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The Impact of Forestry Carbon Sink on Land Use Space Based on FLUS Model

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Abstract: Environmental issues are an important issue facing the world in the 21st century. While China's economy is developing rapidly, the problem of environmental pollution is becoming more and more serious, especially the problem of carbon emissions. Faced with the severe natural ecological environment, China has proposed a dual-carbon goal, that is, China will achieve carbon peaks by 2030 and carbon neutrality by 2060. In order to improve the ecological environment and complete the dual carbon goals on time, in addition to adjusting the industrial structure and improving the technical level to reduce carbon emissions, forestry carbon sink transactions should also be actively used. Forestry carbon sequestration is one of the few carbon sequestration measures that can be implemented at this stage, but the sustainable development of forestry carbon sequestration requires support from land resources, and reasonable land use planning is the premise to ensure forestry carbon sequestration. This research will use the FLUS model based on the artificial neural network algorithm (ANN) and cellular automata algorithm (CA) to analyze the future spatial changes of land use under forestry carbon sink trading and formulate reasonable land planning for sustainable forestry carbon sink trading. FLUS model is a land use simulation algorithm, which is specially used to study the development prediction of land use under different scenarios. The study found that if the forestry carbon sink transaction was implemented, the forest land area in Shenyang could be increased by 303 km^2 and 454,500 tons of CO_2 could be absorbed annually. The forest land would take the lead in choosing the northern and eastern hilly areas for expansion.

Keywords: FLUS model; forestry carbon sink; land use; ecological environment

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1. Introduction

With the development of the economy, ecological environment problems are becoming more and more prominent. Since the Industrial Revolution, human economic development has often come at the cost of environmental damage. Today, environmental problems can no longer be ignored, and a series of necessary measures must be taken. While achieving economic development, environmental constraints must also be considered so as to achieve sound and fast economic development. The excessive use of fossil fuels such as coal, natural gas, and oil by humans emits a large amount of greenhouse gases, which leads to global climate change. The Fifth Assessment Report on Climate Change of the Intergovernmental Panel on Climate Change (IPCC) pointed out that, in the past 130 years, the global temperature has increased by 0.85 °C and greenhouse gas emissions have contributed 0.5% of the increase in surface temperature between 1951 and 2010: 1.3 °C (IPCC). China is the world's largest CO_2 emitter; if it wants to achieve the IPCC's goal of keeping the global temperature rise within 2 °C by 2100, from the perspective of the remaining carbon emission credits, China must increase its carbon footprint by 8% to 10% per year and reduce CO_2 emissions [1]. Forestry is an important part of ecology, an important oxygen supplier and an important absorber of carbon dioxide in the atmospheric environment. Forestry is very important for maintaining the carbon and oxygen balance in the atmosphere. The Kyoto Protocol believes that the synergistic effect of afforestation and reforestation, reducing deforestation, alleviating forest degradation and sustainable forest management must be achieved by 2030 and for a longer period of time in the future. It has enormous potential for mitigating global climate change. Forestry activities affect the planet's carbon balance, with harvesting increasing human CO_2 emissions, while activities such as reforestation, wildland afforestation and tree-enhancing forestry cultivation remove atmospheric CO_2 and store it in woody biomass. Forestry carbon sink has the advantages of multiple benefits, low cost, economic feasibility, etc. It is an important measure to increase carbon sink and reduce emissions in the next 30 to 50 years (IPCC). Therefore, the potential of forestry carbon sink is huge. However, forestry is facing an unprecedented crisis [2–4]. The reason is that the contribution of forestry to ecology cannot be effectively converted into economic contribution and its economic value and ecological role are not recognized by society [5,6]. The public good's attributes and externalities of forestry's contribution to ecology make it impossible to effectively convert it into economic contribution [7], and thus it cannot use economic means to protect and develop forestry. In 1964, the proposal of UNESCO's forestry carbon sink theory made it possible to commercialize the ecological benefits of forestry and became an important economic means to protect and develop forestry [8].

The supply of forestry carbon sinks needs the support of land, and only reasonable land use planning can make the best judgment on the sustainable development of forestry carbon sinks [9]. This study will use the FLUS model based on the artificial neural network algorithm (ANN) and cellular automata algorithm (CA) and use GeoSOS software to simulate the spatial changes of forest land under three scenarios and analyze them. The reason provides a theoretical basis for the development of forestry carbon sinks. At present, there are few studies that use the FLUS model to analyze the expected results of the implementation of forestry carbon sink projects on land use structure change. The conclusions of this study will provide theoretical support for the supply potential of forestry carbon sink and provide practical basis for the implementation of forestry carbon sink projects.

2. FLUS Model and Land Use

The FLUS model is a newly developed model based on the GeoSOS system [10–12] for simulating future land use changes (Future Land use Simulation Model) [13]. The model mainly relies on two basic algorithms. One is the artificial neural network algorithm (ANN) and the other is the cellular automata algorithm, indicating that the operation of the model requires two parts. One is the artificial neural network algorithm (ANN)-based land use algorithm. The second is to simulate the changes of land use types in the study area with cellular automata based on the adaptive inertial competition mechanism selected by roulette betting. The specific principles of the two parts of the FLUS model are as follows.

2.1. Probability Calculation of Suitability Based on Artificial Neural Network Model (ANN)

Artificial Neural Networks (ANNs) are a family of machine learning models inspired by biological neural networks which have been successfully applied to the analysis and modeling of various nonlinear geographic problems [9]. ANN is a multi-layer feedforward neural network, and its basic structure includes an input layer, one or more hidden layers and an output layer. This method has been proved to effectively improve the calculation accuracy [14,15]. The ANN in the FLUS model generally includes two stages of training and prediction. The training stage is to obtain the weights of different land use types, and the prediction stage is to obtain the spatial distribution probability between different land types.

The specific formula of ANN is:

$$p(k,t,l) = \sum_j W_{j,t} \frac{1}{1+e^{-net_j(k,t)}} \tag{1}$$

In the formula: $p(k,t,l)$ is the suitability probability of the t kinds land use type at grid k and time l; $w_{j,t}$ is the weight between the hidden layer and the output layer; $net_j(k,t)$ represents the received value of the j-th hidden layer grid k at time l signal of. For the suitability probability output by ANN, at the iteration time l grid k, the sum of the suitability probabilities of all types of land use is identical to 1 [16], that is:

$$\sum_t p(k,t,l) = 1 \tag{2}$$

When calculating the spatial distribution probability of different land types, it is necessary to use the driving factors of land use change. The driving forces of land use are generally divided into static natural driving factors and dynamic socio-economic driving factors. Natural driving factors often include static driving factors such as regional elevation, slope and aspect; socioeconomic driving factors often include dynamic driving factors such as distance from major railways and highways. According to the spatial distribution characteristics of land use in the study area and considering the accuracy and availability of spatial data, this paper selects elevation, slope, slope aspect, distance from the nearest river, distance from the nearest highway, distance from the nearest railway, distance from the nearest county and distance. A total of 8 elements of the nearest city distance are used as spatial driving factors. The raster data production of each driving factor was completed in ArcGIS 10.8 software. ArcGIS10.8 software was provided by Shenyang Agricultural University, Shenyang, Liaoning Province, China in 2020.

2.2. Adaptive Inertial Mechanism Cellular Automata

There are more and more studies of cellular automata (CA) to simulate the change of urban land use structure [17–19]. Whether or not a land grid will develop into a particular land use type depends not only on the probability of occurrence, but also on other variable components of different development states over the forecast period. Therefore, the FLUS model combines the probability of occurrence with conversion costs, neighborhood conditions and competition between different land use types to estimate the combined probability of each land grid [20–22].

The core of the adaptive inertia competition mechanism is the adaptive coefficient. The inertia coefficient of each land type is determined according to the difference between the existing land demand and the amount of land and is adaptively adjusted in the iteration so that the number of various types of land can develop towards the target [14]. The adaptive relationship coefficient $Inertia_t^l$ of the t-th land type at time l is:

$$Inertia_t^l = \begin{cases} Inertia_t^{l-1} & \left|D_t^{l-2}\right| \le \left|D_t^{l-1}\right| \\ Inertia_t^{l-1} \times \frac{D_t^{l-2}}{D_t^{l-1}} & 0 > D_t^{l-2} > D_t^{l-1} \\ Inertia_t^{l-1} \times \frac{D_t^{l-1}}{D_t^{l-2}} & D_t^{l-1} > D_t^{l-2} > 0 \end{cases} \tag{3}$$

In the formula, D_t^{l-1} and D_t^{l-2} are the difference between the grid number and the demand quantity of the k-th land use type at times $l-1$ and $l-2$, respectively.

According to the above steps, the total probability of each grid is calculated separately, and each land type is allocated to the grid through CA iteration. The total probability $Tprob_{k,t}^l$ that grid p is transformed into land use type t at time l can be expressed as: $Tprob_{k,t}^l = p(k,t,l) \times \Omega_{k,t}^l \times Inertia_t^l \times (1 - sc_{c\to t})$.

In the formula: $sc_{c\to t}$ is the cost of converting land use type C to type T; $1 - sc_{c\to t}$ is the difficulty of conversion; $\Omega_{k,t}^l$ is the neighborhood effect, and its formula is: $\Omega_{k,t}^l = \frac{\sum_{N\times N} con(c_k^{l-1}=t)}{N\times N-1} \times \omega_t$.

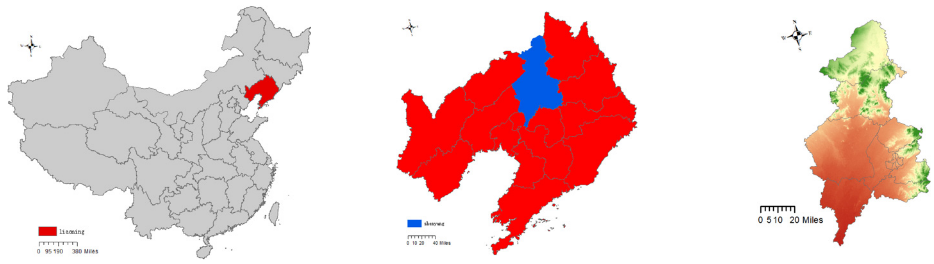
In the formula: $\sum_{N\times N} con(c_k^{l-1} = t)$ represents the total number of grids of k land types in the Moore neighborhood window of $N \times N$ after the last iteration; ω_t is the neighborhood effect weight of each type of land.

On the basis of calculating the total probability, the FLUS model adopts the roulette selection model with random characteristics to realize the transformation of land use types so as to reflect the uncertainty of land use changes in the real world and the alternating changes of land use and better reflect competition among land types [16].

3. Experiment

3.1. Study Area

The area of this study is Shenyang, China. Shenyang is the provincial capital. Shenyang is located in the southern part of Northeast China, the central part of Liaoning Province, with the Liaodong Peninsula in the south, the foothills of Changbai Mountain in the north, and is located in the Bohai Rim Economic Circle. The important junction of the northeast region is located between 41°48′11.75″ north latitude and 123°25′31.18″ east longitude. The total area of the city exceeds 12,948 square kilometers, and the urban area is 3495 square kilometers. As shown in Figure 1, Shenyang is located in the middle of the Liaohe Plain, with the Liaodong hills and mountains to the east, and the Liaobei hills to the north. The city's industrialization level and urbanization level are relatively high, indicating that the city's carbon emission problems are more serious and environmental problems are more prominent. It is an ideal area for forestry carbon sink analysis, so this study selects this area as the simulation object.

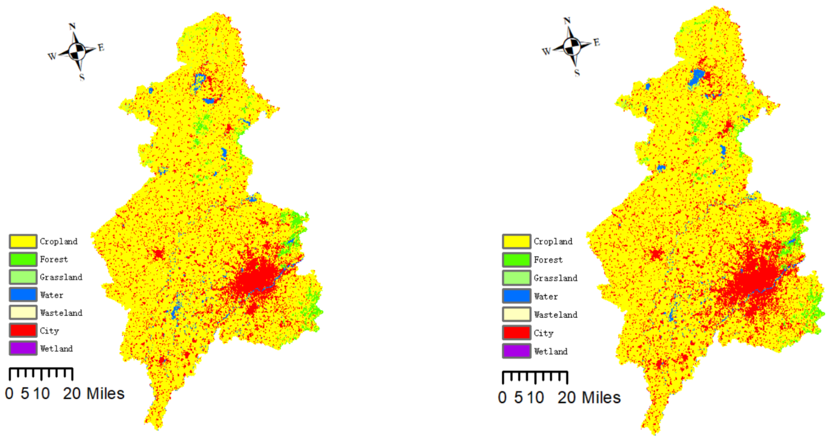


(**a**) (**b**) (**c**)

Figure 1. Study area. Subfigure (**a**) is the region of China, subfigure (**b**) is the region of Liaoning Province, and subfigure (**c**) is the region of Shenyang City.

3.2. Land Use Data Processing in the Study Area

The soil utilization change data in the study area can be analyzed using Landsat data, but, like many satellite data, Landsat data needs to be interpreted and a series of calibrations are required before use, which not only increases the difficulty of the experiment, but also may cause different scholars differences in research findings. Therefore, this study directly uses the data that has been interpreted by Wuhan University, mainly using the data of 2010 and 2019; the data comes from https://zenodo.org (accessed on 15 May 2020) and are processed and analyzed in ArcGIS 10.8, as shown in the Figure 2.



(**a**) (**b**)

Figure 2. Land use type data. Subfigure (**a**) is the land use types in 2010. Subfigure (**b**) is the land use types in 2019.

Figure 2 shows the land use types in Shenyang in 2010 and 2019, respectively. In ArcGIS 10.8, the land use types are divided into seven categories, namely farmland, forest land, water body, wasteland, impervious (urban) and wetland. The resolution of the image is 30 m × 30 m, that is, each pixel element represents 900 m^2. For convenience, the data of the pixel element are directly used for description. Judging from the development of land use in the past 10 years, the amount of farmland has decreased from 15,618,757 to 1,506,8738, a drop of nearly 5%. This is related to the process of urbanization in China. In the process of expansion, cities will annex farmland in surrounding areas. At the same time, the process of peasants going to cities to work led to the phenomenon of abandonment of farmland, which in turn accelerated the disappearance of farmland. The number of woodlands and grasslands is increasing, of which the number of woodlands has increased from 458,568 to 517,355, and the number of grasslands has increased from 76,116 to 113,523. The main reason is that, in recent years, China has attached great importance to environmental protection. The project, meanwhile, in 2015 completely banned the logging of natural forests, which directly or indirectly increased the amount of woodland and grassland. The number of water bodies has decreased, but not by much, from 315,065 to 287,633. The number of wastelands is also decreasing, from 5740 to 4554. The urban area is increasing, whether in absolute or relative terms, the expansion of cities is very significant, from 2,809,425 to 3,291,868, which is inseparable from the rapid development of China's economy.

3.3. Calculation and Evaluation of Suitability Probability Based on ANN

First, the driving factors of land use change should be processed. The number of driving factors comes from Resource and Environment Science and Data Center. The driving factors include the elevation data, slope data, aspect data, the distance to the nearest river, the distance to the nearest highway, the distance to the nearest rail, the distance to the nearest city and the distance to the nearest county. All drivers were collected in 2010. The data types are shown in Table 1. And tif is a format of geographic information file. The Euclidean distance is calculated in ArcGIS 10.8, as shown in Figure 3.

Table 1. Driver data types.

Training Sample Name	Data Type	Rows	Columns
Status of land use in Shenyang in 2010.tif	Int8	7184	7740
Elevation.tif	Float16	7184	7740
slope.tif	Float32	7184	7740
Distance to nearest river.tif	Float32	7184	7740
Distance to nearest highway.tif	Float32	7184	7740
Distance to nearest rail.tif	Float32	7184	7740
Distance to nearest city.tif	Float32	7184	7740
Distance to nearest county seat.tif	Float32	7184	7740
Aspect.tif	Float32	7184	7740

After preparing the driving factors affecting land use change, start the neural network training module (ANN-based Probability-of occurrence Estimation) in the model in the FLUS2.4 software and input the land use data and driving factor data of Shenyang in 2010 as training sample data. FLUS2.4 software is an extended development on the GeoSOS system to use a variety of land use change simulation. FLUS2.4 software was provided by Beijing City Laboratory, Beijing, China in 2020. After the input of the training samples is completed, the training of the neural network model and the calculation of the occurrence probability of each land use type are started. The root mean square error (RMSE) of model training is 0.197, indicating that the training accuracy is high, and the resulting land type occurrence probability is a 0–1 value.

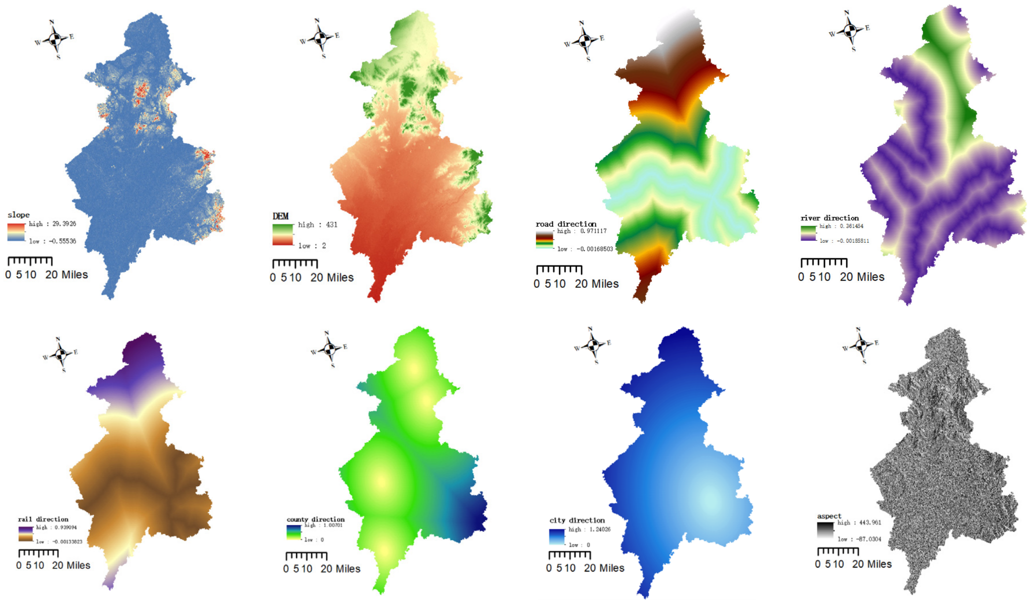


Figure 3. Euclidean distance grid map of driving factors of land use change.

3.4. Cellular Automata Based on Adaptive Inertial Mechanism

The calculation process of cellular automata mainly includes the following points:

(1) Basic data required for simulation;

The basic data required for the cellular automata simulation based on the adaptive inertia mechanism mainly include three parts: the initial year land use data, the input suitability probabilistic data and the input limit data that restricts the change of land use. This is shown in Table 2.

Table 2. Basic data.

Basic Data Required for Simulation	Data Content	Type of Data
Land use data for initial year	Status quo data of land use in Shenyang in 2010	raster data
Suitability Probabilistic Data	The output data after ANN training	raster data
Restricted data to constrain land use changes	Unrestricted area in this study	raster data

(2) Set the simulation parameters;

In this paper, the default iteration number of FLUS software is 300. This sets the neighborhood size for cellular automata simulations to extended neighborhood. Using acceleration factor, through the experience of many simulation tests, this paper sets the acceleration factor as 0.9.

(3) Land use change transfer cost matrix;

When one land use type does not allow conversion to another, the corresponding value of the matrix is set to 0; when conversion is allowed, it is set to 1. This study will simulate three scenarios, namely the natural development scenario, the economic priority scenario and the forestry carbon sink trading scenario. The natural development scenario means that no adjustment will be made to the existing industrial policies. The economic priority scenario means that the government gives priority to economic development and ignores other factors when formulating the policy. The scenario of forestry carbon sink trading refers to the government paying attention to pollution while considering economic development and uses forestry carbon sink trading to mitigate environmental pollution. Different simulation scenarios have different land use change transfer cost matrices. The specific settings are shown in Tables 3–5:

Table 3. Land use change transfer cost matrix in natural development scenario.

Ground Type	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
Cropland	1	1	1	0	0	1	0
Forest	1	1	0	0	0	0	0
Grassland	1	1	1	0	0	1	0
Water	0	0	0	1	0	1	1
Barren	1	1	1	0	1	1	0
Impervious	0	0	0	0	0	1	0
Wetland	0	0	0	0	0	0	1

Table 4. Land use change transfer cost matrix in economic priority scenario.

Ground Type	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
Cropland	1	1	1	0	0	1	0
Forest	1	1	0	0	0	1	0
Grassland	1	1	1	0	0	1	0
Water	0	0	0	1	0	1	1
Barren	1	1	1	0	1	1	0
Impervious	0	0	0	0	0	1	0
Wetland	0	0	0	0	0	0	1

Table 5. Land use change transfer cost matrix in forestry carbon sink scenarios.

Ground Type	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
Cropland	1	1	1	0	0	1	0
Forest	1	1	0	0	0	1	0
Grassland	1	1	1	0	0	1	0
Water	0	0	0	1	0	1	1
Barren	1	1	1	0	1	1	0
Impervious	0	0	0	0	0	1	0
Wetland	0	0	0	0	0	0	1

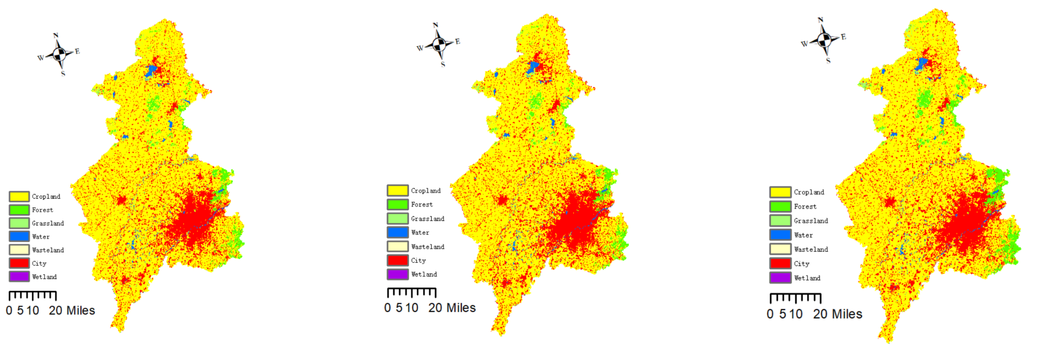
(4) Neighborhood factor expansion parameters.

The focus of this study is to analyze the spatial impact of forestry carbon sinks on land use change. In the process of land use simulation, forestry carbon sinks are mainly reflected in the expansion parameters of neighborhood factors. For comparative analysis, this study simulated three types of development scenarios, including the natural development scenario, the economic priority scenario and the forestry carbon sink trading scenario. Different scenarios have different expectations for the amount of land in the future, and the expansion parameters of the neighborhood factor are also different. Under the forestry carbon sink trading scenario, it is expected that, by 2028, the forestry land will increase by 65%. The expansion parameter of the neighborhood factor is set to 1, indicating that the forest expansion ability is the strongest. In this paper, according to the actual situation of land use change in Shenyang, the neighborhood factor expansion parameters of land use types are set as shown in the following Table 6:

Table 6. Neighborhood factor expansion parameters under different scenarios.

	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
run its course	0.1	0.6	0.5	0.2	0.3	0.7	0.4
Economic priority	0.1	0.5	0.5	0.1	0.1	0.9	0.1
Forestry carbon sequestration transaction	0.1	0.9	0.8	0.1	0.1	0.7	0.1

When all parameters are set, run the model. When the area distribution of each category reaches the established standard, the model simulation ends, and the simulation map of land use types under the natural development, economic priority and forestry carbon sink scenarios in 2028 can be obtained, such as those shown in Figure 4. From the simulation Figure 4, we can see that in the economic priority scenario, the urban area has been expanded to a large extent, the agricultural land has been shrinking and the ecological environment has not been well maintained. Under the scenario of forestry carbon sink, the urban area will still expand, but under the constraint of carbon sink mechanism, it can effectively restrict the environmental pollution problem and effectively improve the ecological environment [23]. This research result is very similar to the existing literature results. In the study using the FLUS model, the situation very similar to the forest carbon sink scenario is the study on returning farmland to grassland [24]. In addition, some studies directly assume the low-carbon development scenario [25]. When any development scenario is set, it is a simulation of the implementation effect of environmental protection policies. Although they are motivated by protecting the environment and reducing pollution, their internal impact mechanisms are different. The internal mechanism of the implementation of forestry carbon sink works through the market, and the urban land use structure can be adjusted through the price, which is more in line with the concept of market economy and makes the economy develop well and quickly.



(**a**) (**b**) (**c**)

Figure 4. (**a**) Natural development scenario; (**b**) economic priority scenario; (**c**) forestry carbon sink scenario.

4. Conclusions

By analyzing the simulation graphs under the three scenarios in ArcGIS 10.8, it can be found that, under the condition of natural development, the land use types in Shenyang will continue to follow the development trend from 2010 to 2019 and the farmland will shrink further. The city expanded further, the farmland decreased from 15,068,738 to 14,555,022, 462 km^2 reduced, and the city increased from 3,291,868 to 3,757,145, 419 km^2 increased. Forests and grasslands are increasing, but not by much. It shows that if the existing economic development model is not subjected to an intervention, it will be difficult for the natural environment to be effectively improved. The reason why the scale of forest land can be guaranteed lies in legal means, not economic means. Badlands and bodies of water remain largely unchanged. Under the economic priority scenario, it can be found that the degree of urban expansion is significantly greater than that of the natural development scenario, and the spatial development is characterized by expansion around the original towns and some smaller villages will die out. Urban expansion poses the greatest threat to agricultural land. Under China's policy of ensuring the scale of agricultural land, local governments are likely to destroy forests to maintain the area of agricultural land, which is not conducive to the improvement of the ecological environment. Under the forestry carbon sink scenario, both forest land and grassland have been greatly increased, especially the forest land, which has increased from 517,355 to 853,637, added 303 km^2, indicating that the forestry carbon sink can significantly increase the forest land area. The existing research shows that 1 km^2 forest land can absorb 1500 tons of CO_2 every year, so if the forestry carbon sink project is implemented, Shenyang can increase 454,500 tons of carbon sink every year [26]. In the past, the surrounding areas of forest land agglomeration areas were expanded because the slopes of the original forest land agglomeration areas were relatively steep, and the terrain was not conducive to food production and urban development, but it was very suitable for the development of forestry. Low, unfavorable sloping land has become the first choice for forest land expansion. Therefore, the forest land expansion in Shenyang is mainly distributed in the hilly areas in the north and east. With the increase in the transaction price of forestry carbon sinks, the forest land will be further integrated with the agricultural land, generating competition. Different land conditions are suitable for different crops. Agricultural land with high production costs and low profit margins is likely to be converted into forestry land, which can not only ensure the income of farmers, but also improve the ecological environment and achieve sustainable development. For a long time, the development of forestry has been restricted by the demand side. Among the traditional forest products, it has high substitutability, which leads to the long-term stagnation of the development of forest products. The enthusiasm of forest farmers is not high, and the forest resources need the protection of the government to maintain the existing area. However, the implementation of forestry carbon sink trading can change this situation. With the development of social economy, the national requirements for environmental quality are becoming higher and higher. Forestry carbon sink is an effective means to alleviate environmental degradation, which will greatly increase the value of forest resources, increase the area of forest land, increase the income of forest farmers and relieve the pressure of the government to protect forest resources. The implementation of forestry carbon sink trading can also stimulate the progress of emission reduction technology of enterprises. In any case, forestry carbon sink trading increases the operating costs of enterprises, and enterprises have the power to increase R&D investment, improve production efficiency and reduce pollution emissions.

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References

1. Zhang, Y.; Shan, Y.J. Analysis of supply, demand and trade in my country's forest carbon sink market. *Environ. Prot.* **2016**, *44*, 37–41.
2. Dixon, R.K.; Solomon, A.M.; Brown, S.; Houghton, R.A.; Trexier, M.C.; Wisniewski, J. Carbon pools and flux of global forest ecosystems. *Science* **1994**, *263*, 185–190. [CrossRef] [PubMed]
3. Pan, Y.; Birdsey, R.; Fang, J.; Houghton, R.; Kauppi, P.E.; Kurz, W.A.; Phillips, O.L.; Shvidenko, A.; Lewis, S.L.; Canadell, J.G.; et al. A large and persistent carbon sink in the world's forests. *Science* **2011**, *300*, 988–993. [CrossRef] [PubMed]
4. Li, Z.; Zhang, K. Comparison of Three GIS-Based Hydrological Models. *J. Hydrol. Eng.* **2008**, *13*, 364–370. [CrossRef]

5. Guo, B.; Wang, Y.; Zhou, H.; Hu, F. Can environmental tax reform promote carbon abatement of resource-based cities? Evidence from a quasi-natural experiment in China. *Environ. Sci. Pollut. Res.* **2022**, *26*. [CrossRef]
6. Zhuo, Z.; Du, L.; Lu, X.; Chen, J.; Cao, Z. Smoothed lv distribution based three-dimensional imaging for spinning space debris. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 1–13. [CrossRef]
7. Jiang, X. Analysis of China's forestry carbon sink potential under the new economic normal. *China Rural. Econ.* **2016**, *11*, 57–67.
8. Li, S.L. Research on the Economic Problem of Forest Carbon Sink. Doctoral Dissertation, Northeast Forestry University, Harbin, China, 2005.
9. Yan, Y.; Jarvie, S.; Liu, Q.; Zhang, Q. Effects of fragmentation on grassland plant diversity depend on the habitat specialization of species. *Biol. Conserv.* **2022**, *275*, 109773. [CrossRef]
10. Liu, X.; Li, X.; Tan, Z.; Chen, Y. Zoning farmland protection under spatial constraints by integrating remote sensing, GIS and artificial immune systems. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 1829–1848. [CrossRef]
11. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [CrossRef]
12. Xia, L.; Yeh, A.G.O. Knowledge discovery for geographical cellular automata. *Sci. China Ser. D: Earth Sci.* **2005**, *48*, 1758–1767.
13. Openshaw, S. Neural network, genetic, and fuzzy logic models of spatial interaction. *Environ. Plan. A* **1998**, *30*, 1857–1872. [CrossRef]
14. Wang, F. The use of artificial neural networks in a geographical information systems for agricultural land suitability assessment. *Environ. Urban Syst.* **1994**, *24*, 265–284. [CrossRef]
15. Zhou, J.; Civco, D. Using genetic learning neural networks for spatial decision making in GIS. *Photogramm. Eng. Remote Sens.* **1996**, *62*, 1287–1295.
16. Zhu, S.H.; Shu, B.G.; Ma, X.D.; Liang, X.; Yao, Q. Research on the boundary delineation of urban land use growth based on the concept of "anti-planning" and FLUS model—Taking Jiawang District of Xuzhou City as an example. *Geogr. Geogr. Inf. Sci.* **2017**, *33*, 80–86+127.
17. White, R.; Engelen, G. Cellular automata and fractal urban form: A cellular modelling approach to the evolution of urban land use patterns. *Environ. Plan. A* **1993**, *25*, 1175–1199. [CrossRef]
18. Batty, M.; Xie, Y. From cells to cities. *Environ. Plan. B* **1994**, *21*, 531–548. [CrossRef]
19. Wu, F. An experiment on the generic polycentricity of urban growth in a cellular automatic city. *Environ. Plan. B* **1998**, *25*, 103–126. [CrossRef]
20. Liang, X.; Liu, X.P.; Li, D.; Zhao, H.; Chen, G.Z. Urban growth simulation by incorporating planning policies into a CA-based future land-use simulation model. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 2294–2316. [CrossRef]
21. Liang, X.; Liu, X.P.; Li, X.; Chen, Y.M.; Tian, H.; Yao, Y. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landsc. Urban Plan.* **2018**, *177*, 47–63. [CrossRef]
22. Liang, X.; Liu, X.P.; Chen, G.L.; Leng, J.Y.; Wen, Y.Y.; Chen, G.Z. Coupling fuzzy clustering and cellular automata based on local maxima of development potential to model urban emergence and expansion in economic development zones. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1930–1952. [CrossRef]
23. Li, J.; Charles, L.S.; Yang, Z.; Du, G.; Fu, S. Differential mechanisms drive species loss under artificial shade and fertilization in the alpine meadow of the tibetan plateau. *Front. Plant Sci.* **2022**, *13*, 832473. [CrossRef] [PubMed]
24. Deng, Y.J.; Yao, S.B.; Huo, M.Y.; Zhang, T.Y.; Lu, Y.N.; Gong, Z.W.; Wang, Y.F. Assessing the effects of the Green for Grain Program on ecosystem carbon storage service by linking the InVEST and FLUS models: A case study of Zichang county in hilly and gully region of Loess Plateau. *J. Nat. Resour.* **2020**, *35*, 826–844.
25. Li, L.; Hu, R.; Li, S. Scenario simulation of low-carbon land use in Beijing City based on the improved FLUS model. *Remote Sens. Nat. Resour.* **2022**, 1–9.
26. Fang, J.; Guo, Z.D.; Piao, S.L.; Chen, A.P. Estimation of terrestrial vegetation carbon sink in china from 1981 to 2000. *Sci. Sin. (Terrae)* **2007**, *6*, 804–812.