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Assessment of the Effects of Urban Expansion on Terrestrial Carbon Storage: A Case Study in Xuzhou City, China

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Received: 27 January 2018; Accepted: 26 February 2018; Published: 28 February 2018

Abstract: Carbon storage is closely connected to the productivities and climate regulation capacities of ecosystems. Assessing the effects of urban expansion on carbon storage has become increasingly important for achieving urban sustainability. This study analyzed the effects of urban expansion on terrestrial carbon storage in Xuzhou City, China during 2000–2025. The cellular automata (CA) model was developed to simulate future urban expansion under three scenarios, namely, the business as usual (BAU), ecological protection (ECO), and planning strengthened (PLS) scenarios. The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was further applied to explore the consequences of urban expansion on carbon storage. The results show that urban expansion resulted in 6.099 Tg of carbon storage loss from 2000–2015. Moreover, significant differences in the effects of the urban expansion scenarios on carbon storage were identified in terms of both magnitude and spatial pattern from 2015–2025. Compared with the other scenarios, the PLS scenario could be considered as a good option that would allow future development to achieve the objectives of the lowest carbon storage losses. The findings improve the understanding of the effects of urban expansion on carbon storage and may be used to support urban planning and management.

Keywords: urban expansion; carbon storage; InVEST model; cellular automata model; scenario

1. Introduction

Ecosystem services (ESs) affect human well-being and refer to the benefits that people directly or indirectly obtain from a natural ecological system [1]. ESs are mainly composed of provisioning, regulating, supporting and cultural services, which play a critical role in accomplishing sustainable development [1–3]. Among the ESs, carbon stocks are important component that closely connected to the productivities and climate regulation capacities of terrestrial ecosystems [4,5].

The relationship between urban expansion and ESs is one of the most crucial issues in ecosystem and land research all over the world [6,7]. It is widely reported that urban expansion has a significant impact on terrestrial carbon storage and the carbon balance [8–10]. Urban expansion is a dynamic complex process that takes place around the globe, which has resulted in dramatic variations in land cover and land use [11]. While urban areas currently cover only a small proportion of the global land surface [12], their ecosystem structures and functions have significant impacts on global change [13]. Due to remarkable urban expansion, increasing areas of non-urban land have been transformed to urban land, which has caused the variation of terrestrial carbon storage in ecosystems, with serious consequences to the climate system as well as human life. Therefore, exploration of the relationship between urban expansion and carbon storage can offer a better understanding of the interactions between humans and ecosystems as well as support effective urban planning.

Against the background of dramatic urbanization, several recent studies have quantified and mapped terrestrial carbon storage. The current methods used to estimate carbon storage include field surveys [9,14], remote sensing (RS) [15,16], and models [17,18]. Previous studies have proven the usefulness of the Integrated Valuation of Environmental Services and Tradeoffs (InVEST) model in calculating terrestrial carbon storage. For example, Zhang et al. adopted the InVEST model to calculate carbon storage in the Beijing-Tianjin-Hebei urban agglomeration in China from 2013 to 2040 [19]. Leh et al. analyzed the effects of land use and land cover change on carbon storage for the period of 2000–2009 using the InVEST model [20]. Jiang et al. applied the InVEST model to estimate the carbon storage in the Changsha-Zhuzhou-Xiangtan urban agglomeration under different scenarios [17]. Nelson et al. applied the InVEST model to assess the effects of global urban land change on carbon storage [21].

Although emphasis has been placed on the quantitative aspects of carbon storage for historical periods, analysis of the carbon consequences of future urban expansion, that consider different urban development policies, is lacking. The shortages of these types of assessments could be attributed to the lack of ability by ecosystem models to predict future urban expansion scenarios. It is widely accepted that urban expansion is a complex dynamic process [22] that can be affected by several natural and socioeconomic factors. However, the existing carbon storage estimation models cannot assess future carbon storage under different urban expansion scenarios [23].

Modeling the complex urban system provides an effective way to analyze alternative urban expansion consequences, thereby assisting with urban planning and decision making [24]. The cellular automata (CA) model can be adapted to simulate very complex behaviors using a set of simple transition rules [25–27]. In addition to reproducing historical development situations, simulation and optimization are the most important tasks of a CA model [28]. Simulation is utilized to simulate alternative scenarios under certain conditions, and optimization aims to provide an optimal solution for future development. CA models have been extensively applied in modeling urban expansion due to their simplicity, flexibility, and intuitiveness. By integrating simulation with optimization, CA models can assist planners and decision makers with analyzing the consequences of urban expansion under different future urban development scenarios.

This study presents a case study of Xuzhou City in China. The changes in ecosystem services due to the urban expansion provide good representative of the medium sized Chinese cities, because most of them have experienced the similar urban expansion process. The overall objective of this study is to provide a better understanding of how urban expansion affects terrestrial carbon storage, as well as recommendations for the regional planning and development strategies. The specific objectives are as follows: (1) to document the temporal variations in land use change within Xuzhou City, (2) to simulate the future urban expansion scenarios using a CA model, (3) to estimate the future carbon storage under various urban expansion scenarios by adopting the InVEST model, and (4) to analyze the effects of urban expansion on carbon storage.

2. Materials and Methods

2.1. Study Area

Xuzhou City (33°43′–34°58′N, 116°22′–118°40′E) in China was selected as the study area, which is located in the plains of the Huaihe River and the Yellow River (Figure 1). The area of Xuzhou City is 1160 km^2, and it is composed of five municipal districts: Yunlong, Quanshan, Jiawang, Tongshan, and Gulou, and the total urban population was 3.19 million by the end of 2015. Benefiting from mining and industrial manufacturing, the local socio-economy has experienced significant improvement since the implementation of reform and opening policy in 1978. The gross domestic product (GDP) of Xuzhou City grew from 29 billion Yuan in 2000, to 294.2 billion Yuan in 2015.

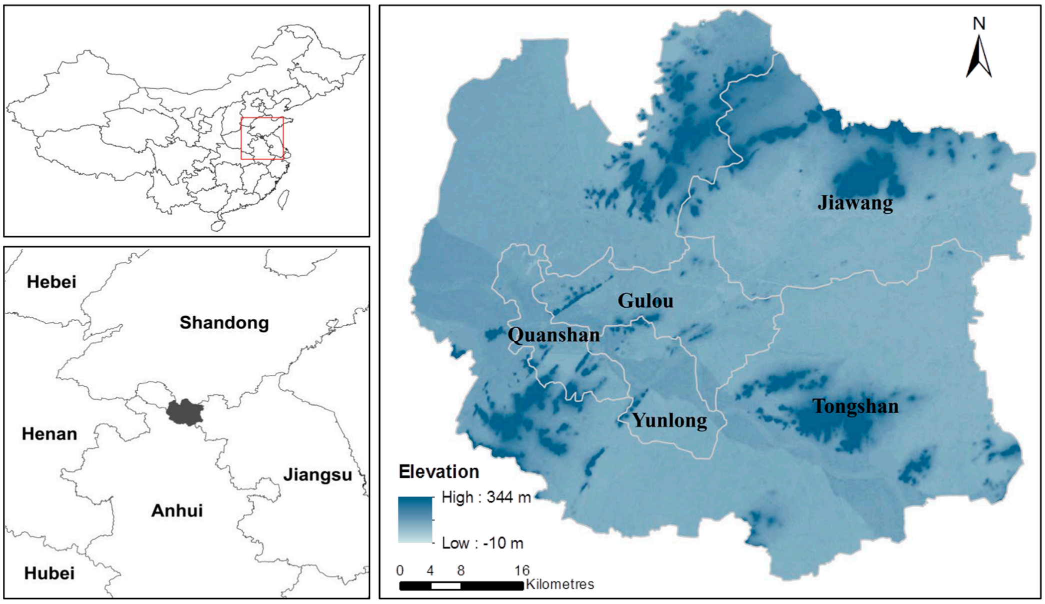

Figure 1. The study area.

2.2. Materials

In this study, a series of Landsat Thematic Mapper (TM) images acquired in August 2000, May 2005, and April 2010 and Landsat Operational Land Imager (OLI) images from June 2015 were collected from the United States Geological Survey (USGS) and used to interpret the land cover data for Xuzhou City. The maximum likelihood classifier method was applied to classify the RS images into built-up land, cultivated land, vegetation land, and wetland. The overall accuracy of the classification was greater than 86%, which is sufficient to capture accurate land cover information for further analysis. To simulate the urban expansion process of Xuzhou City, ancillary geographical data were also collected in this study, including digital elevation model (DEM) data, administrative boundaries, road networks, rivers, population data, and the master plan for 2025. All spatial data were resampled to the spatial resolution of 100 m, which is sufficient to capture detailed information on urban dynamics while maintaining a manageable computation volume.

2.3. Estimation of Carbon Storage

The InVEST model can be used to quantify and map the amount of carbon storage based on four carbon pools [5]. To calculate the amounts of the four carbon pools, the carbon densities for the four carbon pools of each land cover type must be obtained. Therefore, the total carbon storage for a given cell (x,y) with land cover type p can be calculated as follows:

$$C_{x,y,p} = A \times \left(D_{above,p} + D_{below,p} + D_{soil,p} + D_{dead,p}\right), \quad (1)$$

where $C_{x,y,p}$ indicates the total carbon storage for cell (x,y) with land cover type p. A represents the area of cell (x,y). $D_{above,p}$, $D_{below,p}$, $D_{soil,p}$, and $D_{dead,p}$ denote the aboveground carbon density, belowground carbon density, soil organic carbon density, and dead organic matter carbon density for land cover type p, respectively.

The carbon density data for the InVEST model in this study are presented in Table 1 and were obtained according to previous studies [29,30]. It was assumed that the carbon storage for built-up land is zero according to the report by Davies et al. [31].

Table 1. Carbon density of each land cover type (Mg/hm^2).

Land Cover Type	Aboveground Carbon Storage (AGC)	Belowground Carbon Storage (BGC)	Soil Organic Carbon Storage (SOC)	Dead Organic Matter Carbon Storage (DOC)
Built-up Land	0	0	0	0
Cultivated Land	5.7	0.7	92.6	0
Vegetation Land	42.4	10.8	120.8	7.8
Wetland	0	0	0	0

The carbon storage change for cell (x,y) between times $t1$ and $t2$ can be expressed as follows:

$$\Delta C_{x,y} = C_{x,y}^{t1} - C_{x,y}^{t2}, \tag{2}$$

where $C_{x,y}^{t1}$ and $C_{x,y}^{t2}$ indicate the carbon storage for cell (x,y) at times $t1$ and $t2$, respectively.

2.4. Modeling Urban Expansion

A CA model was developed and applied to model the urban expansion process for Xuzhou City during the study period of 2000–2015. By using simple transition rules, a CA model can simulate the dynamics of a complex system. A CA model often includes four elements: cells, states, neighborhood effects and transition rules, which are used to determine the change in the state of a cell [32]. The definition of a transition rule is important for CA models. In an urban CA, the transition rule can be represented by adopting the development probability, which identifies the probability that land use change will occur [33]. The calculation of the development probability includes four types of spatial variables that affect urban evolution: transition potential P_{ij}^t, neighborhood effect N_{ij}^t, development constraint $CONS_{ij}^t$, and stochastic perturbation V_{ij}^t. By including a series of spatial variables, the development probability DP_{ij}^t for a given cell (x,y) at time t is expressed as follows:

$$DP_{ij}^t = P_{ij}^t \times N_{ij}^t \times CONS_{ij}^t \times V_{ij}^t, \tag{3}$$

The transition potential P_{ij}^t is determined by a set of global spatial variables, including slope (Slope), population density (Poden), distance to city center (Dis2City), and distance to major roads (Dis2Road). The transition potential for a given cell (i,j) at time t is calculated in a logistic regression as follows:

$$P_{ij}^t = \frac{\exp(z^t)}{1+\exp(z^t)}, \tag{4}$$

where z^t indicates the combination of the independent variables that are the driving factors of land cover change at time t. z^t can be calculated as follows:

$$z^t = b_0 + b_1 x_1^t + b_2 x_2^t + \cdots + b_n x_n^t, \tag{5}$$

where $b_k (k = 1, 2, \ldots, n)$ represents the estimated parameters for the independent variable in the logistic regression model. x_k^t indicates an independent variable.

Instead of adopting stationary neighborhood parameter values in the neighborhood effect calculation, multiple neighborhood parameter values were included and compared to improve the performance of the CA model. The neighborhood effect is calculated as follows:

$$N_{ij}^t = \sum_c W_{mn} \times I_{mn}^t, \tag{6}$$

where N_{ij}^t represents the neighborhood effect for the central cell (i,j) within the neighborhood c at time t. W_{mn} is the weight representing the impacts of the cell (m,n) on central cell (i,j) within the neighborhood [32]. I_{mn}^t indicates the state of cell (m,n) at time t in the binary form. I_{mn}^t = 1 if the state of cell (m,n) is developed, otherwise I_{mn}^t = 0. Moore neighborhood type with varied sizes (from 3 × 3 to 11 × 11) were compared to determine the optimal neighborhood configuration. According to the first law of geography [34], the weight W_{mn} is calculated based on the following equation:

$$W_{mn} = \exp(-\beta \times D_{mn}), \tag{7}$$

where β represents the exponent value of the weighting function. D_{mn} represents the distance between cell (m,n) and the central cell (i,j).

Moreover, constraint values are also included to represent the natural constraints to urban expansion, which are calculated as:

$$CONS_{ij}^{t} = \prod_{g=1}^{n} con_{ij,g}^{t}, \tag{8}$$

where $con_{ij,g}^{t}$ indicates the suitability value of constraint factor g for urban expansion at time t. $con_{ij,g}^{t} = 0$ if cell (i,j) is constrained by factor g, which means that the cell will not be converted to built-up land use.

In addition, a stochastic disturbance variable is introduced into the model to represent the uncertainties in urban expansion and is calculated as follows:

$$V_{ij}^{t} = 1 + (-\ln(r))^{\propto}, \tag{9}$$

where r is a stochastic variable within the range of 0–1. $\propto$ indicates the adjustment parameter that controls the degree of stochasticity.

Once the development probability DP_{ij}^{t} for cell (i,j) is calculated, the transition potential values can determine the probability that each non-urban cell will be converted to a urban cell. For each iteration, the new urban cells are allocated by selecting the non-urban cells with higher development probability values, while the non-urban cells with lower development probability values keep unchanged. The iteration stops when the urban expansion area during the given period reaches the demand.

To ensure accurate simulation of urban expansion, the parameters of the transition rule of the CA model need to be calibrated [26]. In this study, the coefficients of the driving factors, neighborhood types, neighborhood sizes, weighting functions, and adjustment parameters need to be calibrated. The widely used kappa index is adopted to measure the overall performance of the CA model by quantifying the goodness-of-fit between the observed and simulated land cover maps. The best combination of parameters can be determined when the highest kappa index is obtained.

2.5. Analyzing the Carbon Consequence of Future Urban Expansion

The CA model provides an effective way to simulate various urban expansion scenarios while considering different urban development policies. Moreover, a scenario-based analysis can help further assess the consequences of future urban expansion on carbon storage. Therefore, the analysis can provide support for urban planning and decision making to mitigate the negative impacts on a natural ecosystem. A set of urban expansion scenarios are designed according to the three criteria proposed by Xiang and Clarke [35]. To better explore the relationship between future urban expansion and carbon storage, three urban expansion scenarios confined to these three criteria for Xuzhou City were developed for 2025, namely, the business as usual (BAU) scenario, ecological protection (ECO) scenario, and planning strengthened (PLS) scenario. The scenarios are linked to the concerns of the policymakers of Xuzhou City and address the key questions as well as the historical urban expansion trend.

Under the BAU scenario, it is assumed that future urban expansion will be consistent with the historical land conversion trends without any adjustments or limitations.

The ECO scenario considers environmental and ecological protection. Like many other cities in developing countries, Xuzhou City faces many environmental and ecological challenges because of the rapid development in recent decades. Built-up lands occur over large sprawls in some ecologically sensitive areas. Therefore, the ECO scenario was established to protect the environment and ecology as well as prohibit future urban development in ecologically sensitive areas to achieve ecologically friendly development. Therefore, under the ECO scenario, urban expansion decisions are strictly limited to environmental and ecological considerations. The urban development policies and spatial growth limitations were included in the CA model. To simulate this scenario, we prepared a constraint map that prevents environmental protection areas, open spaces, and lands within 200 m of protected rivers and lakes from being converted to built-up land.

The PLS scenario aims to strengthen the restriction of urban planning on future urban development in Xuzhou City. The master plan significantly affects the allocation of newly developed built-up land because it develops the legal framework for future urban development. In addition to environmental and ecological destruction, the conversion from cultivated land to built-up land has been identified as the main threat to sustainable development [36]. In response to this problem, the government of China introduced a number of measures that aim to protect farmlands and ensure that the basic farmlands are not cut down. For example, the Basic Farmland Protection Regulation and New Land Administration Law have been implemented. Considering this situation and the urban development strategies, the allocation of urban expansion under the PLS scenario was strictly limited to the master plan of 2025 for Xuzhou City, which enforces the placement of new built-up land within a predefined list of open areas according to the master plan.

The development of three urban expansion scenarios enables us to assess how Xuzhou City could develop in the future if various development strategies are implemented. Moreover, the carbon storages corresponding to the different scenarios can be quantified, and the impacts of future urban expansion on carbon storage can be explored.

Although the trend of carbon storage loss in Xuzhou City can be quantitatively characterized by using statistical data on carbon storage, the spatial variation characteristics of carbon storage loss cannot be captured. GIS-based buffer analysis was applied to address the question of where carbon storage losses are occurring. Multiple buffer zone areas were created at a distance interval of 2 km around the city center.

The frequency ratio (FR) of carbon storage loss in each buffer zone was further applied to represent the spatial variation in carbon storage loss and compare the potential impacts of various urban development strategies on carbon storage. The FR can be calculated as follows:

$$S_{bz}^{i} = \frac{\Delta C_{bz}^{i}}{\Delta C_{bz}}, \tag{10}$$

$$R_{bz}^{i} = \frac{A_{bz}^{i}}{A_{bz}}, \tag{11}$$

$$FR_{bz}^{i} = \frac{S_{bz}^{i}}{R_{bz}^{i}}, \tag{12}$$

where S_{bz}^{i} is the share of carbon storage loss in buffer zone i. ΔC_{bz}^{i} is the carbon storage loss in a single buffer zone i, and ΔC_{bz} represents the carbon storage loss in all buffer zones (0–30 km). A_{bz}^{i} represents the area of buffer zone i, A_{bz} represents the area of all buffer zones. FR_{bz}^{i} is greater than 1 when higher loss intensities occur in buffer zone i. A value of 1 is an average value for all buffer zones.

3. Results

3.1. Urban Expansion in Xuzhou City from 2000 to 2025

The multitemporal classified land cover maps for Xuzhou City are shown in Figure 2. The areas of the land cover classes for the study period are presented in Table 2. Xuzhou City experienced significant urban expansion, which led to the rapid growth of built-up land. The area of built-up land increased from 354 km^2 in 2000 to 916 km^2 in 2015. The annual growth area of built-up land increased from 15 km^{2}yr^{-1} during 2000–2005 to 61 km^{2}yr^{-1} during 2010–2015, which implies that the expansion rate grew over the study period in Xuzhou City. The pressure of rapid urban expansion was indicated by the reductions in cultivated and vegetation lands. Due to the conversion into built-up land, cultivated and vegetation lands correspondingly declined by 592.5 km^2 and 12.8 km^2, respectively. The majority of the new built-up land came from the conversion of cultivated land. In particular, 94.9%, 96.0%, and 99.9% of the growth of built-up land were from cultivated land during the periods of 2000–2005, 2005–2010, and 2010–2015, respectively. The wetland area increased from 51.12 km^2 to 94.72 km^2, which could be explained by the formation of waterlogged subsidence within the coal mining areas during 2000–2015.

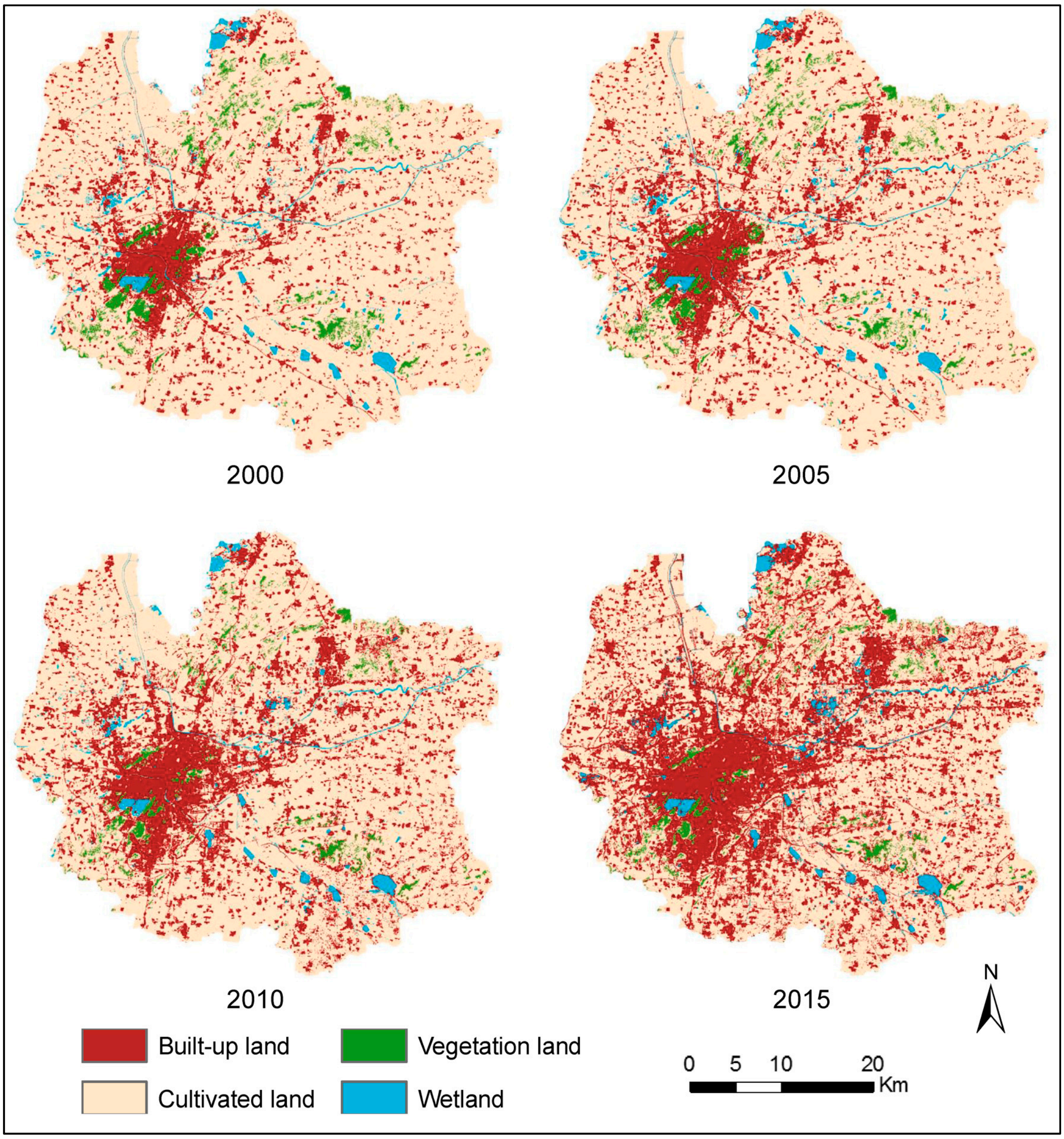

Figure 2. Classified land cover maps for 2000, 2005, 2010, and 2015.

Table 2. Statistics of land cover in Xuzhou City from 2000 to 2015 (km^2).

Land Cover Type	2000	2005	2010	2015
Built-up Land	354.02	429.22	612.76	915.74
Cultivated Land	2417.76	2331.82	2144.85	1825.27
Vegetation Land	70.56	68.31	60.27	57.73
Wetland	51.12	64.11	75.58	94.72

In order to ensure the accuracy of the simulation of CA model, the calibration need to be conducted. In this study, trial and error, as well as logistic regression methods were applied to identify the optimal parameter values of CA model. Firstly, the spatial variable involved in Equation (5) was identified using the logistic regression method according to the historical land cover data. In addition, the neighborhood configuration the adjustment parameter was calibrated through the trial and error method, which can be conducted by running the CA model multiple times with different combinations of parameter values. The CA model was applied to reproduce the urban expansion process during the periods of 2000–2005, 2005–2010, and 2010–2015. The simulated land cover maps of 2005, 2010, and 2015 were compared with the observed land cover data. Kappa indexes are calculated based on a cell-by-cell comparison to quantify the accuracy of the simulation of the historical process. The combination of parameter values with highest Kappa index was identified for the period of 2000–2005, 2005–2010, 2010–2015, respectively. The estimated parameters for the study periods are listed in Table 3. The kappa indexes of 2005, 2010, and 2015 were 0.865, 0.817, and 0.836, respectively, implying the reliability of the simulation results as well as the calibrated CA model.

Table 3. Calibrated parameter values of the CA model for different periods.

Parameters	2000–2005	2005–2010	2010–2015
Dis2City	−1.242	−1.697	−1.964
Dis2Road	−1.359	−1.274	−1.256
Slope	−1.518	−1.112	−0.547
Poden	0.793	0.329	−0.205
Weighting Function	exp(−0.5*D)	exp(−0.5*D)	exp(−0.5*D)
Neighborhood Size	3 × 3	5 × 5	5 × 5
Adjustment Parameter	2.2	2.4	2.5

The calibrated parameter configurations were adopted in the CA model, and the observed land cover map of 2015 was used as initial data. We simulated future urban expansion under the three scenarios (BAU, ECO, and PLS) aiming to predict alternative urban expansion patterns in 2025. According to the annual growth area of built-up land during 2000–2015, the future demand for built-up land under the BAU scenario by 2025 was projected. Under the ECO scenario, it was assumed that built-up land would reach 1160 km^2 by 2025. Moreover, the demands for built-up land under the PLS scenario were estimated according to the master plan 2025 of Xuzhou City.

Figure 3 shows the simulated spatial patterns of land cover under the three urban expansion scenarios. The differences in the land cover spatial patterns due to the implementation of different development strategies can be visualized.

Under the BAU scenario, urban expansion is continuously concentrated around the core of Xuzhou City by 2025 because the future expansion process strictly follows the historical trend without any adjustments. At the same time, a large amount of built-up land continues to sprawl dramatically in the fringe and rural areas. Because of the increase in built-up land, the simulation result shows dramatic reductions in the vegetation and cultivated land areas. Under the ECO scenario, because the environmental and ecological constraints were included in the CA model, the simulation result indicates conversions into built-up land within the core of Xuzhou City. Moreover, the urban expansion in ecologically sensitive areas is restricted. The urban master plan of 2015–2025 aims to solve environmental problems, achieve coordinative development of urban-rural areas. As planned, new development hotspots are observed in the fringe and rural areas under the PLS scenario. By 2025, a large portion of the new built-up land is concentrated around the development hotspots that are established according to the master plan of Xuzhou City.

As indicated in Table 4, the statistical data show that the built-up land area will increase from 915.74 km^2 in 2015 to 1289.97 km^2, 1160.84 km^2, and 1050.74 km^2 in 2025, with average annual growth areas of 37.4 km^2 yr^{-1}, 24.5 km^2 yr^{-1}, and 13.5 km^2 yr^{-1} in the BAU, ECO, and PLS scenarios, respectively. The three scenarios show trends of continuous urban expansion; however, the rates of built-up land increases are different. Although most of the new built-up land comes from cultivated and vegetation lands, different contributions of cultivated and vegetation lands to the conversions to built-up land were observed under these scenarios. The area of cultivated land that was converted to built-up land accounts for 95.2%, 96.4%, and 97.0% of the new developed built-up land under the BAU, ECO, and PLS scenarios, respectively. The area of cultivated land in the PLS scenario is 1694.31 km^2, which is greater than the areas of cultivated land in the BAU and ECO scenarios. Moreover, the area of vegetation land under the ECO scenario is 6.51 km^2 larger than that in the BAU scenario and 0.02 km^2 larger than that in the PLS scenario.

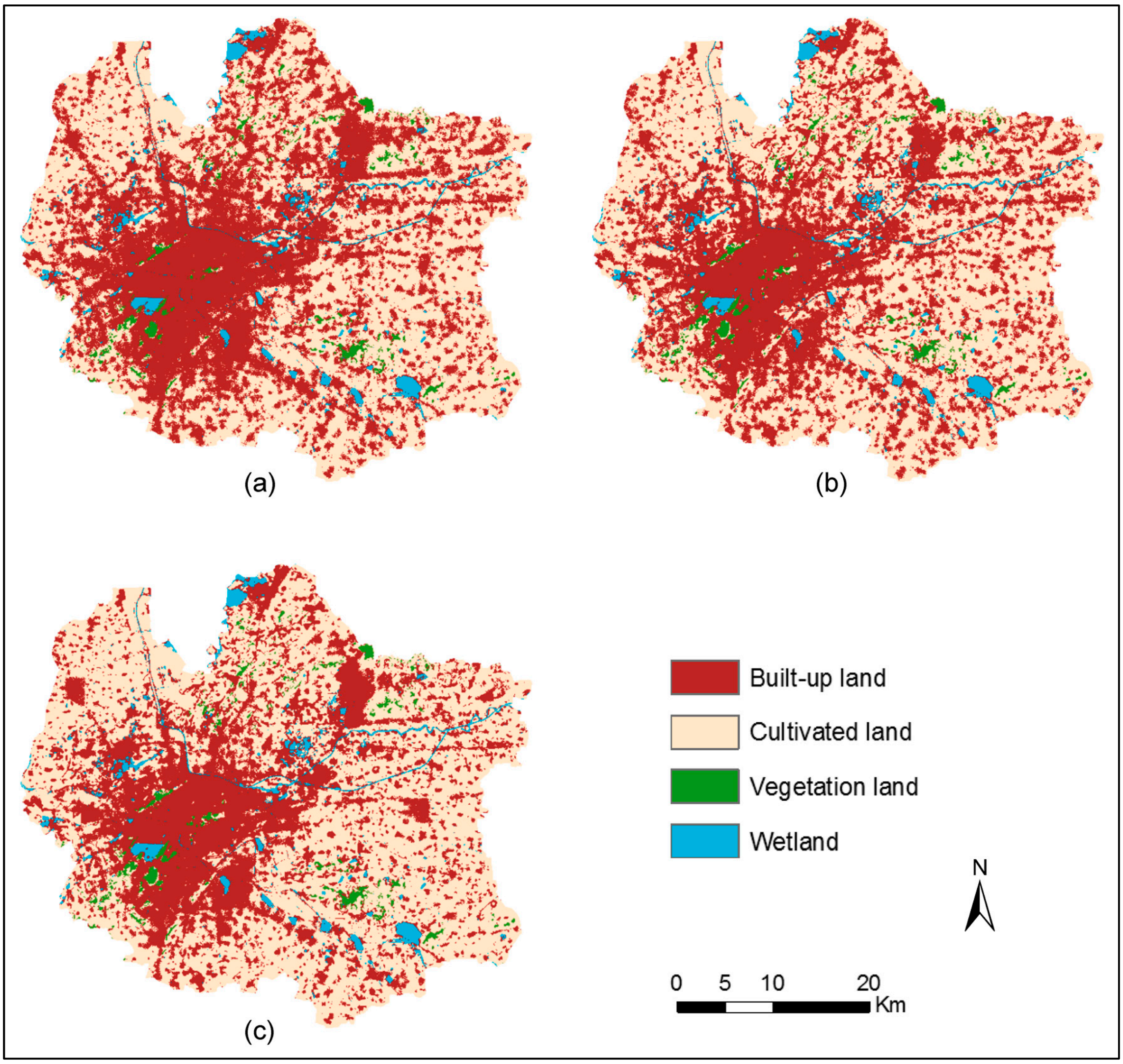

Figure 3. Land cover maps under different scenarios: (**a**) business as usual (BAU); (**b**) ecological protection (ECO); (**c**) planning strengthened (PLS).

Table 4. Statistical land cover data of Xuzhou City under the BAU, ECO, and PLS scenarios (km^2).

Land Cover Type	BAU	ECO	PLS
Built-up Land	1289.97	1160.84	1050.74
Cultivated Land	1469.04	1589.08	1694.31
Vegetation Land	50.81	57.32	57.30
Wetland	83.64	86.22	91.11

3.2. Changes in Regional Carbon Storage

The InVEST Carbon Storage and Sequestration model was applied to calculate the carbon storage based on the land cover maps. The carbon storage losses from 2000 to 2015 is shown in Table 5. The carbon storage in Xuzhou City decreased from 25.219 Tg in 2000 to 19.120 Tg in 2015 during the rapid urban expansion process. This decrease can be attributed to the decline in cultivated and vegetation land, which result in significant carbon storage losses of 5.866 Tg and 0.233 Tg, respectively. In addition, of the four carbon pools, soil organic carbon (SOC) experiences the greatest loss of 5.641 Tg, representing 92.49% of the total carbon storage loss in Xuzhou City. Carbon storage losses of 0.393 Tg, 0.055 Tg, and 0.010 Tg were found for aboveground carbon (AGC), belowground carbon (BGC), and dead organic matter carbon (DOC), respectively. In particular, regional carbon storage losses of 0.892 Tg, 1.997 Tg, and 3.210 Tg occurred during the periods of 2000–2005, 2005–2010, and 2010–2015, respectively.

Table 5. Carbon storage losses in Xuzhou City from 2000 to 2015 (Tg).

Period	Carbon Pool	Cultivated Land	Vegetation Land	Total Carbon Storage Loss
2000–2005	AGC	0.049	0.010	0.892
	BGC	0.006	0.002	
	SOC	0.796	0.027	
	DOC	0.000	0.002	
	Total	0.851	0.041	
2005–2010	AGC	0.107	0.034	1.997
	BGC	0.013	0.009	
	SOC	1.731	0.097	
	DOC	0.000	0.006	
	Total	1.851	0.146	
2010–2015	AGC	0.182	0.011	3.210
	BGC	0.022	0.003	
	SOC	2.959	0.031	
	DOC	0.000	0.002	
	Total	3.164	0.046	

3.3. Impacts of Future Urban Expansion on Carbon Storage from 2015 to 2025

The carbon storage losses in Xuzhou City under the different scenarios were further compared and analyzed to explore the impacts of future urban expansion on carbon storage during 2015–2025 under three scenarios. The CA model was applied to simulate the three urban expansion scenarios by adopting various development policies. As shown in Figure 4, these comparison results reveal that there are variations in the spatial patterns of carbon storage losses. Under the BAU scenario, significant losses in carbon storage were observed around the city core, which is consistent with the spatial distribution of historical carbon storage losses. Moreover, the area that experienced carbon storage loss moved towards the east, which is defined as the new district in Xuzhou City. Carbon storage losses can also be found along the major roads in scattered and irregular patches. In addition, new developments of built-up land lead to the creation of several small and fragmented patches of carbon storage loss in rural areas. Compared with the BAU scenario, urban expansion under the ECO scenario leads to a varied spatial distribution of carbon storage losses. Because of ecological constraints, carbon storage losses are prohibited within the environmentally and ecologically sensitive areas. Most of the carbon storage losses are concentrated within the fringe area where increase of built-up land decreases the carbon storage under the ECO scenario. There are also several isolated pixels and patches in rural areas. The carbon storage under the PLS scenario exhibited a greater increase than the other two scenarios. There are certain degrees of carbon storage loss around the new development hotspots as well as the city center because the other land cover types are forced to convert to built-up land in some of the areas.

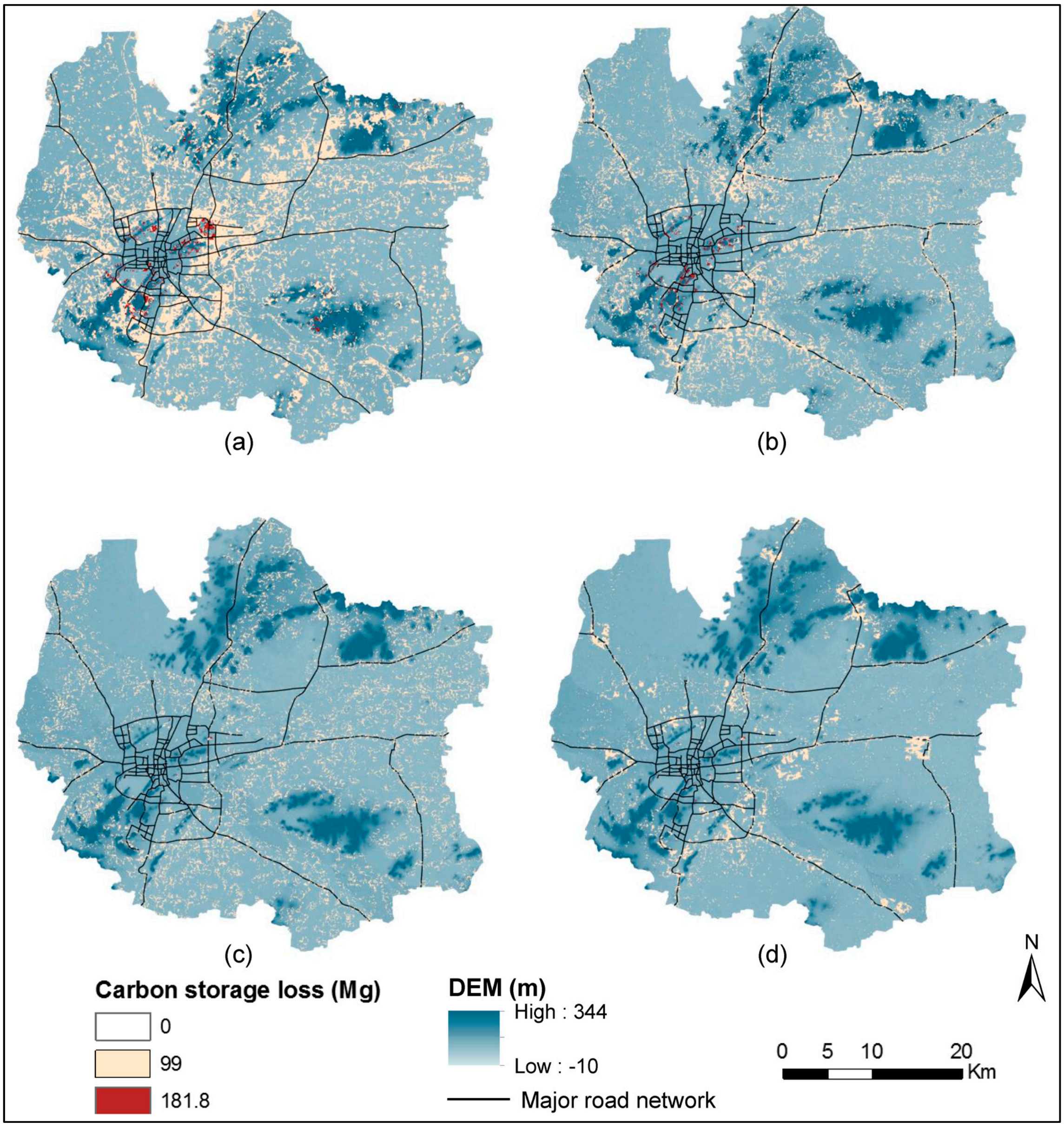

Figure 4. Carbon storage loss in Xuzhou City under different scenarios: (**a**) 2000–2015; (**b**) BAU; (**c**) ECO; (**d**) PLS.

As indicated in Table 6, although continuous urban expansion could result in carbon storage loss from 2015–2025, the results imply that the amount of carbon storage loss varies under the different urban expansion scenarios. Under the BAU scenario, the decrease in carbon storage was greater than that in the other two scenarios. The changes from cultivated and vegetation lands to built-up land leads to carbon storage losses of 3.527 Tg and 0.126 Tg, accounting for 96.55% and 3.45% of the total storage loss in Xuzhou City, respectively. Under the ECO scenario, 236.19 km^2 of cultivated land was converted to built-up land, which resulted in a carbon storage loss of 2.338 Tg, representing 99.70% of the total carbon storage loss. Although the carbon storage in the PLS scenario is greater than that in the other two scenarios, the shrinkage of cultivated land leads to a carbon storage loss of 1.297 Tg, accounting for 99.39% of the total loss. The decreases in SOC lead to carbon storages of 3.383 Tg, 2.192 Tg, and 1.218 Tg under the BAU, ECO, and PLS scenarios, respectively.

Table 6. Carbon storage loss in Xuzhou City from 2015 to 2025 under three urban expansion scenarios (Tg).

Scenario	Carbon Pool	Cultivated Land	Vegetation Land	Total Carbon Storage Loss
2015–2025 (BAU)	AGC	0.203	0.029	3.653
	BGC	0.025	0.007	
	SOC	3.299	0.084	
	DOC	0.000	0.005	
	Total	3.527	0.126	
2015–2025 (ECO)	AGC	0.135	0.002	2.345
	BGC	0.017	0.000	
	SOC	2.187	0.005	
	DOC	0.000	0.000	
	Total	2.338	0.007	
2015–2025 (PLS)	AGC	0.075	0.002	1.305
	BGC	0.009	0.000	
	SOC	1.213	0.005	
	DOC	0.000	0.000	
	Total	1.297	0.008	

To further evaluate and compare these scenarios, a buffer analysis was applied to clarify the differences in the relationships between carbon storage loss and distance from the city center under the various scenarios. Figure 5 shows the share of carbon storage loss in each buffer zone. By using the FR indicator, the results of the buffer analysis of carbon storage loss under the three scenarios are shown in Figure 6, which reflects the losses and spatial dynamics of carbon storage.

Overall, the intensity of carbon storage loss was related to the distance to the city center in Xuzhou City. The intensity of carbon loss increases to a maximum and then exhibits a declining tendency.

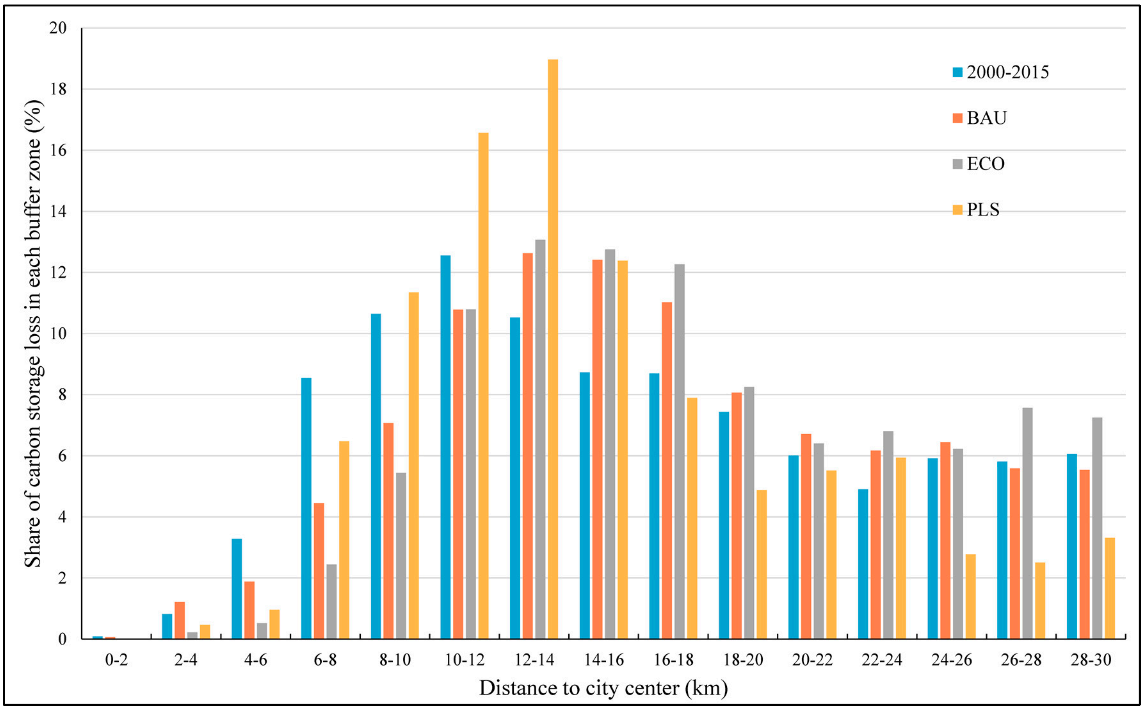

Figure 5. Change in share value with distance to the city center under different scenarios.

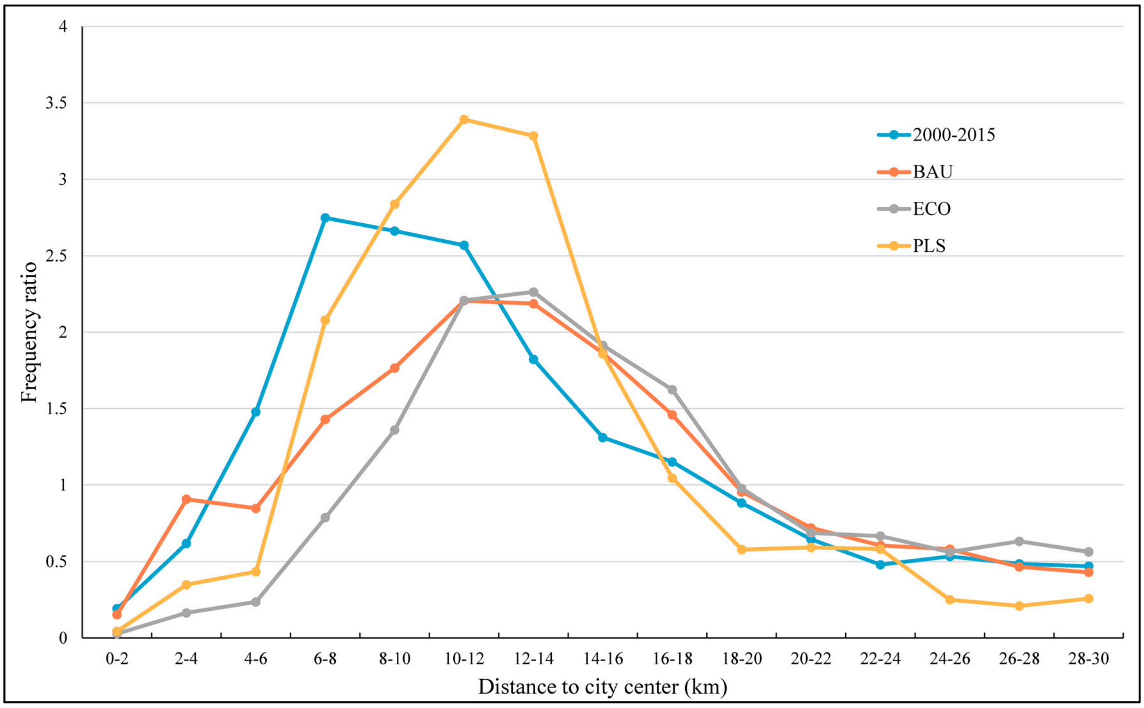

Figure 6. Change in frequency ratio (FR) with distance to the city center under different scenarios.

From 2000–2015, the historical carbon storage experienced the most intensive loss in the 6–8 km buffer zone with a peak FR value of 2.75, which indicates that the area experienced high-intensity carbon storage losses. Beyond 8 km, the FR value decreases gradually as the distance to the city center increases. Furthermore, as illustrated in Figure 5, the amount of carbon storage loss within the 10–12 km radius of the center of Xuzhou City accounted for 12.55% of the total carbon storage loss in the buffer zones of 0–30 km, which suggests that the carbon storage losses were mainly concentrated between the radial distances of 8 and 12 km from the city center in Xuzhou City during 2000–2015.

Compared with the period of 2000–2015, the carbon storage loss curves under the three scenarios present significant differences in both magnitude and intensity of carbon storage loss. Under the BAU scenario, the peak FR value is observed in the 10–12 km buffer zone, which indicates that the area that experienced serious carbon storage losses expanded outward. Thus, this finding can also be considered as an indicator of urban expansion. As the distance to the city center increases, the share value increases from 0.07% within the 0–2 km buffer zone to 12.63% within the 12–14 km buffer zone. The differences indicate that there is little land available for urban expansion within the city core.

Under the ECO scenario, the peak FR value is observed in the range from 12 to 14 km around the Xuzhou City center, which is similar to that of the BAU scenario. Between the radial distances of 0 and 12 km from the Xuzhou City center, the FR values are lower than those in the BAU scenario. This result indicates that the carbon storage losses due to land cover changes are restricted in the environmental protection areas. The carbon storage experienced less intense loss in the buffer zone when there were environmental protection areas around the city core.

Under the PLS scenario, the results of the buffer analysis reflect that the spatial pattern of carbon storage loss had similar characteristics as those in the BAU and ECO scenarios. However, a more significant increase in the carbon storage loss intensity is observed between 0 and 12 km from the city center. The highest FR value of 3.39 is found within 10–12 km, which is higher than the FR values in the other scenarios. The results on the share of carbon storage loss in each buffer zone are also consistent, which show that the share values are greater than those in the other scenarios from 6 to 14 km to the city center. This finding could be attributed to the fact that some areas are defined as future development hotspots that are potential future urban expansion areas according to the master plan of Xuzhou City. Most of the land expansion under the PLS scenario is concentrated in these regions, where a large part of the non-urban land is identified to be converted to built-up land. Therefore, the hotspots are the main areas of carbon storage loss under the PLS scenario.

4. Discussion

4.1. The Integration of the InVEST and CA Models

The main task in urban planning is the consideration and coordination of multiple objectives. However, the involvement of natural ESs in urban planning remains a major challenge and has received less attention in the context of realistic cities [37]. Most of the previous studies have only focused on quantifying the changes in historical ESs without linking these changes to urban planning. This study extends the previous studies by integrating the CA and InVEST models. This integration was proven to be an effective way to explore the impacts of future urban expansion on carbon storage as well as provide support for implementing effective policies towards sustainable development.

This study agrees with the previous reports of the effectiveness of the CA model in predicting future urban development patterns [28]. Moreover, the connection between the CA model and urban planning is established in this study by simulating different scenarios under various urban development strategies. To produce the future spatial patterns of urban expansion, the CA model was developed and applied to simulate three urban expansion scenarios by varying the parameter values. Based on the different future urban expansion scenarios, the amounts and spatial patterns of urban expansion were assessed and analyzed.

Many studies have argued that scenario evaluations are important for testing and comparing the consequences of urban development under different urban development strategies [38]. In this study, the InVEST model was applied to make the impacts on ESs more prominent. Many studies have demonstrated the effectiveness of using the magnitude of carbon storage to evaluate the impact of urban expansion on carbon storage [19,39]. In addition to the widely used magnitude analysis, the spatially varying impacts were captured by using a gradient analysis. By integrating the CA and InVEST models, the analysis of future urban expansion scenarios can assist urban planners in exploring the potential impacts of various urban development strategies on ESs and can support urban planning towards the improvement of ESs.

4.2. The Impact of Urban Expansion on Carbon Storage

The study presented the impacts of urban expansion in Xuzhou City on carbon storage. The results confirmed a general trend of losses in carbon storage due to the conversion from cultivated and vegetation lands to built-up land during the rapid urbanization process. In particular, the decrease in cultivated land is the main cause of the carbon storage losses in Xuzhou City. This result is consistent with several previous studies that demonstrated that carbon storage exhibited significant losses due to urban expansion [17,40].

Unlike previous studies that produce only single scenarios [8], three different urban expansion scenarios were developed in this study to effectively evaluate and compare the amount and spatial pattern of carbon storage losses in response to future urban expansion. Furthermore, this study extends previous studies by investigating the spatially varying impacts on carbon storage. Significant carbon storage losses occurred in the city core and fringe area during 2000–2015. These losses could be because the areas closer to the city center gained better accessibility to socioeconomic resources [9]. After rapid urban expansion in the city core, however, significant losses in carbon storage due to urban expansion occur in the fringe area rather than in the city core in 2015–2025. Moreover, the impacts on carbon storage loss varied over time, which could be attributed to the urban expansion processes and the development policies.

The continuous decreases in the values of ESs are associated with the dramatic urban expansion process and have negative effects on the human population. These impacts bring vast challenges to decision makers for implementing a sustainable urban development strategy. Under the BAU, ECO, and PLS scenarios, the carbon storage losses varied spatially from 2015–2025. The results of the scenario evaluations indicate that the current ecological protection strategy is in a critical stage. If urban expansion continues, such as in the BAU scenario, Xuzhou City will experience significant carbon storage losses. The conflict between rapid urban expansion and ecological protection will become more apparent. Based on the findings, some recommendations to mitigate the carbon storage losses in Xuzhou City are proposed. The carbon storage losses in Xuzhou City are mainly due to the decline in cultivated land area. Although the carbon storage density of cultivated land is lower than that of vegetation land, the area of cultivated land is much larger than that of vegetation land. Therefore, cultivated land has a large capacity for carbon storage [23]. The regulation of cultivated land protection needs to be strictly implemented to control the large-scale conversions to built-up land. However, the prerequisite for avoiding significant carbon storage losses should be the maintenance of rapid urban expansion. Considering this situation, compact development could be an effective method to balance the conflict between carbon storage and rapid urbanization through the intensive utilization of land resources.

4.3. Limitations

The analysis results strongly rely on the accuracy of the future urban expansion scenarios. The CA model was proven to be an effective method to simulate future urban expansion scenarios. In addition to the factors considered in the CA model, other driving factors such as cultural, political, employment, economics factors are not included in the CA model because they are not available [26]. Although high accuracies of the simulation results were obtained, it is necessary to include more driving factors to improve the simulation accuracies. In addition, the InVEST model was used to estimate the carbon storage based on the regional carbon densities of AGC, BGC, SOC, and DOC in the different land cover types. In reality, carbon density varies spatiotemporally [5]. In this study, however, the seasonal variations and the carbon fluxes among the various land cover types were not considered. Moreover, the carbon storages of built-up land and wetland are assumed to be zero. To achieve more accurate carbon storage data, it is necessary to conduct field surveys and obtain field data to calculate the accurate carbon storage capacities for built-up land and wetland [41].

5. Conclusions

Urban expansion is one of the main factors that affects carbon storage and climate change [15,23]. Therefore, quantitative analysis of the carbon consequence of urban expansion plays a crucial role in sustainable development. This study proposed an integration of the CA and InVEST models that can be utilized to effectively evaluate the impacts on carbon storage due to urban expansion. The main conclusions are as follows: (1) The integration of the CA and InVEST models was proven to effectively explore the carbon consequences of future urban expansion under different urban development scenarios; (2) Carbon storage exhibited a decreasing trend from 25.219 Tg in 2000 to 19.120 Tg in 2015. This decrease is mainly attributed to the large-scale conversions from cultivated land to built-up land. Moreover, the carbon storage decreased by 3.653 Tg, 2.345 Tg, and 1.305 Tg under the BAU, ECO, and PLS scenarios, respectively. The carbon storage loss varied spatially during the period of 2000–2025; (3) The evaluation and comparison of the carbon losses under different scenarios offer an effective way for exploring the effects of alternative urban development policies on ESs and for supporting urban planning and decision making; (4) The current ecological protection is in a critical stage. If urban expansion continues as indicated by the BAU scenario, carbon storage will experience significant losses, which could threaten sustainable development.

Acknowledgments: This study was supported by "the Fundamental Research Funds for the Central Universities" (Grant No. 2017QNB18).

Author Contributions: Cheng Li analyzed the data; Jie Zhao, Cheng Li, Jie Zhao, Nguyen Xuan Thinh and Yantao Xi wrote the paper.

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

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