Heliyon 10 (2024) e25305

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Impact of agricultural irrigation and resettlement practices on carbon storage in arid inland river basins: A case study of the Shule river basin

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ARTICLE INFO

Keywords:
Carbon storage
InVEST model
Model correction
Optimal parameters geographical detector model
Shule river basin

ABSTRACT

Agricultural irrigation and resettlement have significant impacts on carbon storage in arid inland river basins. With the background of "Comprehensive development measures for agricultural irrigation and resettlement in Shule River Basin (SRB)", this paper uses land use data to estimate regional carbon storage through InVEST model and revises the result by using net ecosystem productivity (NEP). The influence of land use change on carbon storage and the driving factors of carbon storage spatial differentiation were analyzed by using the optimal parameters geographical detector (OPGD). It can be inferred from the results that: (1) During 2000–2020, the increase of cropland and grassland area is the main type of land use change in the central oasis area of Yumen City and Guazhou County. Cumulative carbon storage increased by 1.75×10^7 t. (2) NEP in the central oasis area of Yumen City and Guazhou County showed a fluctuating upward trend, and it generally behaves as a carbon sink. The average annual NEP was 1.78×10^5 t, and the carbon sink increased by 0.95×10^5 t. (3) The main factors responsible for driving are vegetation, elevation, potential evapotranspiration, and precipitation. The explanatory power of each factor in carbon storage spatial differentiation was enhanced by the interaction between natural and anthropogenic factors. The interaction between vegetation and the human factor is more significant than that of the human single factor. (4) Agricultural irrigation and resettlement measures did not cause a decline in ecosystem carbon storage in Yumen City and Guazhou County in the central part of SRB. Conversely, the region's ecosystems have seen an increase in carbon storage as a result of the increase in cropland. (5) The introduction of the NEP modification method and the OPGD model improves the accuracy of carbon storage estimation and obtains better driving results in spatial differentiation. The study idea provides a new perspective for the estimation of carbon storage as a whole, and provides a reference basis for the formulation of ecological protection policies.

1. Introduction

Human development is facing a hotspot issue called global climate change that is being increasingly noticed by all sectors of society [1–3]. The global climate problem has become a common responsibility of all mankind because climate warming is a threat. In the past six meetings of the IPCC, it has become apparent that human activities are significantly contributing to and impacting climate change.

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https://doi.org/10.1016/j.heliyon.2024.e25305
Received 12 November 2023; Received in revised form 17 January 2024; Accepted 24 January 2024
Available online 1 February 2024

The world must reach zero greenhouse gas emissions by halfway through the 21st century to prevent major harm from extreme climate change [4]. Changes in ecosystem structure and function will be caused by land use change, which will impact carbon emission and carbon sink processes [5]. Carbon storage is the amount of carbon retained in ecosystems. It includes four basic carbon pools [6]: Above ground biological carbon (carbon in all living plant material above the soil), underground biological carbon (carbon in the living root system of plants), soil carbon (organic carbon distributed in organic and mineral soils), dead organic carbon (carbon in litter, and carbon in dead trees standing upside down or standing). However, land use change has a significant impact on carbon storage [7,8]. Carbon sinks are processes or mechanisms by which vegetation uses photosynthesis to absorb atmospheric carbon dioxide and fix it in the vegetation and soil, thereby reducing the concentration of greenhouse gases in the atmosphere. The capacity of ecosystems to sequester carbon is reflected in carbon sinks, which is an important indicator [9,10]. First, arid inland river basins are often important areas for carbon cycling, and the study of their carbon storage can help us to better understand and quantify carbon cycling processes [11]. Second, the study of carbon storage in arid inland river basins, which are often characterized by water scarcity and land degradation, can help us to better assess and predict ecosystem health in these areas [12]. The global carbon balance and climate change can be affected by changes in carbon storage in arid inland river basins, which are often sensitive to increased drought and global warming [13]. Northwest China is a difficult area for the carbon cycle (The carbon cycle is the process by which carbon is exchanged in the biosphere, lithosphere, hydrosphere, and atmosphere. It encompasses a series of key processes and events that enable the continuation of life on Earth.) research due to its high aridity, low species richness, and fragile ecological environment. Assessing the impact of ecosystem carbon storage on spatial differentiation will help protect ecosystems in inland river basins in arid zones [14].

The field sampling method is currently the primary method for estimating ecosystem carbon storage [15], the ecosystem carbon flux (Carbon dioxide transfer from one carbon pool to another per unit area per unit time in the carbon cycle.) monitoring method [16], and the model estimation method [17]. The field sampling method is based on manual sampling and estimates regional ecosystem carbon storage by actual sampling samples. This method is relatively simple in technology, but it has a large workload and a long data sampling period, so it is not suitable for use in regions with significant land use changes [18]. The ecosystem carbon flux monitoring method uses modern measurement technology to estimate regional carbon storage, which has high accuracy but has high instrument requirements and high cost. Compared with the previous two methods, the model estimation method can estimate regional ecosystem carbon storage more quickly and clearly show the space and time arrangement and change traits of Carbon storage at various regional levels [19]. In the model estimation methods, many studies combined with the GLO-PEM model [20,21], CASA model [22,23], and Bookkeeping model [24], to determine how much carbon is stored in the area. The InVEST model is a popular choice for carbon cycle studies, because it is easy to calculate and has low data requirements. Numerous researchers have studied the spatial and temporal distribution characteristics of regional carbon storage using this model from various perspectives over the last few years. From the perspective of urbanization, Hwang et al. [25] evaluated how carbon storage is affected by the establishment of environmental protected areas in the context of megacity expansion. Their findings indicate that the establishment of environmentally protected areas in megacities leads to an increase in regional carbon sinks. The model was used by Lyu et al. [26] to examine and predict the guides of urbanization on carbon storage in Shizuishan City, an arid region in Northwest China. Compact urban growth patterns and environmental protection will reduce the negative impact of urbanization on carbon storage, as has been discovered. From the point of view of ecological preservation, Wu et al. [27] researched the main factors that contribute to forest carbon storage in areas covered by forest protection programs and estimated it in 17 administrative regions of China. In terms of research scale, the influences of land use type conversion and management of vegetation to soil carbon storage were examined by Lai et al. [28]. Their research revealed that carbon storage was significantly impacted by land use management. The PLUS and InVEST models were employed by Zhang et al. [29] to analyze carbon storage in ecosystems in Jiangsu Province, China. Different scenarios were used to predict the connection between carbon storage and land use change. Their findings indicated that areas with rapid economic and urbanization development experienced greater carbon storage losses. The Shiyang River Basin (SRB)'s carbon sinks and carbon sources (Carbon sources refer to processes, activities or mechanisms in the carbon pool that release carbon to the atmosphere, such as deforestation, coal combustion for electricity generation, and other processes.) transitions were analyzed by Zhou et al. [11] through spatial and temporal dynamics. Their findings suggest that oasis-desert transition zones are highly vulnerable to carbon storage loss. The InVEST model is commonly used in studies to estimate carbon storage, but the InVEST model's lack of temporal resolution is a problem, and the dynamic changes in carbon storage were not significant. Correcting carbon storage, which is estimated by the InVEST model was not considered by most scholars because it simplifies the cycle, so by considering the carbon sink during vegetation growth, the accuracy of carbon storage estimation can be improved.

The ecological zoning of SRB is typical for "alpine-oasis-desert". This characteristic has a significant impact on how humans use and exploit natural resources. The central oasis areas of Yumen City and Guazhou County, even though the land use type of SRB is mostly undeveloped, possess strong ecological resilience and potential for development. Agriculture irrigation and resettlement measures have been implemented since 1996, and the land uses and carbon storage have undergone significant changes in the oasis area in the central part of SRB. The carbon storage was calculated and revised using MODIS NPP data and the soil heterotrophic respiration (R_{h}) model simultaneously. Finally, the OPGD is used to find how natural and anthropogenic factors are affecting carbon storage. The primary research goals of this paper are (1) to explore the spatio-temporal distribution characteristics of carbon storage alterations due to irrigated agriculture and resettlement measures in Yumen City and Guazhou County in the middle SRB, (2) to explore the main impacts of agricultural irrigation and resettlement measures on the project area, and (3) to explore the drivers of spatial differentiation of carbon storage in Yumen City and Guazhou County.

2. Study area

SRB is one of the three inland river basins in the Hexi region of China and at the westernmost point of China's Hexi Corridor. In terms of administrative divisions, the Shule River flows through Tianjun County of Qinghai Province, Subei County, Yumen City, Guazhou County, and Dunhuang City of Gansu Province, and finally enters Ruoqiang County of Xinjiang Uygur Autonomous Region, with a total drainage area of 1.03×10^5 km^2. The basin is 830–5738 m above sea level, and the overall terrain is high from north to south and relatively gentle in the middle. The basin is a continental arid desert climate, rich in light and heat resources, long frost-free period, less precipitation, evaporation, annual average precipitation between 46 and 64 mm, annual evaporation of 2894–3043 mm, annual average temperature of 6.7–8.9 °C. The basin is dominated by low vegetation coverage, and the spatial distribution difference is large, mainly concentrated in Yumen City and Guazhou County Hexi corridor oasis agroecological area. This oasis agro-ecological area is the main irrigated agricultural area of SRB with a concentration of migrant population. Therefore, in the following sections, we focus on the carbon storage in this area (Fig. 1).

3. Data and methods

3.1. Data

The land use data used in this paper are derived from the 1990–2020 China Land Cover Annual Dataset (CLUD), with a spatial resolution of 30 × 30 m. The data are used to analyze the land use in China [30]. In this paper, the land use data of SRB from 2000 to 2020 are obtained by cropping, and the land use types include cropland, forest, grassland, water area, unused land, and construction land. The NPP (Net Primary Production) data were derived from MOD17A3HGF NPP data published by LP DACC with a spatial resolution of 500 m. The NPP data were used as a basis for the development of the NPP data. The meteorological data were obtained from the National Earth System Science Data Center (http://www.geodata.cn) with a spatial resolution of 1 km, and were cropped and projected to obtain the annual mean temperature, annual precipitation, and annual potential evapotranspiration for SRB for the years 2000–2020. The digital elevation model (DEM) was obtained from the United States Geological Survey (https://lta.cr.usgs.gov/HYDRO1K) with a spatial resolution of 90 m. The slope as well as the direction of SRB was obtained using the Slope and Slope Direction tool in ArcGIS 10.8. Population density data were obtained from WorldPop (http://www.worldpop.org.uk), which mainly utilizes Landsat remote sensing imagery to identify residential areas, and then uses census and other data to generate regional population raster data using Random Forest Estimation with a spatial resolution of 1 km. The GDP spatial distribution data were obtained from the Resource and Environmental Sciences and Data Center (https://www.resdc.cn/Default.aspx) with a spatial resolution of 1 km. The NDVI data were obtained from the MOD13A3 dataset (https://search.earthdata.nasa.gov/search), which is a month-by-month NDVI data, and the maximum synthesis method was used to obtain year-by-year NDVI data from 2000 to 2020 with a spatial resolution of 1 km. SRB boundary data were obtained from the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn). The administrative division data were obtained from the National Geomatics Center of China (http://www.ngcc.cn).

Projection and resampling of all spatial data, the new projection system being the Albers projection, and the resolution is 1 km. This step can reduce regional distortion and maintain data consistency.

After reviewing the relevant literature, the carbon density (Carbon storage per unit area) data was corrected [6,31,32]. SRB's

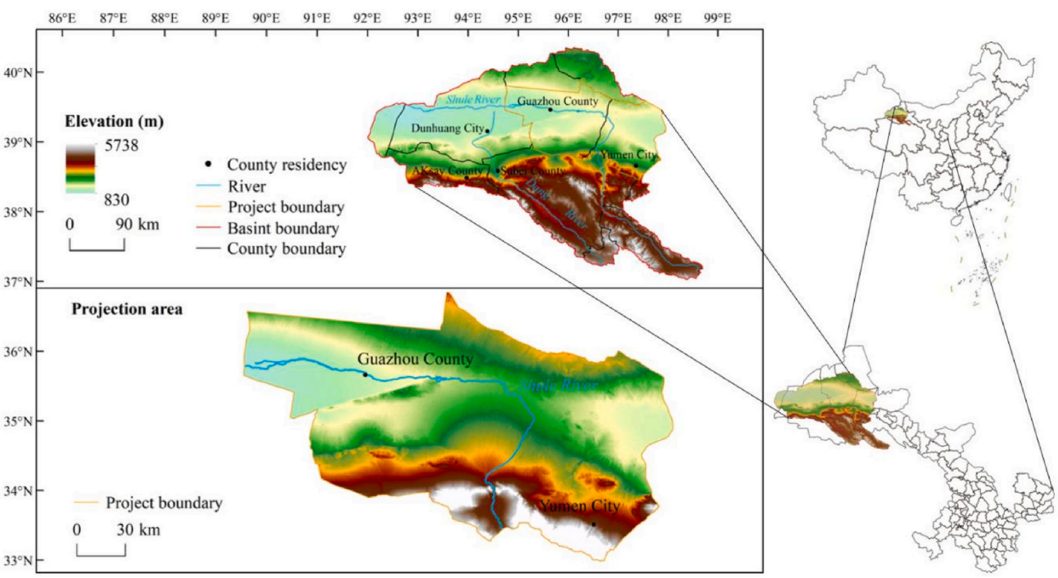

Fig. 1. SRB and the projection area.

climate conditions were utilized to obtain the final carbon density values for every land use type [33,34].

The demographic statistics for Yumen City and Guazhou County are from the China County Statistical Yearbook. The project's basic data were obtained from relevant government websites information and study reports on SRB agricultural irrigation and resettlement practices (http://xbkfs.ndrc.gov.cn/ldzc, http://www.gsdrc.gov.cn).

Table 1 displays the primary data sources.

3.2. Methods

The modified carbon storage in the oases of central SRB has been estimated using a framework presented in this study (Fig. 2). The framework consists of two main parts: estimation and modification of carbon storage in the Yumen City and Guazhou County agricultural irrigation and migration area in the central part of the SRB, and the analysis of its drivers using the OPGD.

3.2.1. Carbon storage estimation and carbon density coefficient correction

The carbon storage in SRB was calculated by using the InVEST model in this paper. This model has four basic carbon pools. As follows is the calculation formula [6]:

$$C_{\mathrm{total}} = C_{\mathrm{above}} + C_{\mathrm{below}} + C_{\mathrm{soil}} + C_{\mathrm{dead}} \tag{1}$$

where C_{total} is the total carbon storage. C_{above} is the amount of carbon stored above the ground. C_{below} is the amount of carbon stored under the ground. C_{soil} is soil carbon storage. C_{dead} is dead organic carbon storage.

This study's carbon density data is based on research findings related to the country and climate zone with SRB. Adjusting carbon density values is necessary due to variations in soil properties and land use. Average annual precipitation influences soil and biomass carbon density through a formula described by Alam et al. [35]. Mean annual temperature and biomass carbon density were correlated using equations improved by Giardina et al. [33] and Chen et al. [34]. As follows is the calculation formula [33,34]:

$$C_{\mathrm{SP}} = 3.398 \times P + 3996.1 \tag{2}$$

$$C_{\mathrm{BP}} = 6.7981 e^{0.00541p} \tag{3}$$

$$C_{\mathrm{BT}} = 28 \times T + 398 \tag{4}$$

where C_{SP} is soil carbon density, C_{BP} and C_{BT} are biomass carbon densities, P is average annual precipitation and T is average annual temperature. Substituting precipitation and temperature for SRB and the whole country into the above equation (2000–2020, average annual temperature of the whole country and SRB is 9.58 °C and 8.8 °C, respectively, and annual precipitation of the whole country and SRB is 673.9 mm and 63 mm), carbon density in SRB is corrected by the ratio of the two. As follows is the calculation formula [33, 34]:

$$K_{\mathrm{BP}} = \frac{C'_{\mathrm{BP}}}{C''_{\mathrm{BP}}} \tag{5}$$

$$K_{\mathrm{BT}} = \frac{C'_{\mathrm{BT}}}{C''_{\mathrm{BT}}} \tag{6}$$

$$K_{\mathrm{B}} = K_{\mathrm{BP}} \times K_{\mathrm{BT}} = \frac{C'_{\mathrm{BP}}}{C''_{\mathrm{BP}}} \times \frac{C'_{\mathrm{BT}}}{C''_{\mathrm{BT}}} \tag{7}$$

Table 1
Data description.

Data	Resolution	Sources
Land use data	30 m	The Earth System Science Data [30] (https://zenodo.org/)
Meteorological data	1000 m	The National Earth System Science Data Center (http://www.geodata.cn)
Population density data	1000 m	The WorldPop (http://www.worldpop.org.uk/)
DEM	90 m	The United States Geological Survey (https://lta.cr.usgs.gov/HYDRO1K/)
NDVI	1000 m	MOD13A3 (https://search.earthdata.nasa.gov/search/)
NPP	500 m	MOD17A3HGF (https://lpdaac.usgs.gov/dataset_discovery)
GDP	1000 m	The Resource and Environmental Sciences and Data Center (https://www.resdc.cn)
Boundary	–	The National Tibetan Plateau Data Center (https://data.tpdc.ac.cn)
Administrative divisions	–	The National Geomatics Center of China (http://www.ngcc.cn/)
Carbon density	–	From related literature [6,31,32]
Demographic data	–	The China Statistical Database (https://www.shujuku.org/)
Project basic data	–	National Development and Reform Commission Gansu Development and Reform Commission

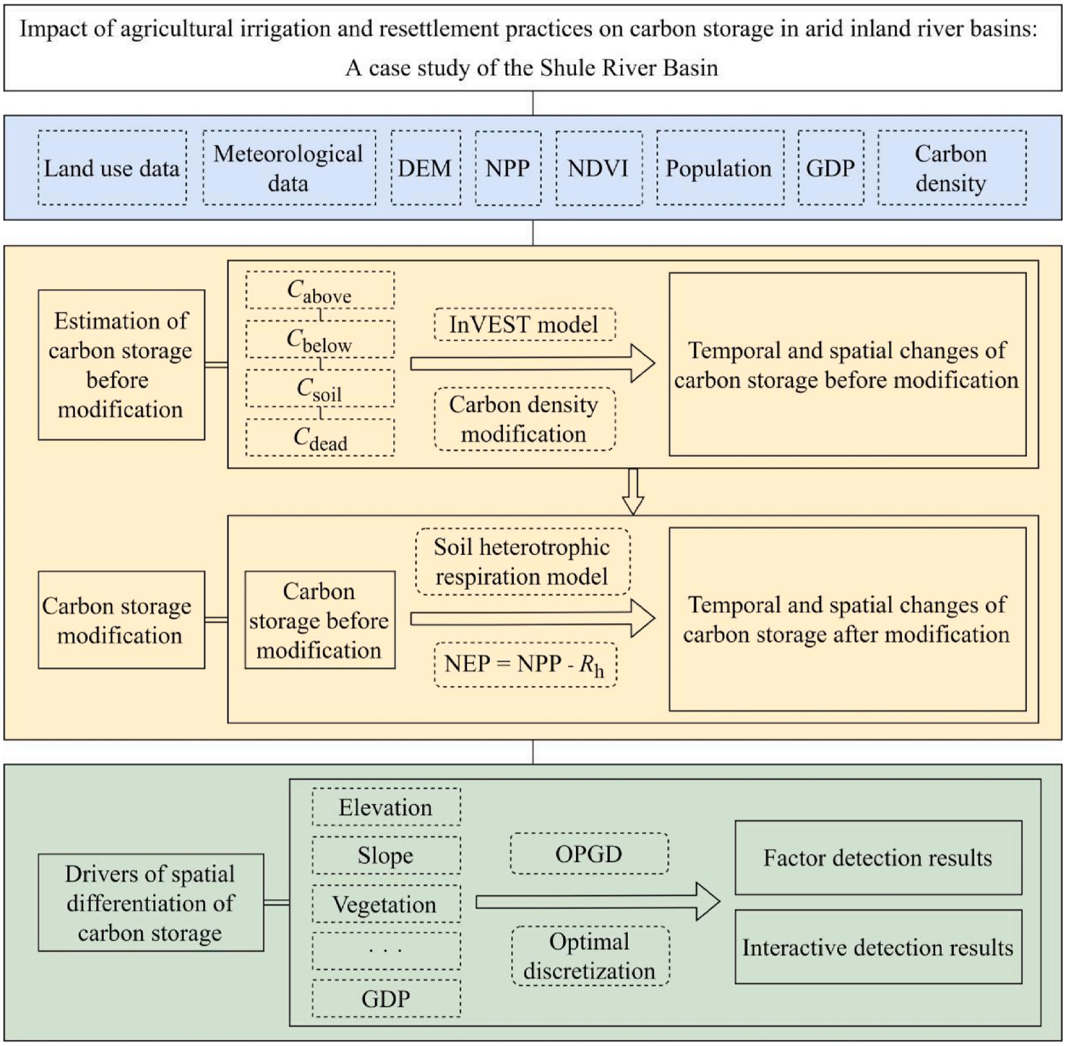

Fig. 2. Research framework.

$$K_S = \frac{C'_{SP}}{C''_{SP}} \tag{8}$$

where K_{BP} and K_{BT} are the correction coefficients of precipitation factor and temperature factor of biomass carbon density. C' and C'' are carbon density data for SRB and the country. K_B and K_S are the correction coefficients of biomass carbon density and soil carbon density. From calculation formula (2) to (8), it follows that the value of K_{BP} is 0.037, K_{BT} is 0.967, K_B is 0.036 and K_S is 0.669. Building on existing references [31,32,36], the corrected carbon density data of SRB is obtained by multiplying the carbon density correction coefficient with the national carbon density value (Table 2).

Table 2
Carbon density in the area of study.

Landuse type	C_{above}/(t·hm^{-2})	C_{below}/(t·hm^{-2})	C_{soil}/(t·hm^{-2})	C_{dead}/(t·hm^{-2})
Cropland	0.21	2.91	72.62	13
Forest	1.53	4.17	158.7	13
Grassland	1.27	3.11	66.92	2
Water area	0.60	0	0	0
Construction land	0.50	0	0	0
Unused land	0.33	0	14.47	0

3.2.2. Net ecosystem productivity estimation model

The strength of carbon sources and sinks is often measured by NEP [37]. The NEP can be got by subtracting soil heterotrophic respiration (R_h) from NPP without taking into account other natural conditions. As follows is the calculation formula [37]:

$$\mathrm{NEP} = \mathrm{NPP} - R_h \tag{9}$$

Soil heterotrophic respiration is greatly influenced by both temperature and precipitation. Pan et al. [38] used temperature, precipitation, and soil heterotrophic respiration models to calculate carbon sinks in arid regions. The study area's location in the semi-arid zone resulted in its model being used for estimation. As follows is the calculation formula [38]:

$$R_h = 0.22 \times \left[\left(e^{0.0912T}\right) + \ln(0.3145P + 1)\right] \times 30 \times 46.5\% \tag{10}$$

where T is average annual temperature and P is average annual precipitation.

3.2.3. Trend analysis

In this paper, a single linear regression analysis method [39] was used to perform linear regression on pixel-by-pixel carbon storage and NEP respectively. Next, we analyzed the trend of its carbon storage and NEP. As follows is the calculation formula [39]:

$$\mathrm{Slope} = \frac{n \times \sum_{i=1}^{n}(i \times C_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} C_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{11}$$

where slope indicates the slope of the trend line, n is the length of the time series, i is the chronological order, C_i is the value of carbon storage in the year i, NEP, and modified carbon storage pixel.

3.2.4. The OPGD model

The detection of spatial divergence and the identification of its drivers can be achieved through the use of geodetector, a statistical method [40]. However, traditional geodetector is highly subjective. Discrete continuous variables yield similar spatial distributions between the two variables when the independent variable has a significant impact on the dependent variable. The optimal size of spatially stratified heterogeneity will be affected due to this. Geographic features and spatial variables can be used by the OPGD to extract more information during the parameter optimization modeling process. It is versatile enough to be applied to many types of

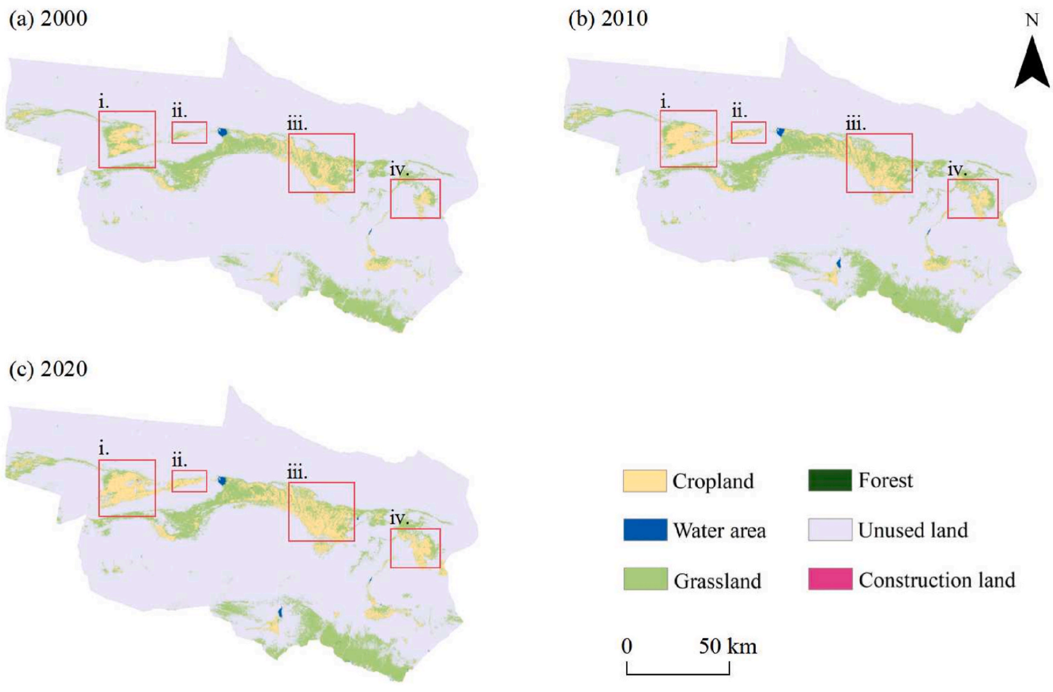

Fig. 3. Land use types in Yumen City and Guazhou County.
Note: i includes Xihu Township and Guazhou Township; area ii includes Lianghu Township; area iii includes Liuhe Township, Huangzhawan Township, Shimousihoro Township, and Hedong Township; and area iv includes Liuhu Township, Xiaojinwan Township, Chijin Township, and Qingquan Township.

spatial data for global and regional spatial analysis [41]. The OPGD is used to examine how spatial differentiation affects carbon storage in SRB. We apply several classification methods in R. And the classification level is 3–9. For spatial discretization, the combination of parameters with the highest q value is selected. The extent of interaction and whether there is an interaction between two factors can be determined by calculating the one-factor q value and the two-factor interaction q value. As follows is the calculation formula [40]:

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \tag{12}$$

$$SST = N\sigma^2 \tag{13}$$

$$q = 1 - \frac{SSW}{SST} \tag{14}$$

where the factor's explanatory power is expressed through q, which ranges from 0 to 1, and the higher the number, the stronger its power. The explanatory variable is stratified in h. The variance of layer h and whole region Y values is represented by σ_h^2 and σ^2. SSW and SST can be employed to represent the total variance of the entire region and the sum of intra-layer variance.

4. Results

4.1. Agricultural irrigated land and immigration status

Agriculture irrigation and resettlement measures have been implemented since 1996. The operating period of the immigration measures is 10 years, and the later period is the stable period of agricultural irrigation and the implementation effect of immigration. The central oasis area around Yumen City and Guazhou County had the highest growth in agricultural irrigated farmland area between 2000 and 2010 (Fig. 3), while the area of grassland around Yumen City also increased correspondingly. From 2010 to 2020, scattered parts of grassland in Yumen City and Guazhou County were converted into agricultural irrigated land. The distribution of grassland around Yumen City remained unchanged, and most of the other areas were unused. The areas in the red boxes are areas of high variability in land-use types.

In Yumen City and Guazhou County, between 2000 and 2010, the shift in land use type was dominated by the change of unused land to grassland (Fig. 4a), the change area was 9.00×10^4 hm^2 (Table 3). The area that was converted from unused land to cropland was 1.34×10^4 hm^2, and the area that was converted from grassland to cropland was 2.36×10^4 hm^2. However, the change area from cropland to grassland was 0.74×10^4 hm^2 (Table 3). From 2010 to 2020, the amount of unused land transfer declined, while the amount of grassland transfer increased significantly (Fig. 4b). Among them, the change area of unused land to cropland was 0.60×10^4 hm^2, the change area of grassland to cropland was 2.63×10^4 hm^2, the change area of grassland to unused land reached 3.47×10^4

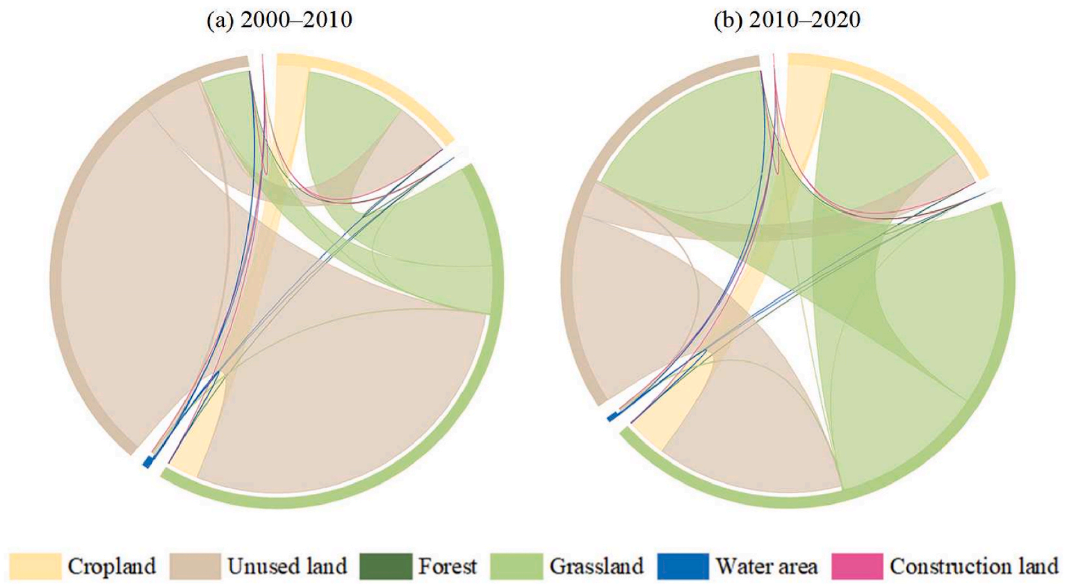

Fig. 4. Amount of land use change in Yumen City and Guazhou County.
Note: (a) denotes land use type changes in Yumen City and Guazhou County from 2000 to 2010; (b) denotes land use type changes in Yumen City and Guazhou County from 2010 to 2020.

Table 3
Yumen City and Guazhou County land use change situation from 2000 to 2010 (hm^2).

	2010							Total
		Cropland	Forest	Grassland	Water area	Construction land	Unused land	
2000	Cropland	79351.6	–	7435.7	177.4	16.5	213.5	87194.7
	Forest	7.0	78.9	2.8	–	–	1.6	90.3
	Grassland	23615.3	3.8	206734.0	231.9	64.6	11265.9	241915.5
	Water area	97.7	–	187.9	1859.3	1.3	199.0	2345.2
	Construction land	1.4	–	2.7	2.0	112.6	0.2	118.9
	Unused land	13453.2	2.4	90031.3	689.5	41.7	2164230.0	2268448.1
	Total	116526.2	90.1	304394.4	2960.1	236.7	2175910.2	2600112.7

hm^2, and the change area of unused land to grassland was 3.27×10^4 hm^2 (Table 4). Among them, the net increase of cropland was about 5.41×10^4 hm^2, and the net increase of grassland was about 4.12×10^4 hm^2.

The population of the central oasis area in Yumen City and Guazhou County has shown obvious fluctuation characteristics since the implementation of the immigration policy (Fig. 5). Between 2000 and 2010, there was a fluctuating upward trend for the population, followed by a downward trend in 2010. In 2012, the population peaked at about 3.14×10^5, a net increase of about 3.30×10^4 compared to 2000. The agricultural population showed a rapidly rising trend from 2000 to 2012, reaching a peak of about 2.19×10^5 in 2012, and maintaining a relatively stable level from 2012 to 2020. Compared with 2000, the net increase of agricultural population was about 9.80×10^4.

4.2. Temporal and spatial changes of carbon storage in Yumen City and Guazhou County

The calculations from the carbon storage module of the InVEST model were imported into Origin software to visualize the results (Fig. 6). The central oasis region is where high carbon storage areas are concentrated. Carbon storage in the central oasis areas of Yumen City and Guazhou County follows a pattern of change that involves first increasing and then stabilizing. The regional storage of carbon underwent a significant growth trend from 2000 to 2010. After 2008, the trend of increase slowed down, reaching its highest value in 2013, approximately 1.631×10^8 t, and then maintaining a relatively stable level. The average annual carbon storage in 20a is about 1.552×10^8 t.

The western townships of Lianghu, Xihu Township, and Guazhou County hold the majority of the high carbon storage areas in terms of spatial concentration. (Fig. 7i–7ii); a high-value carbon storage area in the middle, with Huangzhawan Township, Liuhe Township, and Hedong Township as the main areas (Fig. 7iii); carbon storage in the east is highly valued, with Liuhu Township and Xiaojinwan Township being the primary areas (Fig. 7iv). The remaining areas with high carbon storage show a decentralized spatial pattern. In most areas, cropland and grassland have high carbon storage. The land that was not used had a less effective carbon storage capacity and was mostly distributed on the northern and southern sides of the central oasis area. From 2000 to 2010, carbon storage increased mainly in the western region dominated by Guazhou Township, and in the central region dominated by Huangzhawan Township. From 2010 to 2020, carbon storage increased mainly in the eastern region of Liuhu Township and Xiaojinwan Township (Fig. 7iv).

4.3. Temporal and spatial changes of NEP in Yumen City and Guazhou County

The NEP values were calculated by formula (9) to (10). Then the spatial statistics were carried out in ArcGIS, and finally, the spatial statistics results were imported into Origin software to visualize the results (Fig. 8). During 2000–2020, the trend of change showed an upward trend in the total amount of NEP in the study area. The mean NEP in 20a is about 1.78×10^5 t. The maximum amount of NEP in 2019 was 2.24×10^5 t. The minimum value was 1.29×10^5 t in 2001. Although the total amount of NEP shows an overall increasing trend, the change is not stable enough, and the annual fluctuation is large. The total amount of NEP decreased in 2020, reaching 1.87×10^5 t.

Table 4
Yumen City and Guazhou County land use change situation from 2010 to 2020 (hm^2).

	2020							Total
		Cropland	Forest	Grassland	Water area	Construction land	Unused land	
2010	Cropland	108954.0	–	7152.9	61.5	18.2	331.2	116517.8
	Forest	–	80.1	1.7	–	–	3.5	85.3
	Grassland	26316.3	6.5	243076.0	180.9	29.4	34783.7	304392.9
	Water area	32.1	–	148.0	2676.4	1.4	102.5	2960.4
	Construction land	2.3	–	5.6	4.3	221.7	2.9	236.8
	Unused land	6026.3	1.5	32773.1	334.7	25.2	2136750.0	2175910.8
	Total	141330.9	88.1	283157.3	3257.9	295.9	2171973.8	2600103.9

Note: “-” indicates that parts of the land use type with insignificant changes in area are not counted.

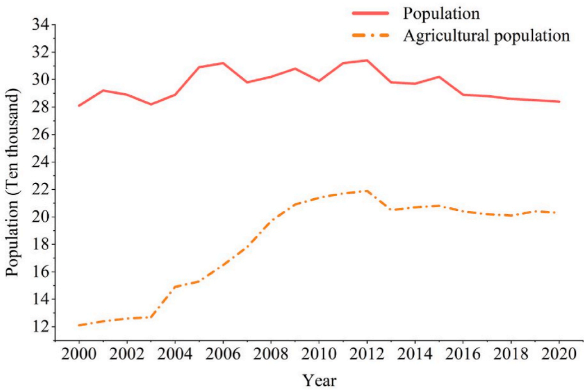

Fig. 5. Population and agricultural population of Yumen City and Guazhou County. Note: The population represented by the red dashed line is the total population of the study area; agricultural population represented by the yellow line is the number of people engaged in agricultural activities in the study area. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

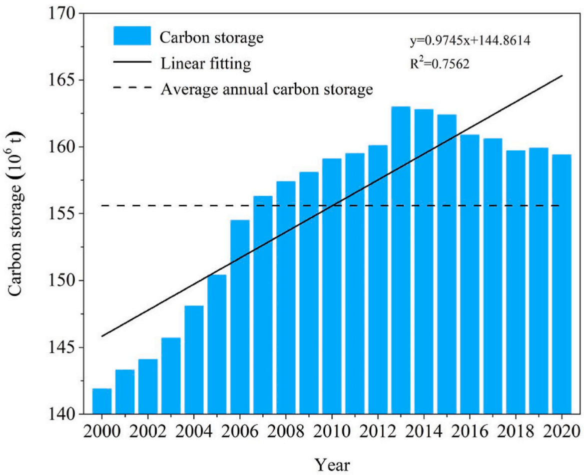

Fig. 6. The variation of carbon storage in Yumen City and Guazhou County.

In terms of space, the total amount of NEP in Yumen City and Guazhou County presents a spatial distribution characteristic that the central oasis region is high and the north and south are low (Fig. 9), and Hedong Township are the main areas with high carbon sink value (Fig. 8iii), and Chijin Township and Xiaojinwan Township (Fig. 9iv). The internal changes of NEP in Yumen City and Guazhou County are showing an upward trend in terms of spatial trends. Among them, the changes in the central oasis region were significant (Fig. 9ii–9iii), while the changes in the southern oasis region were not significant, and the partially dispersed carbon sink region disappeared.

4.4. Temporal and spatial changes of carbon storage after modification in Yumen City and Guazhou County

The modified carbon storage values were spatially counted using ArcGIS, and then the spatial statistics were imported into Origin software to visualize the results (Fig. 10). Based on the annual NEP amount in the study area, the calculation result of the InVEST model was revised. Because the total amount of NEP is smaller than that of carbon storage, the change trend and numerical representation of the result after carbon storage revision have a general change trend compared with that before revision. The modified carbon storage has a different spatial and temporal distribution. The modified carbon storage in the central oasis region of Yumen City and Guazhou County still showed a change characteristic of "first increasing and then stable", which showed an increasing trend in general. The trend of carbon storage increased significantly from 2000 to 2010, and reached the highest value in 2013, about 1.625×10^8 t. After 2008, the increase trend slowed down.

In terms of space, the regions that have a high carbon storage value after modification are concentrated in Guazhou County, Lianghu Township, Liuhe Township, Xiaojinwan Township, and Chijin Township, showing a spatial pattern of regional aggregation and scattered distribution on the whole (Fig. 11). Regarding the trend of spatial variation, carbon storage has mainly increased after modification. The modified high carbon storage areas are concentrated in the central and eastern parts (Fig. 11). In 2010 and 2020, the

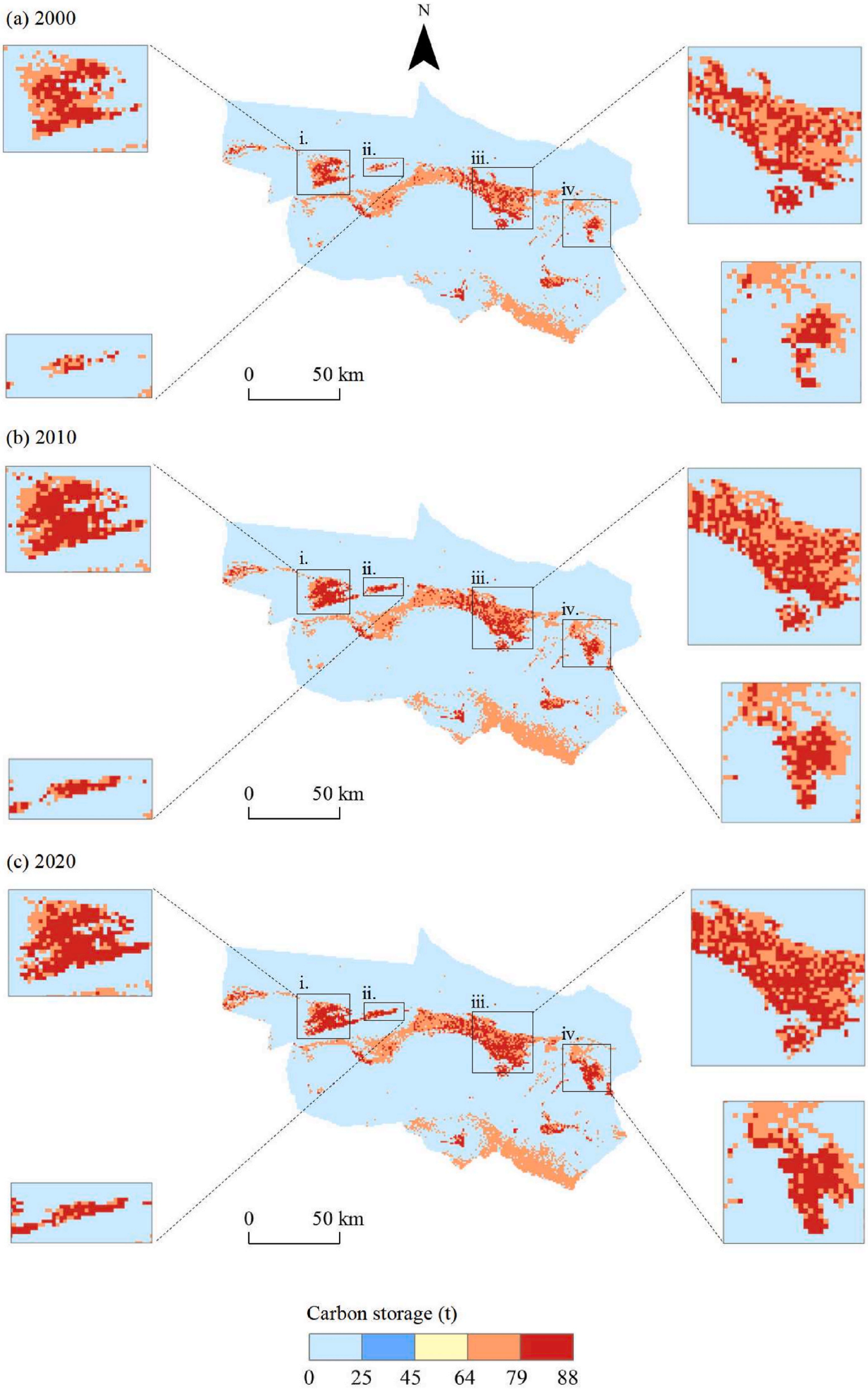

Fig. 7. Spatial distribution of carbon storage in Yumen City and Guazhou County. Note: Area i includes Xihu Township and Guazhou County Township; area ii includes Lianghu Township; area iii includes Liuhe Township, Huangzhawan Township, Shimousihoro Township, and Hedong Township; and area iv includes Liuhu Township, Xiaojinwan Township, Chijin Township, and Qingquan Township.

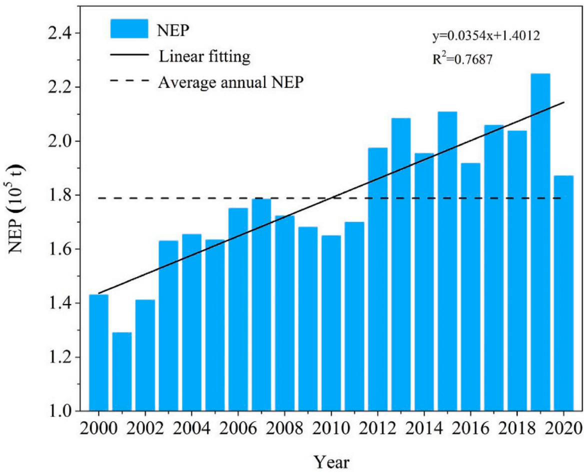

Fig. 8. The variation of total NEP in Yumen City and Guazhou County.

carbon storage of Huangzhawang Township, Xiaoxihao Township, and Chijin Township showed an obvious high-value area (Fig. 11iii–11iv). An increase in cropland area in the central oasis of Yumen City has resulted in an increase in carbon storage. High carbon storage is also present in Jinwan Township located in the east of the oasis (Fig. 11iv).

4.5. Drivers of spatial differentiation of carbon storage

4.5.1. Determination of optimal parameters of driving factors

In this paper, nine influence factors including elevation (X1), slope (X2), aspect (X3), temperature (X4), vegetation (X5), population (X6), GDP (X7), potential evapotranspiration (X8) and precipitation (X9). The optimal parameter results show that different discretization methods and the choice of different intervals will make the q values of drivers different. Specifically, elevation (X1) has a maximum q value at an equal interval classification of 7 (Fig. 12a); slope (X2) has a maximum q value at a standard deviation classification of 9 (Fig. 12b); aspect (X3) has a maximum q value at a standard deviation classification of 9 (Fig. 12c); temperature (X4) has a maximum q value at a natural breaks classification of 9 (Fig. 12d); vegetation (X5) has a maximum q value at a standard deviation classification of 9 (Fig. 12e); population (X6) has a maximum q value at a natural breaks classification of 8 (Fig. 12f); GDP (X7) has a maximum q value at a quantile classification of 6 (Fig. 12g); potential evapotranspiration (X8) has a maximum q value at an equal interval classification of 7 (Fig. 12h); and precipitation (X9) has a maximum q value at an equal interval classification of 9 (Fig. 12i). From the above optimal discretization results, the discretization of the driving factors in this study is mainly based on equal interval, standard deviation, and natural breaks. Moreover, the main classification interval is 9.

4.5.2. Factor detection and interactive detection

The q value is obtained from formula (12) to (14). The single-factor detection results (Table 5) reveal that each factor has a prominent impact on spatial distribution characteristics of carbon storage in the study area. Vegetation is the most significant factor in explaining the spatial differentiation in carbon storage among natural factors. Elevation, potential evapotranspiration, and precipitation have a slightly weaker ability to explain spatial differentiation in carbon storage. The natural factor with the weakest explanatory power for spatial differentiation is aspect. GDP is the most significant contributor to the spatial differentiation among the anthropogenic factors, while Population is the least significant.

The interaction test revealed that the interaction between the two factors was greater than the effect of the single factor (Fig. 13). Double-factor enhancement and nonlinear enhancement were the main characteristics of the interactions among the factors. Nonlinear enhancement is observed when X1, X2, X3, X4, and X6 interact with X3, X4, X6, X7, X8, and X9. This suggests that the influence of factors on the spatial distribution of carbon storage can be greatly enhanced by specific combinations. The main interaction between vegetation and other factors involved double-factor enhancement, which had an effect on carbon storage spatial differentiation that exceeded 69 %. According to the results, the main factor that influences the spatial distribution characteristics of carbon storage in Yumen City and Guazhou County is the interaction between vegetation and other factors. From the perspective of time change, the interaction between population, GDP and vegetation has significantly increased from 2000 to 2020, and the interaction between other natural factors and vegetation has also greatly increased (Fig. 13a–c). Each factor's explanatory power for the spatial differentiation of carbon storage is enhanced by the interaction between natural and anthropogenic factors.

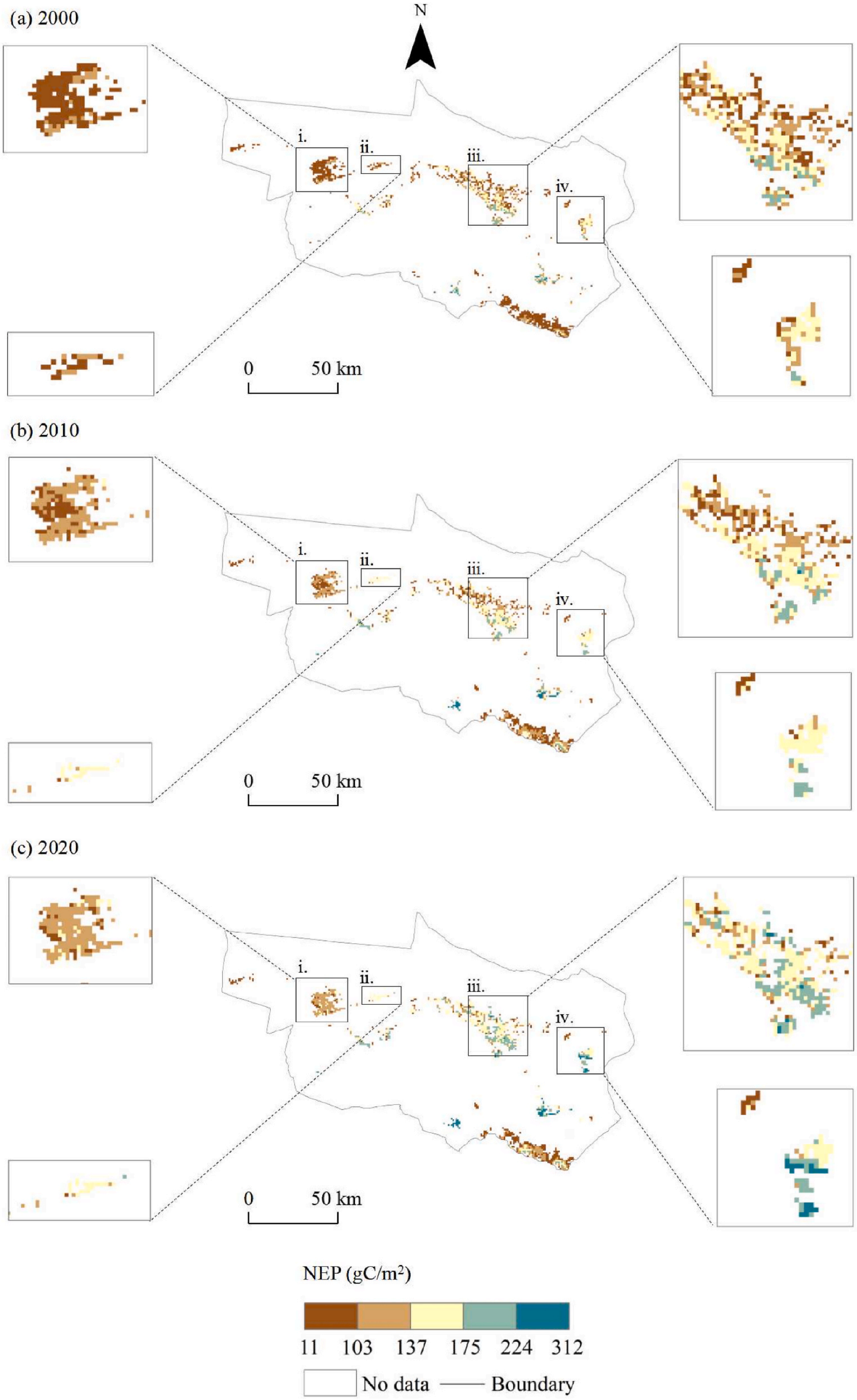

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Fig. 9. Spatial distribution of total NEP in Yumen City and Guazhou County.
Note: Area i includes Xihu Township and Guazhou County Township; area ii includes Lianghu Township; area iii includes Liuhe Township, Huangzhawan Township, Shimousihoro Township, and Hedong Township; and area iv includes Liuhu Township, Xiaojinwan Township, Chijin Township, and Qingquan Township. The blank areas are due to the fact that some of the areas in the MOD17A3HGF raw data have a value of No data.

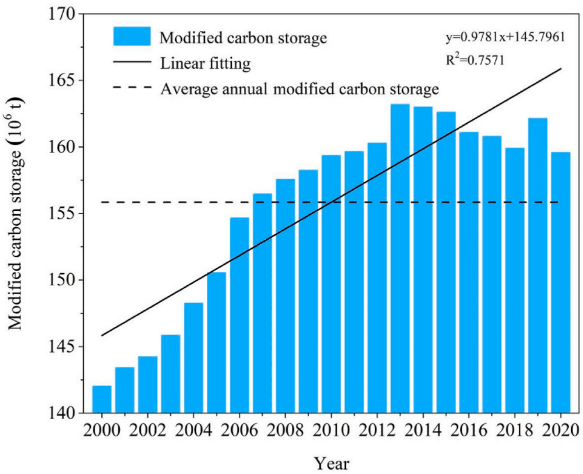

Fig. 10. The variation of modified carbon storage in Yumen City and Guazhou County.

5. Discussion

5.1. Reliability of the NEP modified carbon reserves

The InVEST model is not without its limitations in studying carbon storage changes in long-term ecosystems. The model relies on land use type changes to get changes in carbon storage. Secondly, this model ignores the carbon sink in the vegetation growth process, which leads to a certain deviation between the actual carbon storage and the estimated carbon storage. Using NEP to modify the InVEST model estimates can improve the accuracy of carbon storage estimates to some extent. Based on this, NEP was used to quantify the carbon sink during vegetation growth to correct the carbon storage in the central oasis area in Yumen City and Guazhou County. Ren et al. [32] obtained carbon density for Gansu Province only by correcting the national carbon density data. The impact of land use change on carbon storage was assessed by them. By correcting carbon storage using NEP, this paper offers a new approach to improve carbon storage estimation accuracy. This paper extends the temporal resolution of the study area simultaneously. The spatial and temporal changes in regional carbon storage become more clearly characterized due to the improved temporal resolution.

5.2. The main impacts of agricultural irrigation and resettlement measures on the project area

The carbon cycle in terrestrial vegetation can be analyzed qualitatively and quantitatively using NEP, making it an important index to characterize regional carbon sources and sinks. 2000–2020, the total amount of NEP in Yumen City and Guazhou County showed an upward trend on the whole, and the carbon sink capacity was significantly changed. This is similar to the results of Li et al. [42] who argue that the increase in precipitation delays the Gross Primary Productivity (GPP) peak, which makes semi-arid grassland ecosystems behave as carbon sinks in the carbon cycle. NEP's trend will be directly influenced by changes in soil heterotrophic respiration (R_h) and NPP. The response of R_h and NPP to temperature and precipitation was examined by Naidu et al. [43]. According to their findings, precipitation is the primary factor influencing the change in soil heterotrophic respiration when the climate is warming. Since the implementation of agricultural irrigation and resettlement measures in SRB, the cultivated land area and grassland cover area in Yumen and Guazhou Oasis have increased significantly, which makes the regional ecosystem NPP show a significant increasing trend. Although precipitation and temperature increased, the amplitude of soil heterotrophic respiration did not change much during this period, indicating an overall increasing trend in regional NEP. The spatio-temporal evolution and drivers of carbon storage in the Yangtze River Delta (YRD) were analyzed by Gao et al. [44]. The YRD has seen a significant loss of carbon storage due to population growth and urbanization, according to their findings.

Different from the above studies, the focus of this study is on the changes in carbon storage in the oasis region of the Middle SRB over time, considering agricultural irrigation and resettlement measures. The central oasis region of SRB experienced a significant increase in carbon storage due to the increase in cropland and grassland area from 2000 to 2020, as shown by the results. Since the implementation of the agriculture irrigation and resettlement measures in 1996, the population of Yumen City and Guazhou County at the end of the year showed a trend of fluctuation and decline after reaching a peak in 2012, but the agricultural population showed an

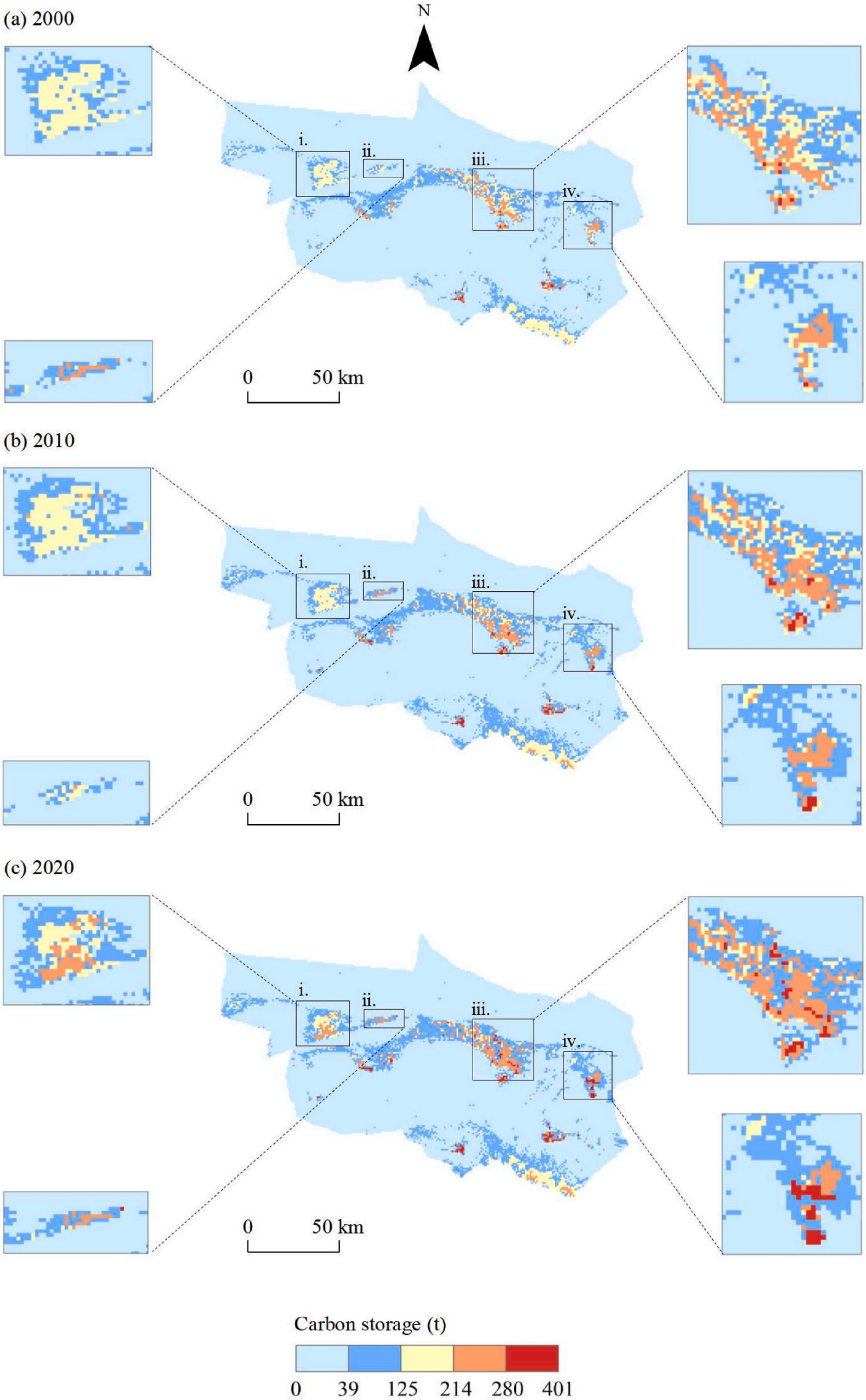

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Fig. 11. Spatial distribution of modified carbon storage in Yumen City and Guazhou County.
Note: Area i includes Xihu Township and Guazhou County Township; area ii includes Lianghu Township; area iii includes Liuhe Township, Huangzhawan Township, Shimousihoro Township, and Hedong Township; and area iv includes Liuhu Township, Xiaojinwan Township, Chijin Township, and Qingquan Township.

upward trend, with a net increase of about 98,000. The migrating population is predominantly agricultural, and the region's carbon storage has increased because of the expansion of cropland and grassland areas. Following the implementation of measures like returning pastures to grasslands, the Government has adopted projects to improve irrigation area support facilities and conserve water. The ecological environment has been improved by these projects. Nie et al.'s findings are similar to this. The impact of land use change on carbon storage under different scenarios was assessed by Nie et al. [14] by combining the CLUMondo and InVEST models. They discovered that under the natural growth scenario, carbon storage in urban development zones would decrease, while that in agricultural production areas and key ecological functional areas would increase.

From the ecological point of view, the migration and agricultural irrigation measures not only did not reduce the regional carbon storage but increased it to a certain extent. The promotion of regional economic development from a social and economic perspective is greatly influenced by migration and irrigated agriculture measures. Population migration increased the agricultural population in Yumen City and Guazhou County. Agricultural irrigation projects greatly increased the cultivated land area, and agricultural crop yields increased to varying degrees (Fig. 14). Among them, grain output and oil-crop output showed an upward trend, but the fluctuation range was large. Cotton production is at a relatively stable level. Although meat production is low, it is on the increase trend in general, from 0.74×10^4 t in 2000 to 1.78×10^4 t in 2020. The area used to grow feed crops has significantly increased due to the increase in cropland. In the primary sector, the industrial model is gradually changing from traditional agriculture to a combination of agriculture and livestock husbandry. The growth value of the primary industry increased from 4.15×10^4 million *yuan* in 2000 to 3.79×10^5 million *yuan* in 2020 (Fig. 14). The agricultural population's growth has been a significant factor in the development of the primary industry in the study area. Moreover, the per capita disposable income of the rural population in Yumen City and Guazhou County increased significantly in 2020, from 0.66×10^4 *yuan* in 2000 to 3.93×10^4 *yuan* in 2020. Rural residents have seen a significant increase in their standard of living and quality of life, which is reflected in their per capita disposable income. Therefore, resettlement and agricultural irrigation measures not only increased the carbon storage in Yumen City and Guazhou County, but also played a big role in promoting the advancement of its primary industry and improving the living conditions of rural residents.

5.3. Spatial drivers

Yumen City and Guazhou County's oasis area in the central area have been detected by single-factor detection, which shows that vegetation, potential evapotranspiration, and precipitation are the main driving factors. Unexpectedly, this paper finds that the single-factor detection results of GDP and population are relatively small, which is different from the results of Li et al. [45] and Xiang et al. [46]. Because the population in the study area is concentrated in the population gathering area such as the county seat and the land type of this part of the region is mainly construction land, and the rest of the agricultural population is scattered in various regions by township. Population dispersion and sparseness are the main characteristics of population distribution in northwest China. Thus, in agricultural irrigation, fewer people are needed to manage a large portion of the cultivated area. Because Worldpop is the source of population density data used in this paper [47]. The data set was produced taking into account the number of administrative unit population and night light intensity, and the night light intensity of Yumen City and Guazhou County is very low, so the population density of this area appears low on the grid. The low explanatory power of population density for the spatial differentiation of carbon storage in single-factor detection results could be due to these factors. Under certain combination conditions, the spatial distribution of carbon storage can be greatly enhanced by the influence of both anthropogenic and natural factors, as revealed by the results of interaction detection. This indicates that the central oasis area of Yumen City and Guazhou County has spatial distinctions in carbon storage as the result of the joint action of natural and socio-economic factors. Although the single-factor explanatory power of human factors is weak, it has high explanatory power in the interaction, indicating that agricultural irrigation and resettlement projects greatly increase carbon storage in the central oasis region.

5.4. Limitation and prospect

This paper is set in the context of SRB's agricultural irrigation and migration measures. The results of the InVEST model are corrected by using NEP. The accuracy of carbon storage estimation is improved to some extent. In addition, OPGD was used to discretely optimize the continuous variable factors and to more objectively analyze the impact of each driver on the spatial differentiation of carbon storage. Nevertheless, there are some uncertainties in this paper. First, the InVEST model fails to account for the many factors that influence the carbon cycle, such as photosynthesis rates and soil microbial activity. Secondly, the potential impact of water resource factors on carbon storage in oasis regions is not considered in this paper, because the distribution of water resources will cause changes in vegetation, which will indirectly cause changes in carbon storage, and such changes are difficult to measure. Finally, the exploration of factors that affect carbon storage will be affected by the distribution of population density, because compared with the population concentration area in the southeast of China, the population distribution in the semi-arid area is scattered and the migration rate is high. Therefore, higher spatial and temporal resolution population density data will be utilized in future studies, and the effects of the introduction of water resources on vegetation growth and distribution will be considered, which will better improve

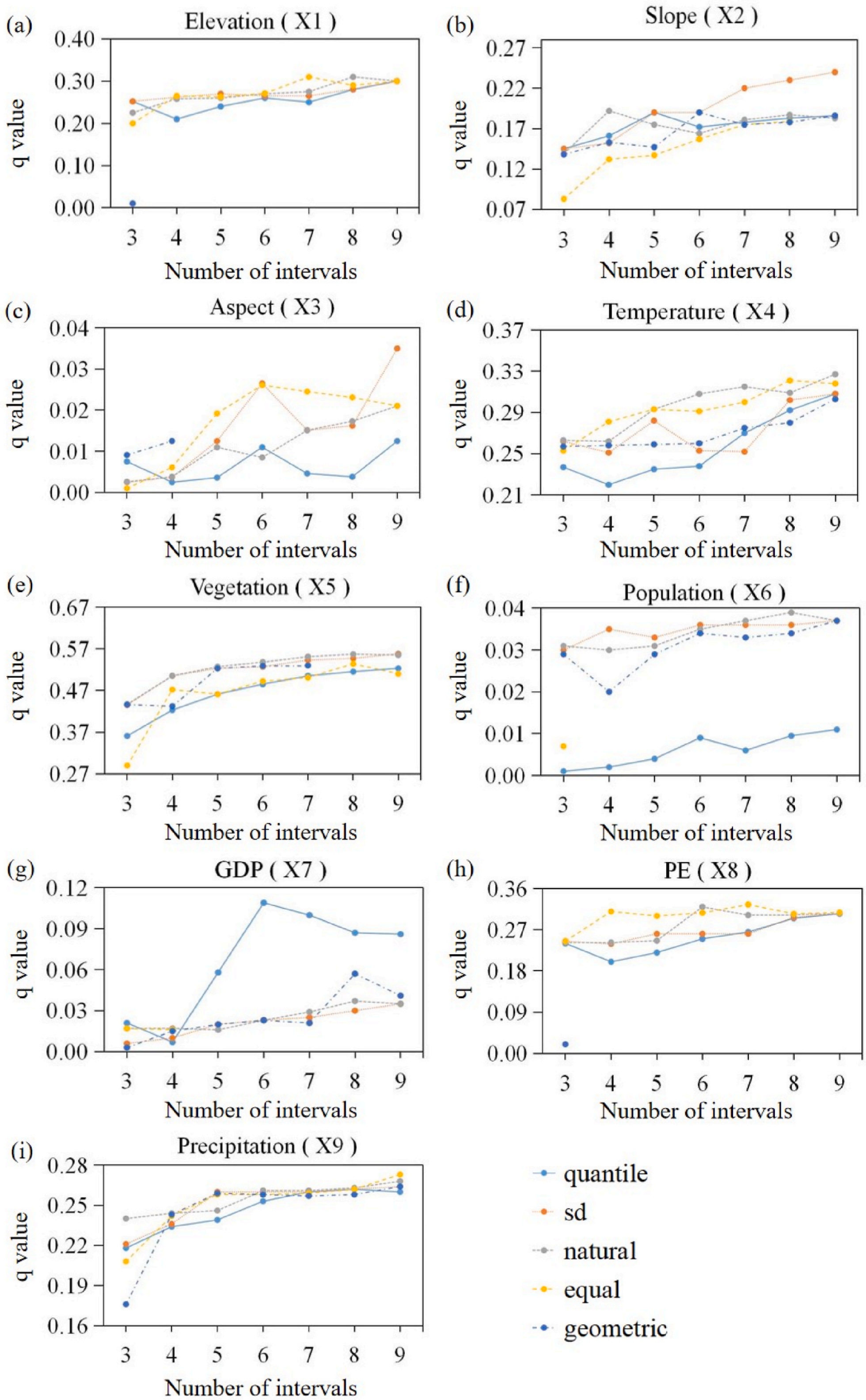

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Fig. 12. Continuous factor optimal discretization.
Note: Quantile, standard deviation (sd), natural breaks (natural), equal interval (equal), and geometrical interval (geometric) are five spatial data classification methods in ArcGIS. The OPGD model optimally discretizes the driving factors in the study, and (a)–(i) are the discretization results for different driving factors, with the value of the horizontal axis is the number of discretization intervals and the value of the vertical axis is the q value.

Table 5
q value of driving factors for spatial differentiation of carbon storage in Yumen City and Guazhou County.

	Natural factor							Anthropogenic factor	
	Elevation (X1)	Slope (X2)	Aspect (X3)	Temperature (X4)	Vegetation (X5)	PE (X8)	Precipitation (X9)	Population (X6)	GDP (X7)
2000	0.413	0.283	0.05	0.291	0.753	0.432	0.354	0.039	0.154
2010	0.371	0.246	0.03	0.296	0.689	0.395	0.407	0.042	0.075
2020	0.367	0.253	0.04	0.284	0.823	0.381	0.349	0.055	0.204

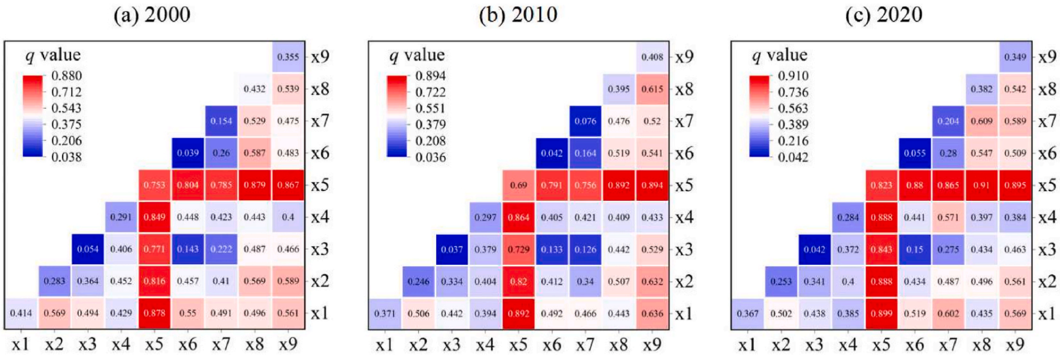

Fig. 13. Interaction detection results of driving factors for spatial differentiation of carbon storage in Yumen City and Guazhou County.
Note: (a) is the result of driver factors interaction detection in 2000, (b) is the result of driver factors interaction detection in 2010, and (c) is the result of driver factors interaction detection in 2020. In the figure, the color changes from blue to red, indicating that the q value is from low to high. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

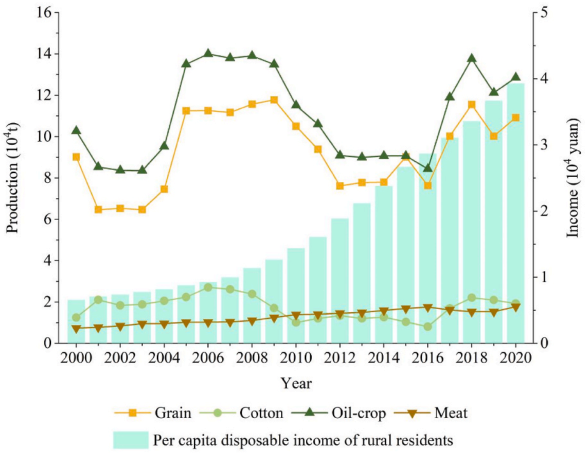

Fig. 14. Agricultural, livestock production, and per capita disposable income of rural residents in Yumen City and Guazhou County.
Note: Agricultural, livestock production, and per capita disposable income of rural residents in Yumen City and Guazhou County are from the China County Statistical Yearbook.

the accuracy of carbon storage estimation.

Overall, the use of the NEP modification method can improve the accuracy of carbon storage estimation in the study area. Meanwhile, the introduction of the OPGD model to determine the optimal parameters of driving factors has better analytical results compared to the traditional GD model. Moreover, in terms of spatial and temporal distribution, the carbon storage in the study area showed an elevated trend in the context of agricultural irrigation and migration measures. This is contrary to the conclusion in most current studies that human activities have led to a decline in ecosystem carbon storage, which provides a new perspective for similar studies. Finally, research on carbon storage in arid inland river basins will be an important part of overall ecological conservation and will help to provide a reference for the formulation of ecological conservation policies in arid areas. In future studies, exploring the coordinated relationship between human social development and ecological preservation and finding a balance between them will be an issue worth pondering.

6. Conclusion

Taking into account the agriculture irrigation and resettlement measures, the central oasis area around Yumen City and Guazhou County is the focus of this paper. The InVEST model was used to estimate regional carbon storage using land use data, and the results were adjusted by using NEP. Finally, the OPGD was utilized to evaluate the factors that contribute to the spatial heterogeneity in carbon storage in the central oasis areas of Yumen City and Guazhou County. Here are the main findings.

(1) 2000–2020, the net growth of cropland area and grassland area in Yumen City and Guazhou County is about 5.41×10^4 hm^2 and 4.12×10^4 hm^2. The net increase in population was approximately 9.80×10^4 people. Carbon storage increased from 1.421×10^8 t in 2000 to 1.596×10^8 t in 2020. Cumulative carbon storage increased by 1.75×10^7 t. The central and eastern regions are the main locations for high carbon storage, while some areas in the north and south are low carbon storage areas.
(2) 2000–2020, the NEP trend in the study area's central oasis area fluctuated upwards. Average annual NEP was 1.78×10^5 t, and the cumulative increase of carbon sink was 0.95×10^5 t. Significant differences exist in the spatial distribution of NEP, with higher levels in the east and lower levels in the west and south.
(3) The OPGD indicates that there are significant variations in the effects of various drivers on the spatial differentiation of carbon storage. Vegetation, elevation, potential evapotranspiration, and precipitation are the main driving factors. The explanatory power of spatial differentiation of carbon storage is enhanced when natural and anthropogenic factors interact. In particular, the interaction between vegetation and anthropogenic factors is greater than the role of anthropogenic single factors.
(4) Agricultural irrigation and resettlement measures did not cause a decline in ecosystem carbon storage in Yumen City and Guazhou County in the central part of SRB. Conversely, the increase in cropland has led to an increase in carbon storage in the ecosystems of the region. The standard of living of agricultural settlers has improved to some extent.
(5) NEP modification method can improve the accuracy of carbon storage estimation. The introduction of the OPGD model to determine the optimal parameters of driving factors has better analytical results compared to the traditional GD model. This study provides a new perspective for carbon storage estimation as a whole, and provides a reference basis for the formulation of ecological protection policies.

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 42361040].

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Xiuwei Zhu: Writing – original draft, Software, Methodology, Investigation. **Jinghu Pan:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition. **Xueting Wu:** Validation, Software, Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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