maximization objective, and in order to minimize carbon emissions, the cultivated land will maintain a status quo under the low-carbon objective and the increase will decrease to 4.6% under the coordinated development scenario. The increase in forest land will decrease to 20% under the low-carbon, economic, and coordination scenarios, and the construction land area will be at the 2020 level.

Comparing the area of land types between the two objectives shows that the area of grassland and water under both objectives will be the same as in 2020, although unchanged, and indirectly protected through ecological conservation constraints towards the natural development scenario. The presence of forest land with higher or lower areas under the three scenarios of the economic objective than under the low-carbon objective indicates that forest land will be both an economic and low-carbon land type, which is consistent with reality. The area of cultivated land will increase under both the economic and low-carbon targets compared to 2020, suggesting that there will be scope for cultivated land to increase under existing economic and low-carbon constraints. Construction land area will grow considerably under the economic target but remain consistent with 2020 under the low-carbon target, suggesting that construction land should not expand further under the low-carbon target.

3.3. Optimization Results of Land Use Structure and Layout

The results in Section 3.2 were taken as the quantitative data of spatially optimized land use, combined with the driving factors, domain weights, transfer matrix, and other data, obtaining the optimization results of land use structure (Table 7) and spatial layout optimization (Figures 4 and 5) in the study area. After comparing Tables 6 and 7, it was found that there is not much difference between the optimized area and quantity demanded for each category, which again verifies that the model's accuracy is good.

Table 7. Results of optimizing the land use structure in 2030 (thousand km^2).

Target	Scenario Setting	Cultivated Land	Forest	Grassland	Water	Construction Land	Unused Land	Total Economic Benefits/10^8 ¥	Total Carbon Emissions/10^8 t
Economic target	Low-carbon development	26.98	2.61	59.01	1.75	5.38	98.21	1.57	20.67
	Economic development	28.23	2.59	59.01	1.75	8.12	94.23	2.30	30.34
	Coordinated development	26.98	2.60	59.01	1.75	5.38	98.21	1.57	20.67
Low-carbon goal	Low-carbon development	22.48	2.61	58.93	1.75	3.40	104.77	1.03	13.42
	Economic development	28.23	2.59	55.43	1.75	3.40	102.55	1.05	13.80
	Coordinated development	23.53	2.74	59.01	1.75	3.40	103.52	1.03	13.49
2020		23.53	2.59	57.21	1.73	4.49	104.40	1.32	17.30
Natural development		22.48	2.60	59.01	1.75	3.40	104.70	1.03	13.42

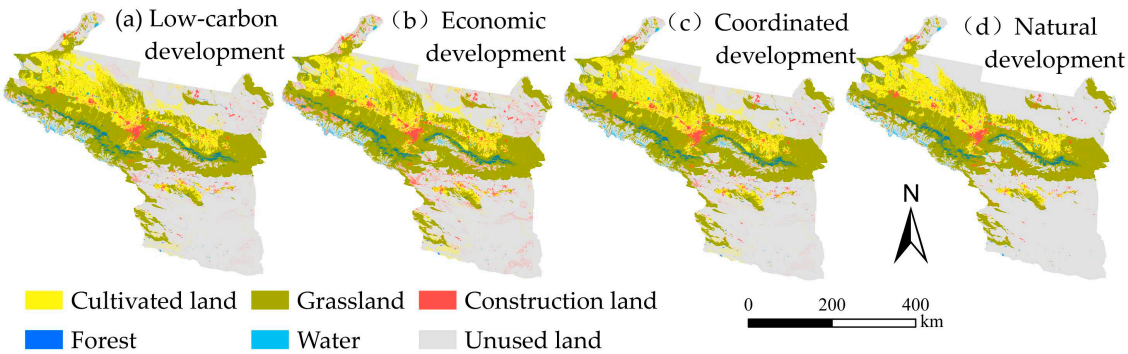

Figure 4. Optimization results of land use allocation in 2030 under the economic objective.

According to Figure 4, it can be seen that the source of the increase in cultivated land under the economic objective is mainly the exploitation of unused land at the edge of cultivated land, which is distributed primarily in the central northwestern part of the study area. The increase in construction land comes from unused and cultivated land, which is more widely distributed, mainly dispersed around the edge of cultivated land and mainly distributed in the study area's central and central northeastern parts. The increase in forest land under the low-carbon target compared to 2020 is obtained from the conversion of cultivated and unused land, which is mainly distributed in the central southeastern part of the study area.

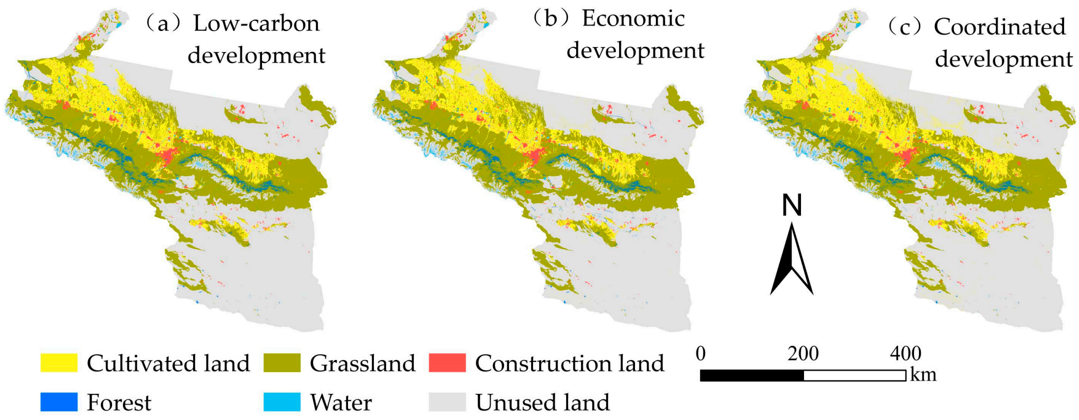

Figure 5. Optimization results of land use allocation in 2030 under carbon emission minimization.

Analyzing the total economic benefits and total carbon emissions shows that compared to 2020, while total carbon emissions decrease by 22.4% under the natural development scenario in 2030, total economic benefits also decrease by 22.2%. Under the economic objective, total economic benefits increase by 19.1%, 74.6%, and 19.1% under the low-carbon, economic, and harmonization scenarios, respectively. Total carbon emissions increase by 19.4%, 75.3%, and 19.4%. Total economic benefits and total carbon emissions decrease by about 20% under the low-carbon goal for all three scenarios. Total economic benefits and total carbon emissions increased more in all three scenarios under the economic goal than in the natural development scenario, while total economic benefits and total carbon emissions stopped decreasing in all three scenarios under the low-carbon goal, and all were positive.

A further analysis revealed that the total economic benefits and total carbon emissions will be the largest under the economic development scenario with the economic objective and the smallest under the low-carbon development scenario with the low-carbon objective, showing a trade-off between economic development and carbon emissions. Under the economic objective, the values of total economic benefits of the three scenarios will be higher than those of the natural development scenario, but the growth of land categories with high economic coefficients such as cultivated land and construction land will make the total carbon emissions of the three scenarios higher than the total carbon emissions of the natural development scenario. The total economic benefits of the three scenarios will decrease under the low-carbon target compared to the economic target but will increase by 1.98% and 0.39% for the economic and coordinated development scenarios, respectively. The total carbon emissions will be slightly higher than the 2020 emissions, but the land use structure of the low-carbon target will achieve a more significant reduction in carbon emissions through a more minor reduction in construction land than the land use structure of the economic target.

3.4. Evaluation of Landscape Pattern Indices

Based on the Fragstats 4.2 platform, the map of land use status quo in 2020 and the map of land use layout optimization under the economic target and low-carbon target in 2030 were used as data sources to calculate the landscape pattern indices of the current status quo of the Tianshan north slope urban agglomeration and the optimization of the layouts under the economic target and low-carbon target (Table 8). The current land use of the Tianshan north slope urban agglomeration has a patch density of 0.08, a mean patch fractal dimension of 1.09, a degree of agglomeration of 99.06, and Shannon's diversity of 0.62, with a low degree of fragmentation of the overall landscape, a high degree of agglomeration, and a general degree of regularity and diversity. Compared with 2020, the four landscape patterns under the three scenarios of economic and low-carbon objectives changed in the same direction, with patch density and Shannon's diversity generally higher than the status quo and the average subdimensional index and degree of aggregation usually lower than the status quo, indicating that the overall landscape became more fragmented, with a lower degree of agglomeration and an improved degree of regularity and diversity. A comparison of landscape pattern indices between targets revealed that patch density and Shannon's diversity under the economic target were generally higher than those under the low-carbon target. The average subdimensional index and aggregation degree were usually lower than those under the low-carbon target, which indicates that the degree of landscape fragmentation, agglomeration, and regularity under the low-carbon target was better than those under the economic target.

Table 8. Landscape pattern indices for different objectives and contexts.

Target	Scenario Setting	Patch Density	Mean PatchFractal Dimension	Aggregation Index	Shannon's Diversity Index
Economic target	Low-carbon development	1.33	1.06	97.68	0.66
	Economic development	1.68	1.05	97.28	0.68
	Coordinated development	1.33	1.06	97.68	0.66
Low-carbon goal	Low-carbon development	0.11	1.08	99.03	0.62
	Economic development	1.07	1.06	98.08	0.64
	Coordinated development	0.46	1.07	98.72	0.63
2020		0.08	1.09	99.06	0.62

4. Discussion

Land use is often oriented to multiple objectives, and scientific land use structure and spatial optimization according to different objectives is an important step to achieve the objectives [23,53]. In the context of promoting urbanization and implementing the "dual-carbon" strategy, how to better weigh the dual objectives of economic development and carbon emission reduction has become a significant challenge for the Tianshan north slope urban agglomeration [54]: whether it is to continue to take economic development as the goal and increase the consideration of low-carbon development or to pursue a certain value of economic efficiency based on the guarantee of minimizing carbon emissions. This paper quantitatively compares the optimization results of land use structure and layout in three scenarios of economic development, low-carbon development, and coordinated development under the two objectives of economic and low-carbon goals by coupling the GMMOP and PLUS models. This paper has three main contributions: Firstly, the article quantifies national policies to achieve inter-objective trade-offs. Secondly, low-carbon, economic, and coordination scenarios are set for each goal. The past literature has only explored the trade-offs between economic and low-carbon objectives or the optimization of land patterns under low-carbon objectives based on the energy perspective only. Thirdly, it enriches the research object, as the past literature tends to use developed regions as the research object, with less research on less-developed regions.

The results of this paper have both similarities and differences with the existing literature. In terms of simulating the spatial allocation of land in 2030, compared with 2020, the land pattern changes significantly under the two targets, and the low-carbon target brings about a more significant reduction in carbon emissions compared with the economic target and the natural development target, which is consistent with the results of the studies by Ding et al. [5,55] and Zeng et al. [25]. The values of total economic benefits and total carbon emissions are the largest in the economic development scenario of the economic targets and the smallest in the low-carbon development scenario of the low-carbon targets, which again verifies the trade-offs between economic development and carbon emissions, which is consistent with the results of the studies by Li et al. [56] and You et al. [27]. In addition, this paper adds to the existing findings that, compared with the economic target, the land pattern of the low-carbon target achieves a more significant reduction in carbon emissions through a more minor reduction in construction land, which suggests that the low-carbon development pattern is also applicable to less-developed urban agglomerations. The area of forest under the three scenarios of the economic target exists higher or lower than that under the low-carbon target, indicating that forest is a medium-attribute land pattern, which neither belongs to the land pattern with very strong economic attributes such as construction land nor to the land pattern with weaker economic attributes such as grassland. This is also different from the results of past studies.

In conclusion, the paper examines the optimization of land patterns under carbon mitigation and economic trade-offs through geographic information technology and mathematical models. It provides theoretical and technical guidance for the integrated management and sustainable development of land in underdeveloped regions and to realize carbon mitigation and economic efficiency trade-offs. In future research, policies at different levels can be quantified to examine the interaction between land use patterns and space. In addition, in this paper, when setting the economic growth constraint threshold under the low-carbon goal, we predicted the regional GDP in 2030 through the gray model based on the regional GDP data from 2000 to 2020 and obtained the growth rate of 2030 relative to 2020, which is used as the economic growth constraint under coordinated development; combined with the existing literature, the economic development and low-carbon development are, respectively, up and down by 2.5 percent. In the future, it can be predicted by different mathematical models and adjusted in combination with reality, and other data can be used for the up and down floating rate to compare the research results under different floating rates, thus forming a new research direction and enriching the existing literature on land optimization.

5. Conclusions

Based on the relevant policies, this paper obtains the quantity demand of each land type under the scenarios of economic development, low-carbon development, and coordinated development under the economic target and low-carbon target by integrating the gray model and the MOP model, then couples the PLUS model simulation to obtain the land use structure and spatial allocation in 2030, and obtains the following three conclusions:

(1) From 2000 to 2020, the land use type of the Tianshan north slope urban agglomeration was dominated by unused land and grassland, followed by cultivated land, forest, and construction land. The total change area was 5767.9 km^2, with grassland being transferred out of the largest area, 3582.6 km^2, accounting for 62.1%, and cultivated land being transferred into the largest area, 3741 km^2.

(2) From 2020 to 2030, some land patterns will change significantly—the area of cultivated land will increase under both the economic and low-carbon targets. Forest will be higher or lower than the area under the low-carbon target in all three scenarios of the economic target. Grassland and water areas will remain consistent with 2020. The construction land area will have a significant increase under the economic target but remain consistent with 2020 under the low-carbon target. The increase in cultivated land will be mainly in the central northwest of the study area, the increase in construction land will be mainly in the central and central northeast, and the increase in forest land area under the low-carbon target will be mainly in the central southeast of the study area.

(3) By calculating the total economic benefits and total carbon emissions of each land space optimization scenario, it was found that, compared with 2020, the total economic benefits and total carbon emissions under the economic objective and low-carbon objective will change in the opposite directions (both will increase under the economic target and decrease under the low-carbon target). Compared with the natural development scenario, the total economic benefits and total carbon emissions of the three scenarios under the

economic target will increase more than those under the natural development scenario, while the total economic benefits and total carbon emissions of the three scenarios under the low-carbon target will stop decreasing; all of them will be positive. In addition, the landscape pattern will change significantly. The four landscape patterns will change in the same direction under the three scenarios of the economic target and the low-carbon target. The degree of landscape fragmentation, agglomeration, and regularity under the low-carbon target will be better than that under the economic target.

6. Policy Implications

The implications of this study for carbon mitigation, resource allocation optimization, and spatial management in the Tianshan north slope urban agglomeration are as follows: Firstly, policymakers should combine the spatial optimization results of each scenario to formulate a land pattern optimization policy suitable for the region. A total of six land pattern optimization results were obtained in this study. It is difficult to determine which result is the optimal solution, and it is necessary for policymakers to determine one or two options according to the actual situation in the study area. Secondly, when formulating a land pattern optimization strategy, it is necessary to comply with national guidelines and policies [27,57], such as strictly observing the red line of permanent basic farmland protection, the red line of ecological protection, and the urban development boundary. Finally, in the new urbanization process, policy implementers should appropriately control construction land expansion. They should try to revitalize the stock of construction land, systematically transform and upgrade industries with low utility in urban land to those with high economic returns and low-carbon emissions, and gradually reduce the increment of construction land. At the same time, mixed industrial land development should be explored under relevant policy constraints.

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