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RESEARCH ARTICLE

Potential effects of oasis expansion on ecosystem service value in a typical inland river basin of northwest China

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Abstract

To satisfy an increasing need for living space and food while preserving ecosystem services remains one of today's biggest challenges. Oases in arid areas have gradually become the main sources for new cultivated land, affecting the supply and transmission of ecosystem services. Yet, little assessment on predicting the effects of oasis expansion on ecosystem service value (ESV) has been available to guide policy makers and ecologists. Here we addressed the connections between oasis expansion and ESV in the middle reaches of the Heihe River Basin in northwest China by linking the Logistic-CA–Markov model and the benefit transfer method. The results showed that the oasis was expected to expand by 419.02 km^2 from 2015 to 2029, with the area of farmland and construction land increasing by 18.87% and 39.05%, respectively. With oasis expansion, the total ESV was expected to increase by 104.25 million RMB from 2015 to 2029. However, oasis expansion encroaches on vegetation, resulting in decline of the values of climate regulation, waste treatment, and biodiversity protection. This study will provide a reference for decision-making in trade-offs involved in land management.

Keywords Oasis expansion · Land use change · Ecosystem service value · The Logistic-CA–Markov model · The benefit transfer method · The middle reaches of the Heihe River Basin

Introduction

Ecosystem services are defined as services and goods that humans obtain directly or indirectly from ecosystems (Daily 1997). Estimation of the ecosystem service in monetary units reflects the impact of human activities on ecosystems (Yang et al. 2021), which can improve people's awareness of the importance of ecosystem service relative to other contributing factors to human well-being (Braat and Groot 2012; Li et al. 2021) and provide a basis for ecological management (Farley et al. 2010; Gao et al. 2021). Most recent advances show that ecosystem services are regulated by various ecological mechanisms exhibiting dynamic change closely related to land use change (Sangermano et al. 2021). Research on changes in ESV with land use change has gradually attracted attention in academic and political circles, because it can provide a scientific basis for countries all over the world to reduce the risk of natural disasters and improve the quality of human life (Cegielska et al. 2018; Ouyang et al. 2016).

As regional granaries, oases play an important role in maintaining food security and have gradually become the main source of newly reclaimed farmland (Liu et al. 2014; Xu et al. 2020). These newly reclaimed farmlands are mainly located in the desert-oasis transition zone, in which material circulation, energy conversion, and information transmission between desert ecosystem and oasis ecosystem occur (Bai et al. 2020). Oasis expansion characterized by farmland reclamation has triggered complex ecological evolution that may affect oasis stability (Chen et al. 2018). It is of

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great significance to study the influence mechanism of oasis expansion on ESV for maintaining oasis safety.

The Hexi Corridor-Alashan Plateau zone is the most unstable area in arid region of China, and the middle reaches of the Heihe River Basin is the oasis with the largest total farmland area and the fastest expansion rate in the Hexi Corridor-Alashan Plateau zone (Feng et al. 2019; Li et al. 2020). Such expansion affects the supply and transmission of ecosystem services (Gong et al. 2019; Rallings et al. 2019). At present, research on the middle reaches of the Heihe River Basin mainly focuses on assessing the impact of previous land use change on ecosystem services, which greatly enriches the oasis ecosystem service theory (Li et al. 2018; Meng et al. 2018). However, few studies have explored the potential effects of oasis expansion on ESV because of the difficulty of predicting future oasis expansion trends, which reduces the feasibility of applying the research results to land use planning.

Field investigation and model simulation are common methods used to assess the effects of oasis expansion on ESV (Fang et al. 2014). Recently, model simulation has been increasingly emphasized because of simplicity of use on different scales (Lu et al. 2018). Currently, models including Land Use Scenario Dynamics (LUSD) (He et al. 2016) and Conversion of Land Use and Its Effects at Small Regional Extent (CLUE-S) (Anputhas et al. 2016) were developed to predict land use change. Among them, the CA-Markov (Cellular Automata-Markov) model has also been widely adopted to simulate land use change and has exhibited reasonable results (Etemadi et al. 2018). The Markov model is used to predict the amount of land use change, and the Cellular Automata (CA) models is used to predict the spatial distribution of landscapes with certain transition rules (Basse et al. 2014). More importantly, the CA–Markov model can be combined with logistic model to simulate land use suitability maps, thereby improving the simulation accuracy in different regions. To date, theoretical and methodological frameworks applying land use data and economic factors for evaluating ESV have been established. Among them, the benefit transfer method is increasingly popular because of its low demand for data and simplicity of use at different scales (Costanza et al. 1997; Xie et al. 2015).

To effectively forecast the effects of oasis expansion on ESV, we linked the Logistic-CA–Markov model to predict oasis expansion and the benefit transfer method to evaluate changes in ESV. The objectives of this study were to (1) predict future oasis expansion pattern and (2) assess the effects of oasis expansion on the provision of ESV. The results of this study allow a quantitative evaluation of the effects of oasis expansion on ESV, providing scientific support for land use planning and ecological management trade-offs and decision-making.

Study area and methodology

Study area

As the second largest inland river in northwest China, the Heihe River originates in the Qilian Mountains and finally flows into the Inner Mongolia Plateau (Song et al. 2016). The middle reaches of the Heihe River Basin is the typical desert oasis area; it is located in the middle of Hexi corridor (97°20′–102°12′ E, 38°28′–39°50′ N) and mainly includes Ganzhou District, Linze County, and Gaotai County of Zhangye City in Gansu Province. The altitude ranges from 1252 to 3609 m, showing a decreasing trend from southeast to northwest (Fig. 1). Most of the study area belongs to the piedmont alluvial-proluvial fan in the Heihe River Basin, with good irrigation conditions, forming a unique desert oasis landscape. The study area belongs to the mid-temperate Gan-Mongolia climate zone, and the annual average temperature is between − 1.1 and 9.5℃. Because it is far away from the water vapor transmission channel, the average annual precipitation in most areas is less than 200 mm, while the average annual evaporation exceeds 1600 mm. Due to its proximity to the desert, the study area are mainly desert soil and gray desert soil. The natural vegetation growing in the middle reaches of the Heihe River Basin is mainly drought-tolerant, salt-tolerant trees, small shrubs, and semi-shrubs.

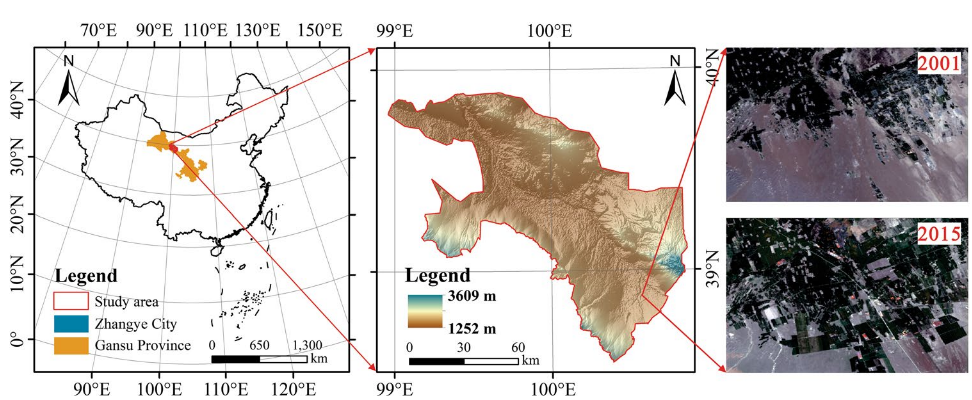

Fig. 1 Location of the study area

The study area is a typical artificial oasis, which has long been transformed by human activities. The issues of ecological security, water resource allocation, and environmental protection in the study area have attracted wide attention of scholars.

Methodology

The Logistic-CA–Markov model and the benefit transfer method were used to assess effects of oasis expansion on ESV. Specifically, the Logistic-CA–Markov model consists of two parts: the logistic regression model was used to produce the land use suitability maps, and the CA–Markov model was used to simulate the land use map. The benefit transfer method was used to quantify changes in ESV with oasis expansion.

The logistic regression model

This method divides the dependent variables into two or more values, analyzes the multiple regression relationships between the dependent variable and several independent variables, and then predicts the probability of the dependent variable. The independent variables involved in the logistic regression model can be discrete or continuous, and it is not necessary to obey normal distribution. In this paper, we used the binary logistic regression model to establish each land use type as a dependent variable. If the grid belongs to this land use type, the value is 1; if it does not, the value is 0. The independent variables were set as different natural and socioeconomic factors. The logistic regression equation can be constructed as follows:

$$logit(P_i) = ln\left[\frac{P_i}{1-P}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m \tag{1}$$

where P_i is the probability of land use type I, β_0 is constant, $\beta_1, \beta_2, \ldots \beta_m$ are regression coefficients of the independent variables, and $X_1, X_2, \ldots X_m$ are independent variables.

In the logistic regression model, the odds ratio (OR) is the ratio of probabilities of a result occurrence to nonoccurrence, that is, when the independent variable changes a unit, the change unit corresponds to the dependent variable; the formula is as follows:

$$\mathrm{OR} = p/(1-p) = exp(\beta) \tag{2}$$

where OR is the odds ratio of an event, P is the probability of the event, and β is the regression coefficient in the logistic regression model.

The area under the relative operating characteristic curve (ROC) is one of the commonly used indicator to test the fit goodness of the logistic regression model (Zhang et al. 2018). The expression of area under the ROC curve is as follows:

$$A = \frac{1}{n_a n_n}\sum_{j=1}^{n_n}\sum_{i=1}^{n_a}\varphi(x_{ai}, x_{nj}), \text{given that} \varphi(x_{ai}, x_{nj}) = \begin{cases} 1, & x_{ai} > x_{nj} \\ 0.5, & x_{ai} = x_{nj} \\ 0, & x_{ai} < x_{nj} \end{cases} \tag{3}$$

where A is the area under the ROC curve, x_{ai} ($i = 1, 2, \ldots, n_a$) is one of the observed abnormal values of n_a group, and x_{nj} ($j = 1, 2, \ldots, n_n$) is one of the observed abnormal values of n_n groups. The larger the area under the ROC, the higher the fit goodness. When $A = 0.5$, it means the simulation result is completely random and the fit goodness is the worst; when $A = 1$, it means the simulation results are consistent with the actual results, and the fit goodness is the highest. Generally, when $A > 0.70$, it is considered that the fit goodness can meet the research needs (Tiné et al. 2019).

The CA–Markov model

The CA–Markov model combines the CA model and the Markov model and used the transition probability matrix to simulate the change of land use pattern in time scale. The following equation in the Markov model can be used to obtain the transition probability matrix of land use change from stage 1 to stage 2 (Zhao et al. 2018):

$$S(t+1) = P_{ij} \times S(t) \tag{4}$$

where $S(t+1)$ and $S(t)$ are the status of the land use type at stages $t+1$ and t and P_{ij} is the transition probability matrix defined as follows:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \left(\left(0 \le P_{ij} \le 1, \sum_{i=1}^{N} P_{ij} = 1 (i,j = 1,2,\ldots,n) \right) \tag{5}$$

However, Markov processes do not account for spatial parameters adequately, and cannot identify the variability of spatial land use pattern (Wickramasuriya et al. 2009). The CA model can simulate the spatial–temporal evolution of multiple processes, including land use change. The temporal and spatial states of each pixel are discrete, and each pixel has only a finite number of states. The definition of the CA model is as follows (Sang et al. 2011):

$$S(t, t+1) = f(S(t), N) \tag{6}$$

where S represents a set of cellular states, $t+1$ and t are different stages, f is the local transition rule of the cellular, and N is the cellular field.

To ensure the reliability of the simulation results, we used the kappa index to test the consistency between the simulated and the actual land use maps (Mitsova et al. 2011):

$$kappa = \left(P_o - P_c\right)/\left(P_p - P_c\right) \tag{7}$$

where *kappa* is the index of simulation accuracy, P_o represents the actual simulation accuracy, P_c represents the expected simulation accuracy in a random state, and P_p represents the ideal simulation accuracy (100%). When $kappa \geq 0.80$, it denotes that these two maps are almost identical; when $0.60 \leq kappa < 0.80$, it denotes these two maps are highly consistent; when $0.40 \leq kappa < 0.60$, it denotes these two maps are moderately consistent; when $kappa < 0.40$, it denotes these two maps are poorly consistent.

The K-means algorithm

The K-means algorithm was chosen to classify each suitability map, as this unsupervised classification method could identify similar clusters without prior knowledge (Hartigan and Wong 1979). We used this method to divide each suitability map into 5 groups, within which group 1 represents the highest suitability, while group 5 represents the lowest suitability.

The benefit transfer method

The benefit transfer method was used to evaluate changes in ESV caused by oasis expansion. This method defines the ESV per unit area corresponding to each land use type and multiplies it by the area of each land use type to estimate the ESV (Xie et al. 2015). The formulas are as follows:

$$ESV = \sum_{k=1}^{n} \sum_{i=1}^{m} U_{ki} \times A_k \tag{8}$$

$$ESV_{\mathrm{i}} = \sum_{k=1}^{n} U_{ki} \times A_k \tag{9}$$

$$ESV_{\mathrm{k}} = \sum_{i=1}^{m} U_{ki} \times A_k \tag{10}$$

where *ESV* is the total ESV of the study area, ESV_i is the value of ecosystem service *i*, ESV_k is the *ESV* of land use *k*, A_k is the area of land use *k*, and U_{ki} is the ESV per unit area of ecosystem service *i* of land use *k*. It should be corrected based on the local natural and social conditions, and the correction formulas are as follows:

$$\mathrm{U_{ki}} = \mathrm{E} \times \mathrm{D_{ki}} \times \mathrm{F_{ki}} k = 1, 2, \ldots, n \tag{11}$$

$$E = \sum_{i=1}^{3} \mathrm{P_i} \times \mathrm{Q_i} \times \mathrm{R} \times \mathrm{Y} i = 1, 2, 3 \tag{12}$$

$$\mathrm{R} = \mathrm{GDP_m}/\mathrm{GDP_n} \tag{13}$$

$$\mathrm{Y} = 1/\left(1 + e^{-t}\right) \tag{14}$$

$$\mathrm{t} = 1/\mathrm{E_n} - 3 \tag{15}$$

$$F_{ki} = \begin{cases} 1) C_k/\overline{C} \\ 2) W_k/\overline{W} \\ 3) M_k/\overline{M} \end{cases} \tag{16}$$

where U_{ki} is the ESV per unit area of ecosystem service *i* of land use *k*, *E* is the economic value of one equivalent, D_{ki} is the equivalent per unit area of ecosystem service *i* of land use *k*, F_{ki} is the functional adjustment index for equivalent of ecosystem service *i* of land use *k*, P_i is the percentage of planting area of crop *I*, Q_i is the net profit for crop *I*, *R* is the index of capacity to pay, *Y* is the index of willingness to pay, GDP_m is the real GDP per capita of the study area, GDP_n is the real GDP per capita of China, ***e*** is the natural logarithm, *t* is the socioeconomic development index, and E_n is the Engel coefficient.

C_k, W_k, and M_k represent the average NDVI of growing season, the average annual precipitation, and average annual amount of soil retention of land use *k* in the study area, respectively; $\overline{C}$, $\overline{W}$, and $\overline{M}$ refer to the corresponding average values in China: (1) includes the ecosystem services of raw material, food production, atmosphere regulation, waste treatment, climate regulation, nutrient cycling, biodiversity protection, and recreation and culture; (2) includes the ecosystem services of water regulation and water supply; and (3) includes the ecosystem service of soil retention.

Model implementation

Land use map for 2029 forecast

Suitability maps

The production of suitability maps was completed using IDRISI17.0 software, including the following five steps:

(1) Selection of driving factors. The middle reaches of the Heihe River Basin contain most of the human activities, so both natural and socioeconomic factors should be considered when selecting driving factors. Based on the regional characteristics with reference to relevant literature (Liang and Liu 2014), a total of nine variables were finally selected: natural factors include average annual temperature, average annual precipita-

tion, DEM, slope, and groundwater depth, and socio-economic factors include road density, village density, canal density, and population density. The sources and processing methods of each variable are shown in Table 1.

(2) Dependent variable extraction of the logistic regression model. The dependent variables need to be extracted before constructing the logistic regression model. When simulating the suitability map of farmland, the pixels with grid attribute as farmland are reclassified to 1, and the others are 0, and the other five dependent variables of forest land, grassland, water body, construction land, and unused land were obtained.

(3) Logistic regression analysis. We input dependent variables and independent variables into the LogisticReg Model of IDRISI17.0 software and used 10% random sampling for regression analysis. By eliminating the variables not related to dependent variables, the six logistic regression equations corresponding to each dependent variable were finally constructed. The equation coefficients are shown in Table 2.

(4) Logistic regression accuracy analysis. The coefficients of each logistic regression equation (blank means the independent variable has no obvious influence on the dependent variable) are listed in Table 2. The simulation results show that the simulation accuracy of farmland is the highest, followed by unused land and construction land. Overall, all the ROCs of the logistic regression equations were greater than 0.70, indicating that the fit goodness were robust and can meet the research needs.

(5) Production of suitability maps. According to the logistic regression equations constructed in Table 2, the suitability maps of each land use type were simulated separately. The suitability probability was between 0 and 1: the higher the value, the higher the suitability. Finally, the Collection Editor Model of IDRISI17.0 software was applied to combine the above suitability map into a suitability atlas (Fig. 2).

Land use map simulation

Based on the land use maps for 2001, 2008, and 2015, the IDRISI17.0 software was used to predict the land use map of the middle reaches of the Heihe River Basin in 2029, which primarily included the following five steps:

(1) Acquisition of the land use transition probability matrix. We established the land use maps for 2001 and 2008 as the initial and last years, respectively, and obtained the land use transition probability matrix through the Markov model of IDRISI17.0 software.

(2) Construction of the CA filter. We chose a 5×5 filter as the neighborhood definition and set the cell size at $30\ m \times 30\ m$ (Gong et al. 2015).

(3) Simulation of land use map for 2015. To simulate the land use map in the middle reaches of the Heihe River Basin more accurately, two different scenarios were set up: a usual scenario (usual interest, UI) and a constrained scenario (constrained interest, CI). In the UI scenario, land use change is affected only by historical land use transition probability, whereas in the CI scenario, land use change is not only affected by historical land use transition probability, but also by constrained factors. According to the Wetland Protection Program, water body could not convert to other land use types, and in practice, construction land generally did not change; thus, water body and construction land were both set as constraints. Then we set the land use map for 2008 as the initial year, input the suitability

Table 1 Database used for producing suitability atlas

Variables	Sources	Processing method
Average annual temperature	Resource and Environment Science and Data Center of Chinese Academy of Sciences	Extraction with ArcGIS software
Average annual precipitation	Resource and Environment Science and Data Center of Chinese Academy of Sciences	Extraction with ArcGIS software
DEM	Resource and Environment Science and Data Center of Chinese Academy of Sciences	Extraction with ArcGIS software
Slope	Resource and Environment Science and Data Center of Chinese Academy of Sciences	Calculation with DEM data
Groundwater depth	Water Affairs Bureau of Zhangye City	Kriging interpolation
Road density	Heihe Plan Data Management Center	Linear density of road
Village density	Land and Resources Bureau of Zhangye City	Point density of administrative villages
Canal density	Heihe Plan Data Management Center	Linear density of canal system
Population density	Resource and Environment Science and Data Center of Chinese Academy of Sciences	Extraction with ArcGIS Software

Table 2 Logistic regression results of each land use type

Variables	Coefficients	Farmland	Woodland	Grassland	Water body	Construction land	Unused land
Average annual temperature	β	0.8416					2.1129
	exp(β)	2.3201					8.2722
Average annual precipitation	β		0.0149	−0.0092	0.0153		−0.0412
	exp(β)		1.0150	0.9908	1.0154		0.9596
DEM	β	0.0039	−0.0341	0.0043	−0.0026	−0.0452	0.0137
	exp(β)	1.0039	0.9665	1.0043	0.9974	0.9558	1.0138
Slope	β	−0.0965		−0.0013		−0.0950	0.0274
	exp(β)	0.9080		0.9987		0.9094	1.0278
Groundwater depth	β	−0.0514	−0.0723	0.0067			0.0431
	exp(β)	0.9499	0.9303	1.0067			1.0440
Road density	β		−1.5743			1.6906	
	exp(β)		0.2072			5.4227	
Village site density	β		1.4035			0.3346	
	exp(β)		4.0694			1.3974	
Canal density	β	2.8736	0.6096				−2.1578
	exp(β)	17.7006	1.8397				0.1156
Population density	β					0.0013	
	exp(β)					1.0013	
Constant	β	−16.3327	−6.5831	−7.5508	−1.8757	−4.6002	−32.3077
	exp(β)	0.0000	0.0014	0.0005	0.1532	0.0100	0.0000
ROC		0.9662	0.8606	0.8845	0.8278	0.9542	0.9576

atlas and the transition probability matrix into the CA–Markov model of IDRISI17.0 software, and simulated land use maps for 2015 based on UI and CI scenarios, respectively (Fig. 3).

(4) Accuracy test. The simulated and actual land use maps for 2015 were input into the CROSSTAB Model of IDRISI17.0 to verify the simulation accuracy of the CA–Markov model. The results showed that the kappa index of the UI scenario is 0.8447, and the kappa index of the CI scenario is 0.8642, indicating satisfactory results (Zhang et al. 2011).

(5) Simulation of the land use map for 2029. The kappa index of the CI scenario is higher than that of the UI scenario, denoting that simulating land use map based on the CI scenario could reflect actual conditions better (Fig. 3). Thus, we established the land use map for 2015 as the initial year and simulated the land use map for 2029 based on the CI scenario.

The benefit transfer method

Xie et al. (2015) proposed the ESV per unit area in China, but when applying it to small-scale areas, it needs to be corrected according to the regional natural and social characteristics. The required data and sources are as follows: the NDVI are derived from the Atmosphere Archive and Distribution System (LAADS); the precipitation and the amount of soil retention are derived from Resource and Environment Science and Data Center of Chinese Academy of Sciences; the real GDP per capita, the Engel coefficient, and crop planting area are derived from Zhangye Statistical yearbook; the net profit of crop is derived from Compilation of National Agricultural Product Cost and Income Data. The obtained ESV per unit area in the study area is as follows (Table 3).

Results

Driving mechanism of land use change

The results of logistic regression model show the driving mechanism of land use change (Table 2). A positive coefficient shows that the factor is positively correlated with land use suitability and vice versa. The absolute value of coefficients reflects the degree of influence of the factor on land use suitability. The results show that as the main land use type of artificial oasis, farmland is primarily distributed in areas with convenient irrigation facilities. The higher the density of canal systems, the higher the farmland suitability. Construction land is mainly distributed in areas with strong accessibility, dense village points, and small slope. The water body is mainly distributed in areas with high precipitation and good catchment conditions. Because forest land has numerous requirements for the growth environment and the proportion of oasis shelter forest in the

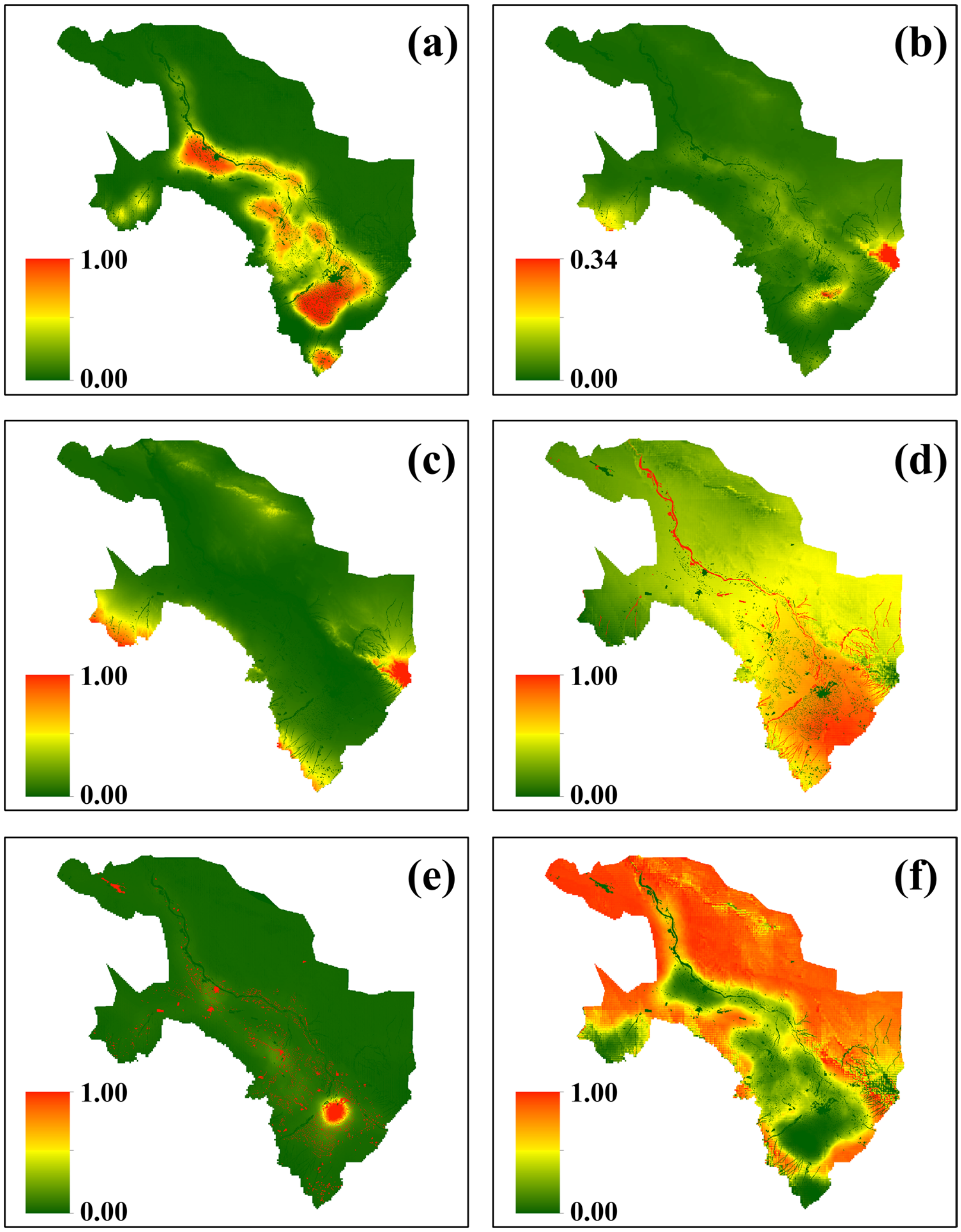

Fig. 2 Suitability maps of each land use type: **a** farmland, **b** woodland, **c** grassland, **d** water body, **e** construction land, **f** unused land

middle reaches is relatively high, it is mainly distributed in areas with good habitat conditions that are suitable for human habitation. Grassland and unused land are mostly naturally formed landscapes, mostly distributed in areas with less precipitation, higher groundwater depth, and worse habitats. The results can provide a basis for land use planning.

Oasis expansion pattern between 2001 and 2029

Oasis expansion pattern between 2001 and 2015

From 2001 to 2015, the oasis expanded by 361.12 km^2, with a total of 6.92% of the land in the middle reaches of the Heihe River Basin converted to other land use types (Fig. 4). Among them, farmland, water body, and construction land showed increasing trends: the growth rate of construction land was the highest, reaching 34.34% (60.76 km^2), followed by farmland, increasing by 20.40% (377.58 km^2), and water body, increasing by 9.50 km^2 with a growth rate of 3.97%. With oasis expansion, the areas of the other three land use types showed downward trends: woodland decreased by 19.97% (29.15 km^2); unused land and grassland decreased by 5.32% (361.12 km^2) and 3.68% (57.58 km^2), respectively, all of which were mainly converted to farmland (Table 4).

Under the background of oasis expansion, the growth rate of farmland and construction land was significantly

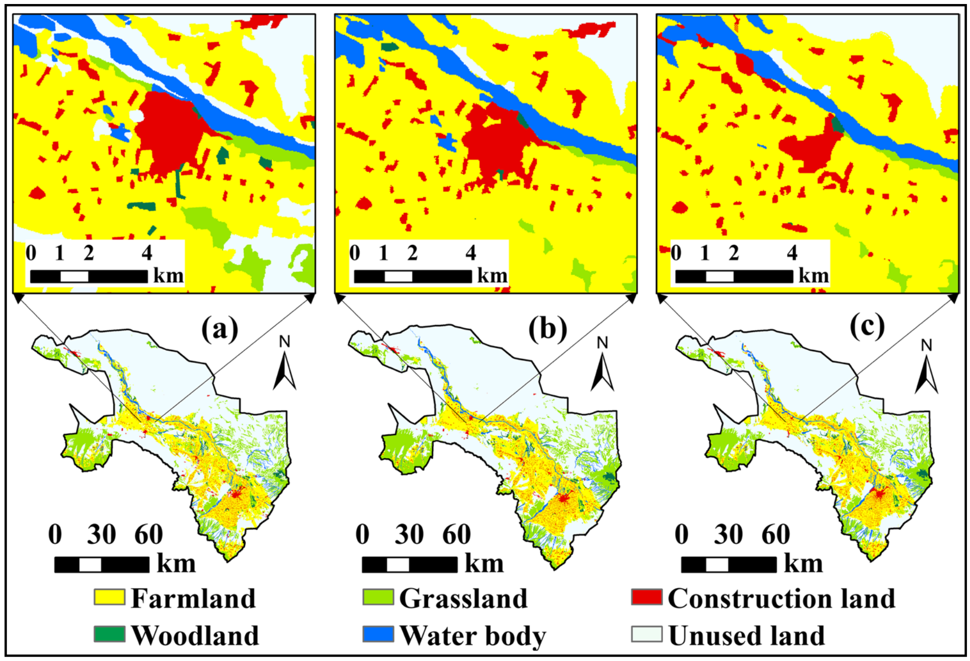

Fig. 3 Comparison between actual and simulated land use maps for 2015: **a** actual land use map for 2015, **b** simulated land use map for 2015 based on the CI scenario, **c** simulated land use map for 2015 based on the UI scenario

Table 3 The ESV per unit area (10^3 ¥/km^2)

Ecosystem service types	Farmland	Woodland	Grassland	Water body	Construction land	Unused land
Food production	45.02	10.88	5.89	58.26	0.00	0.00
Raw material	21.19	24.68	8.24	16.75	0.00	0.00
Atmosphere regulation	35.49	81.05	30.01	56.08	0.00	1.77
Climate regulation	19.07	242.97	78.86	166.78	0.00	0.00
Waste treatment	5.30	72.81	25.89	404.20	0.00	8.83
Nutrient cycling	6.36	7.47	2.94	5.10	0.00	0.00
Biodiversity protection	6.89	90.13	32.96	185.71	0.00	1.77
Recreation and culture	3.18	39.63	14.71	137.65	0.00	0.88
Water supply	0.38	5.74	3.53	237.84	0.00	0.00
Hydrological regulation	5.16	83.63	43.26	2933.26	0.00	2.65
Soil retention	102.92	96.93	44.27	264.75	0.00	4.91

higher than that of the other four land use types. The oasis expansion in the middle reaches of the Heihe River Basin was mainly based on the reclamation of unused land. However, it is worth noting that parts of the woodland and grassland were occupied during the process of oasis expansion, which may result in a series of ecological and environmental problems.

Future oasis expansion pattern between 2015 and 2029

The predicted land use map for 2029 indicates that the oasis in the middle reaches of the Heihe River Basin is expected to further expand 419.02 km^2 from 2015 to 2029, and a total of 6.85% of the land use types will change (Fig. 5). The areas of farmland, construction land, and water body will continue to grow. Farmland is expected to increase by 18.87% (420.37 km$^{2)}$; unused land is the main source of farmland expansion. Construction land has the highest growth rate with an expected increase of 39.05% (92.84 km^2), mainly converted from unused land and farmland. Water body is expected to increase by 4.42%. The areas of the other three land use types are expected to decrease by different degrees: the area of unused land is expected to decrease by 419.04 km^2, followed by grassland (81.27 km^2). Although forest land is expected to decrease by only 23.91 km^2, its change rate is the second highest (20.48%) after construction land. In addition to occupying unused land, the farmland expansion is expected to occupy woodland and grassland, leading to a further decline in vegetation coverage.

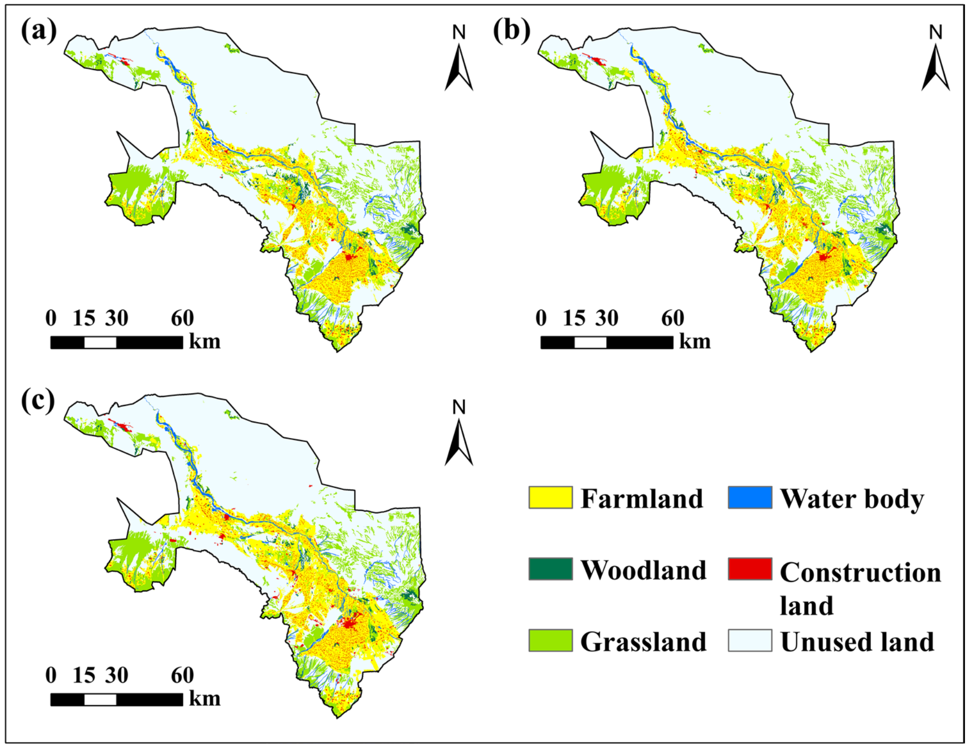

Fig. 4 Land use maps: **a** 2001, **b** 2008, **c** 2015

Table 4 Land use change between 2001 and 2029 (km^2)

Land use types	2001	2008	2015	2029
Farmland	1850.56	2004.64	2228.14	2648.50
Woodland	145.91	131.06	116.77	92.86
Grassland	1564.54	1549.52	1506.96	1425.69
Water body	239.40	244.30	248.91	259.91
Construction land	176.97	190.59	237.73	330.57
Unused land	6785.61	6642.88	6424.49	6005.45

Changes in ESV between 2001 and 2029

Changes in ESV between 2001 and 2015

Our results showed that the ESV of the study area is primarily distributed in the area near the Heihe River because of the superior irrigation conditions and topographical advantages. The total ESV of the study area increased by 90.93 million RMB from 2001 to 2015, and farmland expansion contributed the most to the increase in ESV.

For each land use type, nearly half of the ESV was stored in water body by 2015 because it has a greater

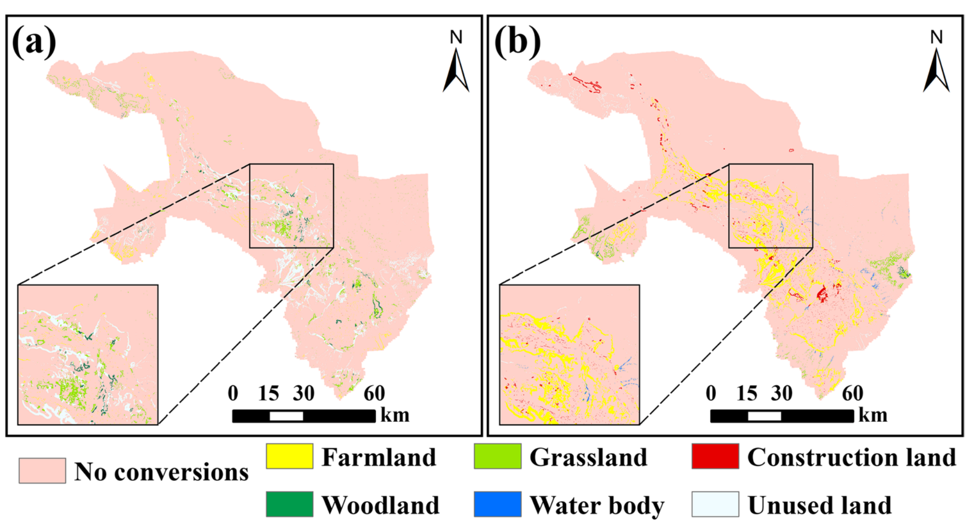

Fig. 5 Land use change from 2015 to 2029: **a** land converted from and **b** land converted to

ability to provide ecosystem services than other land use types (Fig. 6). Followed by farmland, its ESV share is about 20%. The ESV of grassland is close to farmland, but its proportion decreased with the shrinkage of its area. Although the area of unused land is the largest, its ESV accounts for only 6% because of a lower capacity to supply ecosystem services. The proportion of ESV supplied by forest land is less than 5% because of its small area.

For each ecosystem service type, hydrological regulation is the most valuable ecosystem service in the middle reaches of the Heihe River Basin, accounting for nearly 40% of the total ESV (Fig. 7); the value of soil retention accounts for about 17%; the total value of climate regulation and waste treatment accounts for about 9%; the total value of atmosphere regulation, biodiversity protection, and food production accounts for about 5%; and the total value of the other ecosystem service types accounts for less than 4%.

Potential effects of oasis expansion on ESV

Our results show that oasis expansion is expected to lead to an increase in ESV by 104.23 million RMB from 2015 to 2029, with a mean accumulation of 7.45 million RMB per year (Fig. 6). Moreover, the ESV of each land use type is expected to be positively related to the changes in its area; as the area expands, its ESV increases and vice versa. Specifically, as farmland and water body expand, their ESVs are expected to increase by 105.49 million RMB and 49.15 million RMB, respectively. However, shrinkage in grassland, woodland, and unused land are expected to decrease their ESVs by 23.61 million RMB, 18.07 million RMB, and 8.72 million RMB, respectively. Although the values of most ecosystem service types are expected to increase by varying degrees, the values of climate regulation, waste treatment, and biodiversity protection are expected to decrease with continuous farmland expansion (Fig. 8).

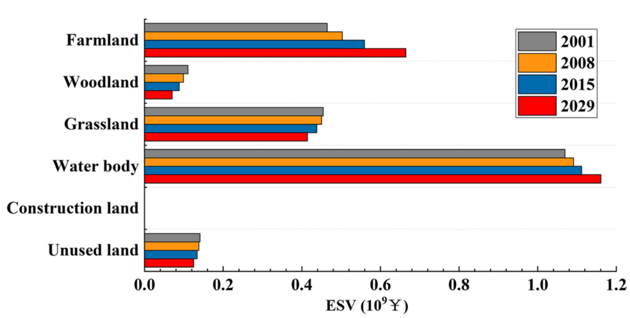

Fig. 6 Changes in ESV for each land use type from 2001 to 2029

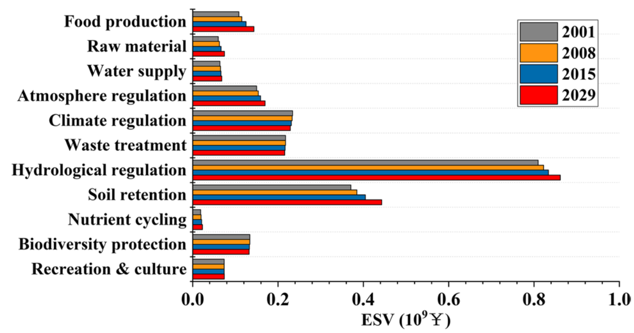

Fig. 7 Changes in ESV for each ecosystem service type from 2001 to 2029

Discussion

Effects of artificial oasis expansion on ESV

The oasis in the middle reaches is the main bearing area of human production and life in the Heihe River Basin. With continuous economic development, the oasis expands rapidly, leading to changes in ESV. Exploring the potential effects of oasis expansion on ESV is greatly significant for land planning and ecological restoration (Gomes et al. 2020). Farmland and construction land growth are the most salient features of artificial oasis expansion, whereas farmland and urban expansion have different impacts on ESV.

Farmland expansion has dual effects on ESV, primarily related to whether the capacity of the occupied land use type to provide ESV is higher than that of farmland; if so, it helps increase ESV and vice versa. Thus, when

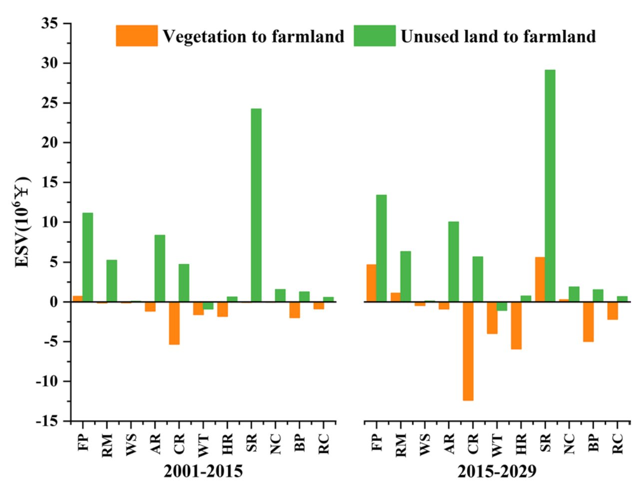

Fig. 8 The effects of farmland expansion on ESV from 2001 to 2029: FP, food production; RM, raw material; WS, water supply; AR, atmosphere regulation; CR, climate regulation; WT, waste treatment; HR, hydrological regulation; SR, soil retention; NC, nutrient cycling; BP, biodiversity protection; RC, recreation and culture

farmland encroaches on woodland and grassland, ESV decreases (Ouyang et al. 2016). From 2001 to 2015, 30.57 km^2 of woodland and 92.59 km^2 of grassland converted to farmland, leading to a total loss of ESV of 19.11 million RMB. Similarly, 24.70 km^2 of woodland and 100.44 km^2 of grassland are expected to convert to farmland, leading to a loss of ESV of 16.45 million RMB. Vegetation degradation reduces the values of climate regulation mostly, followed by hydrological regulation and biodiversity protection, mainly because the ability of vegetation to provide these types of ecosystem services is significantly higher than that of farmland (Xie et al. 2015).

When farmland encroaches on unused land, ESV increases. From 2001 to 2015, 297.32 km^2 of unused land converted to farmland, and ESV increased by 68.43 million RMB. From 2015 and 2029, 361.63 km^2 of unused land is expected to convert to farmland, resulting in an increase in the ESV by 83.23 million RMB. Although the values of most types of ecosystem services are on the rise, the value of waste treatment is on the decline, mainly related to the use of fertilizers, pesticides, and plastic films in the process of crop planting (Vasco et al. 2021).

Compared with farmland expansion, the impact of construction land expansion on ESV is much lower, mainly due to its relatively small expansion area. Despite this, construction land expansion mainly takes over farmland and unused land, resulting in loss of ESV. From 2001 to 2015, 30.43 km^2 of farmland and 33.43 km^2 of unused land were converted to construction land, leading to a loss of 7.63 million RMB and 0.70 million RMB, respectively. From 2015 to 2029, 24.60 km^2 of farmland and 48.12 km^2 of unused land are expected to convert to construction land, leading to a loss of 6.17 million RMB and 1.00 million RMB, respectively. This is because the construction land blocks the communication of the ecosystem and can hardly provide ecosystem services (He et al. 2016).

We concluded that oasis expansion is mainly characterized by farmland expansion. Farmland expansion encroaching on unused land led to a growth of the total ESV, whereas the encroachment on vegetation led to the decline of ecosystem services such as climate regulation. More attention should be paid to reducing the ecosystem services trade-offs caused by oasis expansion. Notably, except for oasis expansion, after the Wetland Protection Program was implemented in the middle reaches of the Heihe River Basin, the growth of water body area also contributed to the growth of ESV.

Suggestions for land use optimization

It is obvious that the invasion of farmland to woodland is the main cause of ESV loss. In order to improve the coordination of ecological protection and economic development, we put forward the land use optimization scheme (Fig. 9). Firstly, we used K-means algorithm to divide the land use suitability maps of farmland and woodland into 5 groups, of which group 1 represents the highest suitability, while group 5 represents the lowest suitability. Then the decision tree method was applied to optimize the land use pattern.

The land use optimization map shows that the reserved farmland is mainly distributed around the existing farmland, which is in line with the actual situation of the study area (Fig. 10). We recommend these areas as the main source of new farmland, which could greatly reduce irrigation costs and facilitate management. As shown in Table 2, the irrigation canal system is the most important factor affecting farmland distribution. Therefore, we suggest that the canal should be built near the reserved farmland in the future to facilitate the reclamation of reserved farmland. In addition, the de-farming area is mainly distributed in areas far away from existing farmland. The ecosystem in these areas is relatively fragile, and the irrigation cost is higher than reserved farmland, so those farmlands should be abandoned. The total area of reserved woodland is small, mainly distributed in the southeast of the study area with better hydrothermal conditions. The general area is mainly distributed in areas with poor natural environment and location conditions. Human disturbance to these areas should be reduced so that they can become grassland or unused land naturally according to local resource carrying capacity. It is worth noting that this study only provides suggestions on the land use suitability, but lacks analysis on resource carrying capacity. For example, the reserved farmland is more suitable to be reclaimed as

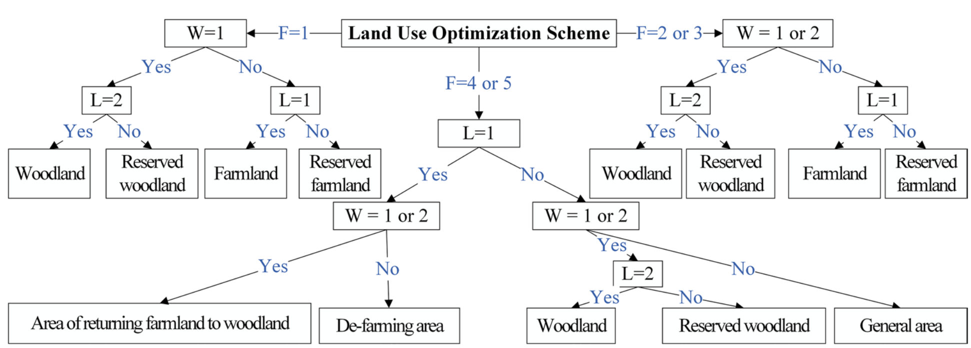

Fig. 9 The land use optimization scheme: F, suitability grade of farmland; W, suitability grade of woodland (1 represents the highest suitability, 5 represents the lowest suitability); L, land use type (1 represents farmland, 2 represents woodland, 3 represents grassland, 4 represents water body, 5 represents construction land, 6 represents unused land)

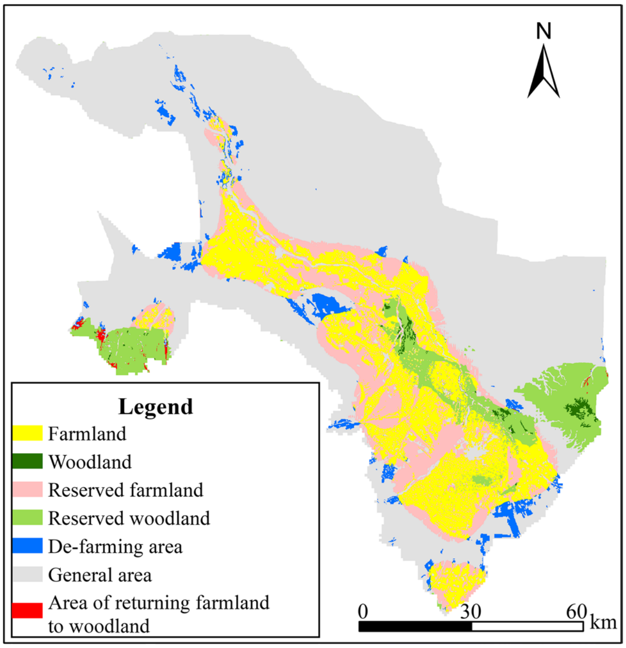

Fig. 10 The land use optimization map

farmland than other areas, but the reclamation scale still depends on the water resource carrying capacity.

Strengths and limitations of the method

Land use change and the resulting changes in ESV have become a research hotspot, and several studies have attempted to assess the effects of land use change on ESV (Cao et al. 2015; Tardieu et al. 2015; Vo et al. 2015). While those studies concentrate on economically developed areas, less attention has been paid to oasis expansion in arid areas. Furthermore, most of those studies examined changes in ESV revolving around previous rather than future land use change, prohibiting applying their results to adjusting land management strategies in advance (Zhao et al. 2018). Thus, exploring a feasible method to study, the potential effects of oasis expansion on ESV is of great significance to ecological protection and land use planning, especially in an oasis with fragile environment.

In this paper, we predict the potential effects of oasis expansion on ESV in the middle reaches of the Heihe River Basin. First, we used the logistic regression model to produce suitability maps: all the ROCs of the six logistic regression equations were greater than 0.70, indicating that the equation fit goodness is robust and can meet research needs. Then we used the CA–Markov model to simulate oasis expansion patterns, with a kappa index over 0.8, indicating that the simulation results of the model are satisfactory. Last, we used the benefit transfer method to evaluate the effects of oasis expansion on ESV. This method requires a small amount of data and is easy to operate. More importantly, this method makes it possible to evaluate ESV on a large scale (Song and Deng 2017).

Linking the Logistic-CA-Markov and the benefit transfer method has promising applications for guiding land management. First, the logistic regression model was used to identify factors and driving mechanisms of land use change. The suitability maps show the areas with higher distribution probability of each land use type. Second, assessing changes in ESV resulting from oasis expansion helps identify areas with lower trade-off and synergy among ecosystem services. The above results are of great significance for policy makers and ecologists to screen out those areas more suitable for farmland reclamation in combination with a low trade-off of ecosystem service changes as sources of oasis expansion (Talukdar et al. 2020).

Although the current linked Logistic-CA–Markov model and the benefit transfer method have achieved success in assessing potential effects of oasis expansion on ESV, further attention should be given to the benefit transfer method because of the limitations it has shown. First, although the ESV per unit area proposed by Xie et al. (2015) has been corrected based on local natural and socioeconomic characters, the evaluation result is still different from the actual results. Second, terrestrial ecosystems provide not only positive services but also negative ones (Shi et al. 2012). Taking the construction land as an example, it has changed the natural landscape of the ecosystem and hindered the original ecological process. However, in this study, the ESV of construction land is set to zero, ignoring the negative ecosystem services provided by it, which will lead to a deviation from ESV assessment (Arnold et al. 2018). Therefore, to evaluate the ESV accurately, developing a feasible way to formulate more accurate equivalents of ESV, and integrating the positive and negative ecosystem services into the ESV accounting framework will be the next research focus.

Conclusions

We combined the Logistic-CA–Markov model and the benefit transfer method to assess the potential effects of oasis expansion on ESV in the middle reaches of the Heihe River Basin. The logistic regression model was used to construct suitability maps, the CA–Markov model was used to predict land use map, and the benefit transfer method was used to assess changes in ESV with oasis expansion. The simulation results pass all tests indicates that the performance of the method in the study area is satisfactory.

The results showed that with the increase of human demand for food and living space, the oasis expanded by 361.12 km^2 from 2001 to 2015, and the value is expected to reach 419.02 km^2 from 2015 to 2029. The farmland, construction land, and water body areas show continuous expanding trends, whereas the grassland, woodland, and unused land show continuous shrinking trends. Oasis expansion is primarily characterized by the rapid growth of farmland and construction land after the exploitation of unused land.

The total ESV of the middle reaches of the Heihe River Basin increased from 2.24 billion RMB in 2001 to 2.33 billion RMB in 2015, and it is expected to reach 2.44 billion RMB in 2029. With oasis expansion, farmland encroachment on unused land increased ESV by 0.07 billion RMB from 2001 to 2015 and will increase ESV by 0.08 billion RMB from 2015 to 2029. The results can provide a basis for trade-offs and decision-making in environmental management.

Overall, oasis expansion is dominated by the exploitation of unused land, which is also an important reason for the increase of ESV. However, farmland expansion occupies vegetation, resulting in a series of ecological problems. Therefore, how to achieve the coordinated development of economic development and environmental protection remains an urgent problem to be solved in the process of oasis development in arid areas.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by MZ, ZH, and SW. The first draft of the manuscript was written by MZ, and all authors commented on previous versions of the manuscript.

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Data availability The sources of data have been duly mentioned in the study.

Declarations

Ethics approval This article does not contain any studies with human participants performed by any of the authors.

Consent to participate All authors consent to participate in the works of the manuscript.

Consent for publication All authors consent to submit and publish the manuscript.

Competing interests The authors declare no competing interests.

References

Anputhas M, Janmaat J, Nichol CF, Wei XA (2016) Modelling spatial association in pattern based land use simulation models. J Environ Manage 181:465–476. https://doi.org/10.1016/j.jenvman.2016.06.034

Arnold J, Kleemann J, Furst C (2018) A differentiated spatial assessment of urban ecosystem services based on land use data in Halle Germany. Land 7(3):101. https://doi.org/10.3390/land7030101

Bai Y, Zhao Y, Wang Y, Zhou K (2020) Assessment of ecosystem services and ecological regionalization of grasslands support establishment of ecological security barriers in northern China. Bull Chinese Acad Sci 35 214(06):675–689

Basse RM, Omrani H, Charif O, Gerber P, Bódis K (2014) Land use changes modelling using advanced methods: cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. Appl Geogr 53:160–171. https://doi.org/10.1016/j.apgeog.2014.06.016

Braat LC, Groot RD (2012) The ecosystem services agenda: bridging the worlds of natural science and economics, conservation and development, and public and private policy. Ecosyst Serv 1(1):4–15. https://doi.org/10.1016/j.ecoser.2012.07.011

Cao V, Margni M, Favis BD, Deschênes L (2015) Aggregated indicator to assess land use impacts in life cycle assessment (LCA) based on the economic value of ecosystem services. J Clean Prod 94:56–66. https://doi.org/10.1016/j.jclepro.2015.01.041

Cegielska K, Noszczyk T, Kukulska A, Szylar M, Hernik J, Dixongough R, Jombach S, Valanszki I, Kovacs KF (2018) Land use and land cover changes in post-socialist countries: some observations from Hungary and Poland. Land Use Policy 78:1–18. https://doi.org/10.1016/j.landusepol.2018.06.017

Chen Y, Li W, Chen Y, Zhu C (2018) Science in supporting the ecological restoration and sustainable development of the Tarim River Basin. Arid Land Geography 041(005):901–907

Costanza R, D'Arge R, Groot RD, Farber S, Grasso M, Hannon B, Limburg K, Naeem S, O'Neill RV, Paruelo J (1997) The value of the world's ecosystem services and natural capital 1. Nature 387(1):3–15. https://doi.org/10.1016/S0921-8009(98)00020-2

Daily GC (1997) Nature's services: societal dependence on natural ecosystems. Pac Conserv Biol 6(2):220–221. https://doi.org/10.1071/PC000274

Etemadi H, Smoak JM, Karami J (2018) Land use change assessment in coastal mangrove forests of Iran utilizing satellite imagery and CA–Markov algorithms to monitor and predict future change. Environ Earth Sci 77(5):208. https://doi.org/10.1007/s12665-018-7392-8

Fang J, Guo Z, Hu H, Kato T, Muraoka H, Son Y (2014) Forest biomass carbon sinks in East Asia, with special reference to the relative contributions of forest expansion and forest growth. Glob Change Biol 20(6):2019–2030. https://doi.org/10.1111/gcb.12512

Farley J, Costanza R, Farley J, Costanza R (2010) Special section: Payments for ecosystem services: from local to global. Ecol Econ 69(11):2060–2068. https://doi.org/10.1016/j.ecolecon.2010.06.010

Feng Q, Yang L, Deo RC, AghaKouchak A, Adamowski JF, Stone R, Yin Z, Liu W, Si J, Wen X, Zhu M, Cao S (2019) Domino effect of climate change over two millennia in ancient China's Hexi Corridor. Nature Sustain 2(10):957–961. https://doi.org/10.1038/s41893-019-0397-9

Gao X, Wang J, Li C, Shen W, Zhang X (2021) Land use change simulation and spatial analysis of ecosystem service value in Shijiazhuang under multi-scenarios. Environ Sci Pollut Res 1:1–16. https://doi.org/10.1007/s11356-021-12826-9

Gomes LC, Bianchi F, Cardoso IM, Filho E, Schulte R (2020) Land use change drives the spatio-temporal variation of ecosystem services and their interactions along an altitudinal gradient in Brazil. Landsc Ecol 35(7):1571–1586. https://doi.org/10.1007/s10980-020-01037-1

Gong J, Liu D, Zhang J, Xie Y, Cao E, Li H (2019) Tradeoffs/synergies of multiple ecosystem services based on land use simulation in a mountain-basin area, western China. Ecological Indicators 99 (APR.):283–293. https://doi.org/10.1016/j.ecolind.2018.12.027

Gong W, Yuan L, Fan W, Stott P (2015) Analysis and simulation of land use spatial pattern in Harbin prefecture based on trajectories and cellular automata—Markov modelling. Intl J Appl Earth Observ Geoinform 34(1):207–216. https://doi.org/10.1016/j.jag.2014.07.005
Hartigan JA, Wong MA (1979) Algorithm AS 136: a k-means clustering algorithm. J Roy Stat Soc 28(1):100–108. https://doi.org/10.2307/2346830
He C, Zhang D, Huang Q, Zhao Y (2016) Assessing the potential impacts of urban expansion on regional carbon storage by linking the LUSD-urban and InVEST models. Environmental Modelling & Software 75 (C):44–58. https://doi.org/10.1016/j.envsoft.2015.09.015
Li F, Liu J, Ren W, Liu L (2018) Land-use change alters patterns of soil biodiversity in arid lands of northwestern China. Plant & Soil:371–388. https://doi.org/10.1007/s11104-018-3673-y
Li S, Zhang Z, Tao W, Yan C, Du H (2020) Oasis functional stability evaluation based on multiple indicators, northwest China. Acta Geol Sin 94(3):624–636. https://doi.org/10.1111/1755-6724.14535
Li X, Guo J, Qi S (2021) Forestland landscape change induced spatiotemporal dynamics of subtropical urban forest ecosystem services value in forested region of China: a case of Hangzhou city. Environmental Research 193 (2):110618. https://doi.org/10.1016/j.envres.2020.110618
Liang Y, Liu L (2014) Economic valuation of ecosystem service in the middle basin of Heihe River, Northwest China. Intl J Environ Eng Natl Resour 1(3):164–170. https://doi.org/10.1007/s10980-014-0089-9
Liu J, Kuang W, Zhang Z, Xu X, Qin Y, Ning J, Zhou W (2014) Spatiotemporal characteristics, patterns and causes of land use changes in China since the late 1980s. Acta Geogr Sin 69(1):3–14. https://doi.org/10.1007/s11442-014-1082-6
Lu F, Hu H, Sun W, Zhu J, Liu G, Zhou W, Zhang Q, Shi P, Liu X, Wu X (2018) Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010. Proc Natl Acad Sci U S A 115(16):4039–4044. https://doi.org/10.1073/pnas.1700294115
Meng J, Wang Y, Jiang S (2018) Study of ecological compensation of the Grain for Green program in the middle reaches of Heihe River based on ecosystem services. Acta Ecol Sin 39(15):5404–5413
Mitsova D, Shuster W, Wang X (2011) A cellular automata model of land cover change to integrate urban growth with open space conservation. Landsc Urban Plan 99(2):141–153. https://doi.org/10.1016/j.landurbplan.2010.10.001
Ouyang Z, Zheng H, Xiao Y, Polasky S, Liu J, Xu W, Wang Q, Zhang L, Xiao Y, Rao E (2016) Improvements in ecosystem services from investments in natural capital. Science 352(6292):1455–1459. https://doi.org/10.1126/science.aaf2295
Rallings AM, Smukler SM, Gergel SE, Mullinix K (2019) Towards multifunctional land use in an agricultural landscape: a trade-off and synergy analysis in the Lower Fraser Valley, Canada. Landsc Urban Plan 184:88–100. https://doi.org/10.1016/j.landurbplan.2018.12.013
Sang L, Zhang C, Yang J, Zhu D, Yun W (2011) Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Math Comput Model 54(3):938–943. https://doi.org/10.1016/j.mcm.2010.11.019
Sangermano F, Pontius RG, Chaitman J, Meneghini A (2021) Linking land change model evaluation to model objective for the assessment of land cover change impacts on biodiversity. Landscape Ecology:1–17. https://doi.org/10.1007/s10980-021-01251-5
Shi Y, Wang RS, Huang JL, Yang WR (2012) An analysis of the spatial and temporal changes in Chinese terrestrial ecosystem service functions. Chin Sci Bull 57(17):2120–2131. https://doi.org/10.1007/s11434-012-4978-5
Song W, Deng X (2017) Land-use/land-cover change and ecosystem service provision in China. Sci Total Environ 576:705–719. https://doi.org/10.1016/j.scitotenv.2016.07.078
Song X, Brus DJ, Liu F, Li D, Zhao Y, Yang J, Zhang G (2016) Mapping soil organic carbon content by geographically weighted regression: a case study in the Heihe River Basin, China. Geoderma 261:11–22. https://doi.org/10.1016/j.geoderma.2015.06.024
Talukdar S, Singha P, Shahfahad MS, Praveen B, Rahman A (2020) Dynamics of ecosystem services (ESs) in response to land use land cover (LU/LC) changes in the lower Gangetic plain of India. Ecol Ind 112:1–14. https://doi.org/10.1016/j.ecolind.2020.106121
Tardieu L, Roussel S, Thompson JD, Labarraque D, Salles JM (2015) Combining direct and indirect impacts to assess ecosystem service loss due to infrastructure construction. J Environ Manage 152(1):145–157. https://doi.org/10.1016/j.jenvman.2015.01.034
Tiné M, Perez L, Molowny-Horas R (2019) Hybrid spatiotemporal simulation of future changes in open wetlands: a study of the Abitibi-Témiscamingue region, Québec, Canada. Int J Appl Earth Obs Geoinf 74:302–313. https://doi.org/10.1016/j.jag.2018.10.001
Vasco C, Torres B, Jácome E, Torres A, Eche D, Velasco C (2021) Use of chemical fertilizers and pesticides in frontier areas: a case study in the Northern Ecuadorian Amazon. Land Use Policy 107. https://doi.org/10.1016/j.landusepol.2021.105490
Vo TQ, Kuenzer C, Oppelt N (2015) How remote sensing supports mangrove ecosystem service valuation: a case study in Ca Mau province Vietnam. Ecosyst Serv 14:67–75. https://doi.org/10.1016/j.ecoser.2015.04.007
Wickramasuriya RC, Bregt AK, van Delden H, Hagen-Zanker A (2009) The dynamics of shifting cultivation captured in an extended Constrained Cellular Automata land use model. Ecol Model 220(18):2302–2309. https://doi.org/10.1016/j.ecolmodel.2009.05.021
Xie G, Zhang C, Lei M, Chen W, Li S (2015) Improvement of the evaluation method for ecosystem service value based on per unit area. J Nat Resour 30(8):1243–1254
Xu E, Zhang H, Xu Y (2020) Exploring land reclamation history: soil organic carbon sequestration due to dramatic oasis agriculture expansion in arid region of northwest China. Ecological Indicators 108:105746. https://doi.org/10.1016/j.ecolind.2019.105746
Yang N, Xi N, Malik N, Wistuba N, Yiguo N, Dong De N, Zhijie N, Jing N, Lingyun N, Ruide N (2021) Spatiotemporal changes in water, land use, and ecosystem services in Central Asia considering climate changes and human activities. Journal of Arid Land 13 (9):10. http://jal.xjegi.com/https://doi.org/10.1007/s40333-021-0084-3
Zhang R, Tang C, Ma S, Yuan H, Gao L, Fan W (2011) Using Markov chains to analyze changes in wetland trends in arid Yinchuan Plain China. Math Comput Modell 54(3):924–930. https://doi.org/10.1016/j.mcm.2010.11.017
Zhang W, Dong W, Ye Y, Kuang C, Liu X, Wang T, Song Y, Zhou Q, Zhong Y, Zhu Y (2018) Advanced course of SPSS statistical analysis. Higher Education Press, Beijing
Zhao M, He Z, Du J, Chen L, Lin P, Fang S (2018) Assessing the effects of ecological engineering on carbon storage by linking the CA-Markov and InVEST models. Ecological Indicators 98 (MAR.):29–38. https://doi.org/10.1016/j.ecolind.2018.10.052

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