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Spatial correlations among ecosystem services and their socio-ecological driving factors: A case study in the city belt along the Yellow River in Ningxia, China

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ABSTRACT

Understanding the spatial distributions of multiple ecosystem services (ESs), their associations, and their underlying socio-ecological contributing factors is critical for ES management. Using the city belt along the Yellow River in Ningxia, northwestern China, as a case study, this study quantified the spatial distribution of six ESs (food production, carbon sequestration, carbon storage, nutrient retention, sand fixation and recreational opportunity), analyzed the synergy and trade-off relations among them through correlation analysis, classified ES bundles through a self-organizing map method (SOM), explored the impacts of socio-ecological factors on the ESs through Ordinary Least Square regression (OLS) and Geo-detector analysis, delineated socio-ecological clusters using the SOM, and characterized the relationship between ES bundles and driver clusters through overlap analysis. The results suggest that spatial associations among ESs can be predicted by their driving mechanisms. Synergy relations existed among crop production, carbon sequestration, carbon storage and nutrient retention, and these were impacted by similar driving mechanisms. Synergy also existed between sand fixation and recreational opportunity, but significant differences existed in their driving mechanisms. Trade-off relations were shown between ESs in these two groups at the whole region scale. Three bundles were detected among the six ESs: bundle 1, characterized by recreational opportunity of high supply and other services of limited supply, was located in the transitional region between the central plain and the fringe mountains, and mainly driven by climate and proximity factors; bundle 2, characterized by high sand fixation, medium carbon storage and limited other services, was located in the northwestern and southern mountains and driven by climate and geography factors; bundle 3, characterized by high food production, carbon sequestration, carbon storage and nutrient retention of medium supply and other two services of limited supply, was located in the central plain and driven by vegetation coverage and proximity factors. Human activities can partly overcome the limitations of ecological conditions, thus specific strategies for different regions are proposed to maintain and improve ESs under global climate change.

1. Introduction

Ecosystem services (ESs) are the benefits and goods that people derive from ecosystems and ecological processes (Costanza et al., 1997). As an important way to connect humans with the ecosystems that support them (Rositano, Bert, Piñeiro, & Ferraro, 2017), ES is a useful concept for the formulation of sustainable management policy. Increasing impervious surface, population growth, socioeconomic development, and resource consumption have placed great pressure on the environment, especially in the last 100 years, which has significantly impacted the ESs provided by ecosystems (Vitousek, Mooney, Lubchenco, & Melillo, 1997). Over the past 50 years, provision of services such as food production increased globally while other services decreased, and overall 60% of all ecosystems are in a state of degradation (Jopke, Kreyling, Maes, & Koellner, 2015; MEA, 2005). A decreased level of ESs, loss of biodiversity, and degraded ecological quality impair ecosystem resilience, and in turn threaten human well-being (Parr, Sier, Battarbee, Mackay, & Burgess, 2003; Wang et al., 2017).

Since multiple ESs may respond to the same socio-biophysical

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factors and ecological processes, associations exist among them (Austrheim et al., 2016; Jopke et al., 2015). Governments and managers always hope to maximize multiple ESs simultaneously through effective management (Tammi, Mustajärvi, & Rasinmäki, 2017), but the fact that correlation exists among ESs makes it difficult (Bennett, Peterson, & Gordon, 2009). For example, land placed into agriculture to expand food supply may come from forests, which help to preserve biodiversity and improve air quality. Ignorance of associations among ESs could easily result in unintentional trade-offs and impact the consequence of management policies (Feng, Zhao, Fu, Ding, & Wang, 2017). Therefore, association analysis (trade-off, synergy, and bundle) among ESs has become an important topic in ES studies (Costanza et al., 2017; Tian, Wang, Bai, Luo, & Xu, 2016). ES bundles, defined as "groups of ESs that appear repeatedly together" (Raudsepp-Hearne, Peterson, & Bennett, 2010), are emergent properties of ESs across space (Queiroz et al., 2015) and time (Renard, Rhemtulla, & Bennett, 2015). As ES trade-offs and synergies change across regions (Lauf, Haase, & Kleinschmit, 2014), the delineation and mapping of ES bundles can help to investigate how multiple ESs are associated across heterogenous landscapes (Bennett et al., 2015). Most existing studies are focused on the general trade-offs and synergies across the whole region, only rarely have studies systematically analyzing these three relations together (Cord et al., 2017).

Land use/land cover (LULC) change and site-specific geographical characteristics (e.g. topography, soil, climate, and socioeconomic conditions, among others) contribute to spatial and temporal variations in the supply of ESs (Daily & Matson, 2008; de Groot, Alkemade, Braat, Hein, & Willemen, 2010). Their spatial associations are also highly affected by the distribution of underlying factors that drive more than one ES (Spake et al., 2017). Only a few studies have quantified the driving mechanisms for ES distribution and association, and most of these only considered physical and climate factors but ignored socio-economic development, not to mention comparing the relative importance of different socio-ecological factors (Feng et al., 2017; Qiao, Yu, & Wu, 2018; Rositano et al., 2017; Xiao, Hu, & Xiao, 2017). In the current study, the most common socio-economic, geography and ecological factors have been considered to investigate the relations between socio-ecological system and ESs, which is helpful to predict ES associations from common socio-ecological datasets and ES management (Spake et al., 2017).

Using the City Belt along the Yellow River in Ningxia (CBYN), located in northwestern China. as a case study, this study presents a reproducible approach to investigate the spatial associations among multiple ESs and their links with the socio-economic environment. This study took the following steps: (1) assessing the spatial supply of ESs, (2) detecting their spatial associations and bundles; (3) identifying potential socio-ecological driving factors, and (4) assessing the linkage between ES bundles and socio-ecological environment gradients. The outcomes provide suggestions for better socio-ecological environment management to reduce ES trade-off and improve synergies.

2. Materials and methods

2.1. Study area

The City Belt along the Yellow River in Ningxia (CBYN) (Fig. 1) is located between 36°54′and 39°23′N and 104°17′E and 106°53′E, and comprises the northern section of the Ningxia Hui Autonomous Region in China. Three deserts surround the region, with the Tengger Desert in the west, Maowusu Desert in the east, and Ulan Buh Desert in the north. The region encompasses four cities in Ningxia Province, and has a total area of 22,000 km^2 supporting a population of 4.39 million in 2015 (Ningxia Statistical Yearbook, 2016). The region has a continental climate, characterized by rare precipitation, abundant sunshine, strong evaporation, windy springs, short summers, early autumns, and long cold winters.

The Yellow River, which passes through the region, provides sufficient water resources for extensive agricultural irrigation, and has allowed the region to become one of the largest crop production centers in China, rare in northwestern China. The river has been severely polluted, as it receives increased inputs of industrial waste, agricultural fertilizers, and domestic sewage (Yan, Yu, Zhang, & Zhang, 2017). The region is undergoing significant changes with population growth (from 2.62 million in 1990 to 4.25 million in 2013), and economic development (GDP increase from 5.05 billion yuan in 1990 to 223.55 billion yuan in 2013), while the ecological environment has been impacted by urban sprawl and deforestation.

2.2. Data collection

Information on the land use and cover in the study area was derived by interpreting Landsat OLI data was provided by the USGS website (glovis.usgs.gov). The images were located in the path/row 129/033, 129/034, and 130/034. These images were first preprocessed in ENVI 5.3 (www.harrisgeospatial.com), including radiometric calibration, atmospheric correction, mosaicing, Gram-Schmidt Pan Sharpening, and clipping to the study area boundary. Land use maps were generated through an object-based classification procedure in eCognition 8.7 software (www.ecognition.com). To evaluate ES, land use included six types: cropland (e.g., irrigated land, paddy land), grassland, forest land (e.g., arbor, scrubland and orchard), water area (e.g., rivers, lakes, lagoons, reservoirs), urban land (e.g., industrial, commercial, transportation, and residential land), and unused land (e.g., sand, bare land). A manual accuracy assessment was performed to ensure the accuracy of the classification. Based on a sample of 317 points derived from a field survey (221 points) and Google Earth images (96 points), the overall accuracy of the land use map was 86.7% for the 2015 image.

Maps of the normalized difference vegetation index (NDVI) for each month in 2015 were derived from the corresponding Landsat OLI images using the NDVI method in ENVI 5.3. Global digital elevation model (GDEM) data was downloaded at a resolution of 30 m from the advanced space-borne thermal emission and reflection radiometer (ASTER) data (search.earthdata.nasa.gov). The meteorological data in this study was derived from meteorological stations distributed throughout the study area, downloaded from the China Meteorological Administration (data.cma.cn), and then interpolated to cover the whole region using the Kriging method in ArcGIS software version 10.2 (esri.com). Soil data was derived from the Harmonized World Soil Database (HWSD) generated from China's second national soil survey. Socioeconomic and food data mainly came from the province statistical yearbook (Ningxia Statistical Yearbook, 2016), including urban population, gross domestic product (GDP), crop production, livestock-raising, yield of meat, fish production, and the average value of crop, meat, and fish. All the raster maps were converted to the UTM coordinate system, zone 48 at a spatial resolution of 30 m (see Table 1).

2.3. Estimation of ecosystem services

Considering the significance of ESs and data availability, 6 ESs were selected in this study, including 1 provisioning service (food production), 4 regulating services (carbon storage, carbon sequestration, nutrient retention and sand fixation) and 1 cultural service (recreational opportunity).

2.3.1. Food production

The food production service was calculated as the annual mean food value per hectare (yuan/10,000 m^2) in 2015. The food was classified into three types: crop, fish, and meat. First, the amount of each food type production was collected at the grid scale, and then multiplied by its annual mean monetary value, and then divided by 900 m^2 (grid area) to convert the crop unit to yuan/m^2. To simulate the spatial distribution of food production, this study hypothesized that the three

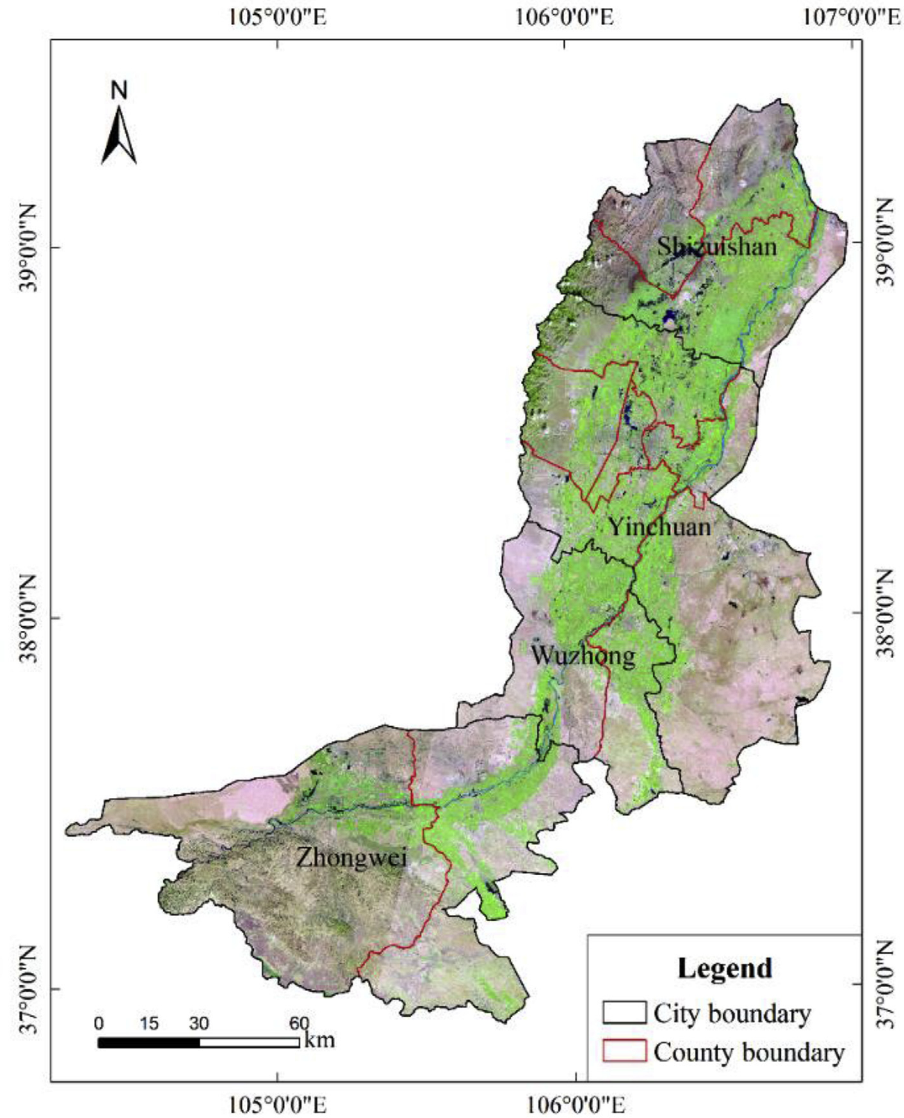

Fig. 1. Study area with background derived from Landsat OLI images.

types of crops, fish, and meat were distributed in cropland, ponds and lakes, and grassland, respectively. The crop types mainly included rice, wheat and corn, while meat mainly came from three primary livestock types of pigs, cows, and sheep. The production level of each food type at the county scale was obtained from the Ningxia Statistical Yearbook in 2016, and averaged for the corresponding land-use grids. After multiplying by the relevant monetary value of each food type, they were summed to generate the distribution of crop production in the units of yuan/m^2.

2.3.2. *Carbon sequestration*

Vegetation is critical for fixing carbon and mediating the increase in greenhouse gases (Canadell et al., 2007). In the CBYN, vegetation types mainly consisted of broadleaf deciduous trees and shrubs in the mountain area, cultivated crops in the central irrigated plain, and grassland in the transition region between mountain and plain (Wang et al., 2017). Net primary production (NPP) can be used as a proxy for carbon sequestration (Li et al., 2016). Annual NPP at a resolution of 30 m was calculated using the Carnegie-Ames-Stanford Approach (CASA) model driven by vegetation cover interpreted from remote sensing images and interpolated maps of climate data (Gao et al., 2013; Zhou, Li, Guo, & Li, 2017). For details, refer to Zhu, Y. P., Yang (2007).

Table 1
Summary of the primary data.

Data type	Resolution or spatial distribution	Data source
Land use map	30 m	Landsat OLI images (USGS website)
NDVI	30 m	Landsat OLI images (USGS website)
Soil data	1:1000000	HWSD
Meteorological data	12 points	China Meteorological Administration
Socioeconomic data	Counties	Ningxia Statistical Yearbook

2.3.3. Carbon storage

The amount of carbon captured by the ecosystem was consisted as two main parts: carbon sequestration in vegetation, and carbon storage in soil (Chuai, Huang, Wang, Wu, & Zhao, 2014). Carbon storage in soil was calculated using the carbon densities of soil types. Carbon density values were related to vector maps of soil types, multiplied by the area of a respective soil type, and converted into grids to acquire the distribution of carbon storage (gC/m^2). The related parameters were derived from the soil data in the Harmonized World Soil Database (HWSD).

2.3.4. Nutrient retention

Nutrient retention refers to the reduction in nutrient load between sources and receiving waters due to the biogeochemical processes involved in nutrient transport. The InVEST nutrient delivery (NDR) model was used to map nutrient retention. The main input included nutrient sources associated with different land-use types, and retention properties of flow paths (e.g. LULC, slope); most of the input coefficients were derived from empirical data (Yang, Zhang, Yang, & Yang, 2009). For details refer to Lyu, Zhang, Xu, and Li (2018).

2.3.5. Sand fixation

Sand fixation represents an ecosystem function of preserving soil and water, and preventing dust storms, which is critical in arid and semiarid areas (Wang et al., 2017). The model established by Dong (1998) was used to evaluate sand fixation, as follows:

$$Q= \iiint_{txy} \left\{ 3.9V^2 \times (1.0413 + 0.0441\theta + 0.0021\theta^2 - 0.0001\theta^3) \times (1 - (8.2 \times 10^{-5})^C) \times \frac{SDR^2}{H^8 \times d^2 \times F}, x, y, t \right\} dxdydt \quad (1)$$

where Q is the amount of wind erosion loss (t), θ is the slope in degrees (°), V is wind speed (m/s), C is annual average vegetation cover (%), SDR is surface structural damage rate (100% in this study), H is relative humidity derived from meteorological stations, d is soil particle size (average of 0.2 mm), F is the hardness of soil (0.9 N/cm^2), t is sand-blowing time (s) (20 days in 2015), and x, y are the distance from the point to the reference point (in km).

2.3.6. Recreational opportunity

Recreational opportunity, or opportunities for recreation and ecotourism, represents the cultural service provided by the ecosystem. Based on the method proposed by Nahuelhual, Vergara, Kusch, Campos, and Droguett (2017), this service was calculated with four attributes and potential activities (horseback riding, recreational fishing, etc.) for the landscape in this study. Using the Analytical Hierarchical Process (AHP), fifteen academics and postgraduate students from Lanzhou University were interviewed to obtain relative preferences for attributes and weights (Table 2 and Table 3). All the raster maps for each indicator (Table 2) were first normalized to a range of 0–100. The maps of accessibility and scenic beauty were derived by adding each indicator in the same attribute with the weights determined by their relative importance. The final maps of the four attributes were normalized to 0–100, and then summed up with the same weight to get the spatial distribution of recreation opportunity.

2.4. Spatial associations among the ESs

2.4.1. Correlation analysis

ES values at 10,000 random points in the study area were sampled using the “Create Random Points” and “Extract Multi Values to Points” tools in ArcGIS 10.3. The values were first standardized using z-score normalization to reduce the impacts of magnitude and variability (Spake et al., 2017). Since the distribution of ES values was non-normal, as suggested by the Kolmogorov-Smirnov test, Spearman rank correlation analysis was used to identify the correlations among the ESs. The matrix of correlation coefficients was graphed using the “corrgram” package in the R statistical software.

2.4.2. ES bundles classifications

Principal component analysis (PCA) (Marsboom, Vrebos, Staes, & Meire, 2018) was used to quantify the main multivariate relationships among the ESs, and to obtain those principal components that represent most of the variability in multiple ESs. PCA is a precursor to cluster analysis, as it can separate signals from noise, and lead to a more stable clustering result (Raudsepp-Hearne et al., 2010; Spake et al., 2017). Then, a self-organizing map (SOM), a spatially constrained form of the K-means method, was applied to allocate each cell into ES bundles based on their similarities in the ES supply (Dittrich, Seppelt, Václavík, & Cord, 2017). PCA and SOM were performed with the “psych” and “kohonen” packages in R, respectively.

2.5. Driving factors for ES distributions and associations

2.5.1. Identification of critical driving factors

Representative factors for the socio-ecological environment were collected from three sources: public cognition, ES assessment and other relevant studies (Ai, Sun, Feng, Li, & Zhu, 2015; Xiao et al., 2017). Seventeen factors were originally selected in this study, classified into two types: ecological and socio-economic (Table 4). To identify candidate factors significantly affecting ESs, redundancy analysis (RDA) and forward stepwise selection were combined to select the factor combination with the highest R^2 and p-value (Spake et al., 2017). These were performed using the “vegan” and “packfor” packages in R.

2.5.2. Impacts of individual factors on ESs

Ordinary Least Square regression (OLS) and Geographical Detector (GD) were combined to investigate the impacts, with the selected driving factors as independent factors and each ES as a dependent factor. All the factors were first standardized to reduce the impacts of units and magnitudes (Su, Xiao, Jiang, & Zhang, 2012). OLS was used to detect the nature of the impacts, e.g. positive or negative (Li, Peng, Yanxu, & Yi'na, 2017), while GD was used to quantify their relative magnitudes (Wang et al., 2010). In the OLS results, the positive standard coefficients represented positive impact and vice versa, while a larger adjusted R^2 indicated a stronger ability of independent factors to interpret dependent factors and vice versa (Li et al., 2017). In GD results, the value q represented the relative impacts of driving factors, in

Table 2
Attributes, factors and weights used to build the recreational opportunities indicator.

Attribute	Factor	Weight	Spatial treatment
Accessibility	Road network	0.7	Euclidean distance
	Station (Airports, Railway and bus stations)	0.3	Euclidean distance
Tourism use aptitude	Land uses		Normalized values assigned to each land use type
Scenic beauty	Public and private protected areas	0.33	Euclidean distance
	National park	0.33	Euclidean distance
	Tourism area	0.34	Euclidean distance
Cultural sites	Archeological sites		Euclidean distance

Table 3
Activities that can be performed on each land use type in CBYN.

	Horseback riding	Mountain climbing	Recreational fishing	Kayaking	Camping	Scientific tourism	Scenic beauty	Shopping	Total
Cropland	0	0	0	0	0	1	0	0	1
Forest	1	1	0	0	1	1	1	0	5
Grassland	1	1	0	0	1	0	1	0	4
Lake	0	0	1	1	0	1	1	0	4
Village land	0	0	0	0	1	0	0	1	2
Unused land	0	0	0	0	0	0	0	0	0
Urban land	0	0	0	0	0	0	0	1	1
River	0	0	0	1	0	1	1	0	3

* River mainly refers to the Yellow River; urban land refers to built-up land in town and county; village land refers to built-up land in the village.

Table 4
Driving factors for ecosystem services change.

Types	Code	Driving factors	Units
Ecological	precip	Annual average precipitation	mm
	temper	Annual average temperature	°C
	wind	Wind speed	m/s
	humid	Air relative humidity	%
	elev	Elevation	m
	slope	Terrain slope	°
	geom	Landforms	–
Socio-economic	Pden	Population density	person/km^2
	GDPden	Gross domestic product density	yuan/km^2
	crop	Per capita cropland area	m^2/person
	NDVI	Vegetation cover	%
	Dcity	Distance to city center	km
	Dcounty	Distance to county center	km
	Droad	Distance to transportation	km
	Dcanal	Distance to canal	km
	Dwater	Distance to water area	km
	Dres	Distance to national natural reserves and national parks	km

the range of [0,1]. They were performed using the “stats” and “geodetector” packages in R.

2.5.3. Classification of socio-ecological clusters

Based on the similarity of socio-economic and ecological factors in their spatial distributions, socio-ecological clusters were delineated through PCA and SOM following the procedure suggested by Section 2.4.2. Then overlay analysis in ArcGIS 10.3 was used to quantify the spatial co-occurrence between ES bundles and socio-ecological clusters.

3. Results

3.1. Spatial patterns of ESs

The six selected ESs demonstrated a clear distinction along both horizontal and vertical gradients (Fig. 2). Some ESs had similar spatial patterns, while others exhibited almost the opposite distributions. For instance, carbon storage, food production, and nutrient retention had similar distributions, and high values of these services were mainly located in the irrigated areas along the Yellow River, while recreational opportunities had the opposite pattern. Distribution of sand fixation was dissimilar to that of the other ESs. The six ESs were spatially clustered and autocorrelated rather than randomly distributed.

The irrigated area along the Yellow River was the main hotspot for food production, carbon sequestration, carbon storage and nutrient retention, but a major “cold” spot for sand fixation and recreational opportunities. Since aquaculture reaches high yields in a limited space, food production exhibited very high values in ponds. Helen Mountain, located in the northwestern part of the study area, was a hotspot for carbon sequestration, carbon storage, sand fixation, and recreational opportunities, but a “cold” spot for food production and nutrient retention.

3.2. Spatial correlations among ESs

Among the 15 pairs of the six ESs, 14 were significantly correlated ($p < 0.05$), and one – between carbon sequestration and sand fixation – was not. Among the 14 significantly correlated pairs, 3 were highly correlated ($|r| \geq 0.5$), 5 moderately correlated ($0.3 \leq |r| < 0.5$), and 6 weakly correlated ($0.1 \leq |r| < 0.3$) (Fig. 3). In Fig. 3, the blue color represents positive correlations, and red - negative, while darker colors and greater saturation represent higher correlation levels.

Food production, carbon sequestration, carbon storage, and nutrient retention were positively correlated with each other, while sand fixation and recreational opportunity had the same positive relations. The first four ESs were negatively correlated with the next two. Correlation coefficients between carbon storage and the three food production services, carbon sequestration, and nutrient retention were close to 0.2, far smaller than the other correlation coefficients. Sand fixation, which is critical for preventing wind storms, was not significantly correlated with other services, except for moderate correlations with food production and recreational opportunity.

3.3. Spatial distribution of ES bundles

Two major components were indicated by the PCA results, which accounted for 61% of the total variation in ESs (Fig. 3b). Thus three ES bundles were detected among thesix ESs. The SOM method was then applied to map the spatial distribution of ES bundles. Bundle 1 was characterized by the highest potential for recreational opportunity and a limited supply for other services, especially in carbon sequestration and carbon storage. It was mainly distributed in grassland with low vegetation coverage, lakes, ponds and the Yellow River. Bundle 2 was characterized by the highest supply of sand fixation, moderate supply for carbon storage and limited supply for nutrient retention and food production. It was mainly located in the mountains with steep terrain. Bundle 3 was characterized by the highest supply of nutrient retention, carbon sequestration and food production, and limited supply of sand fixation and recreational opportunity. It was mainly distributed in the central plain with a large area of irrigated cropland.

3.4. Driving forces for ESs

The results of RDA and forward stepwise selection suggested that the five factors of wind speed, landform, precipitation, GDP_{den} and D_{water} should be removed from driving factors, and the remaining 12 factors explained 55.5% of the variance in ES distributions and their associations. The unexplained variance was mainly in the simulation of food production and carbon storage, as indicated by the low adjusted R^2s of 0.290 and 0.238, respectively. The results from OLS and GD suggested that the individual impacts of each driving factor varied for different ESs (Fig. 5).

Among the 12 factors, NDVI had the largest positive impact on food production, carbon sequestration and nutrient retention, and a moderate negative impact on sand fixation and recreational opportunity.

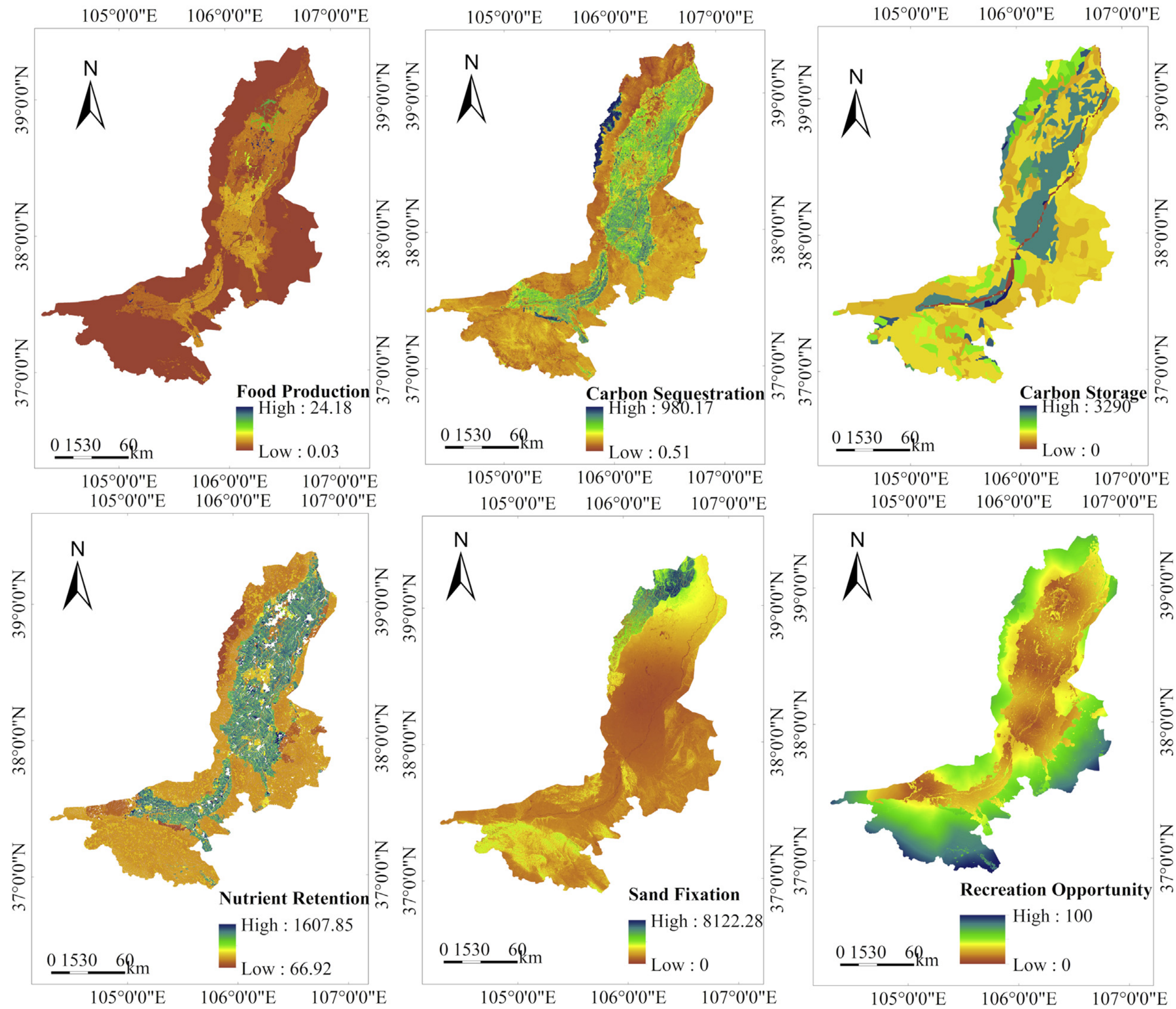

Fig. 2. Spatial distribution of six ESs in 2015.

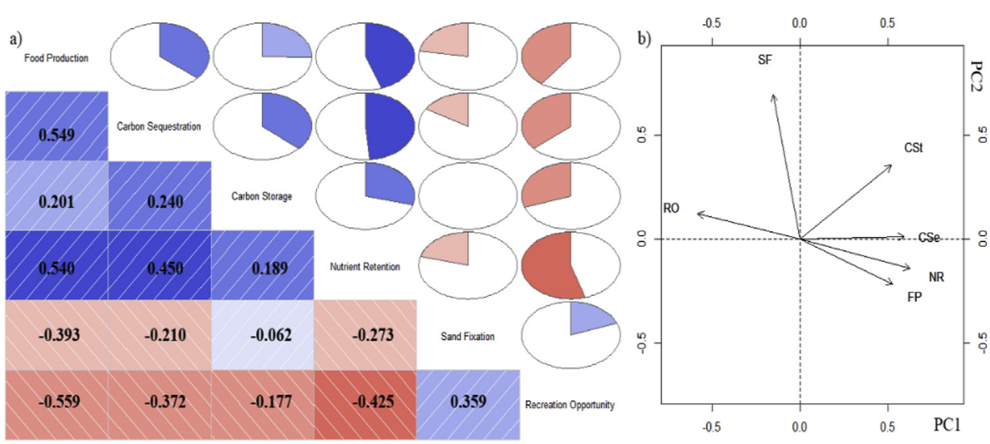

Fig. 3. Results of correlation analysis and PCA (panel a). The corrgram and correlation coefficients for pairs of ESs; panel b). PCA biplot for ESs. FP—food production, NR—nutrient retention, CSe—carbon sequestration, CSt—carbon storage, SF—sand fixation, RO—recreational opportunity).

Thus vegetation coverage was critical and decisive in provision and regulating services, while its impact on sand fixation and cultural services was relatively small. The two climate factors of temperature and humidity both had small impacts on the six ESs, except for the large impact of humidity on sand fixation. Among the two topographical factors, elevation had a large impact on the six ESs, almost all in the second class among the 12 factors, while the impact of slope was relatively small, except on sand fixation. They both had positive impacts on carbon storage, sand fixation and recreational opportunity, negative impacts on food production and nutrient retention, and the opposite

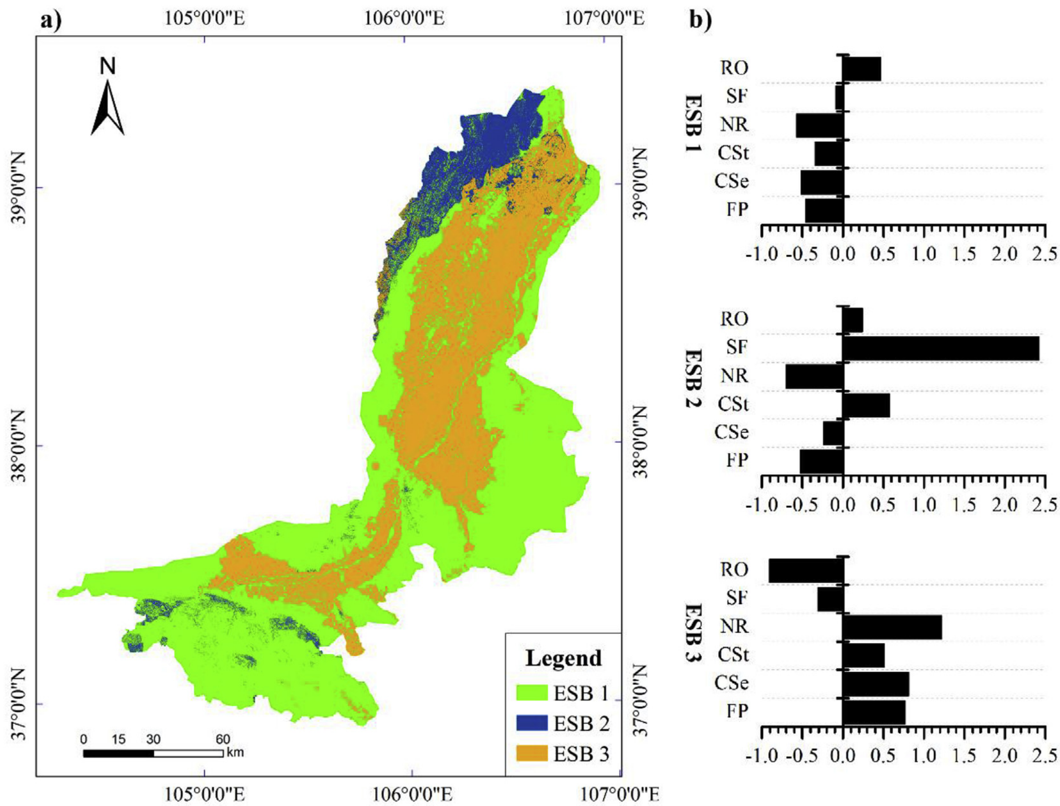

Fig. 4. Ecosystem service bundles in CBYN. (Panel a. Spatial distribution of three bundles. Panel b. Contribution profiles of each ES to the bundle. FP—food production, NR—nutrient retention, CSe—carbon sequestration, CSt—carbon storage, SF—sand fixation, RO—recreational opportunity).

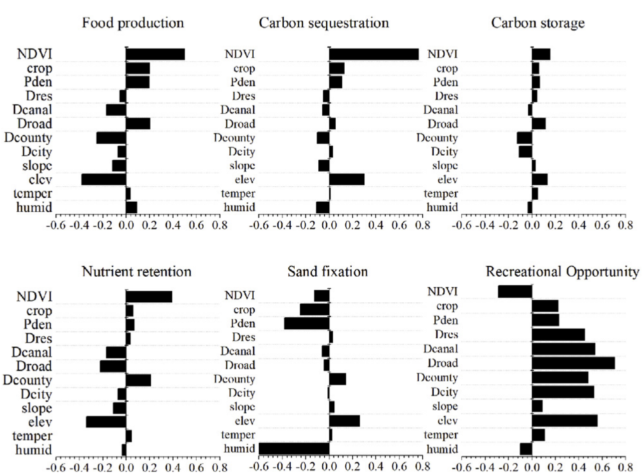

Fig. 5. The relative impacts of 12 driving factors on each ES (the bar length was derived from GD results, the attributes of value (positive or negative) was derived from OLS results).

impacts on carbon sequestration.

The five proximity factors had large impacts on recreational opportunity, small impact on carbon sequestration, and moderate impacts on other services. Specifically, distance to transportation had the largest positive impact on recreational opportunity. Distance to city centers and distance to county centers both had negative impacts on food production and carbon storage and positive impacts on recreational opportunity, but the opposite impacts on other services. Moreover, distance to canals and distance to reserves both had larger impacts on recreational opportunity, while their impacts on other services were relatively small. Population density and per capita cropland area had positive impacts on ESs, except for sand fixation, and their impacts were larger for sand fixation.

3.5. Overlay of ES bundles and socio-ecological clusters

Six socio-ecological clusters were detected and mapped among the 12 driving factors, indicating considerable spatial heterogeneity in the study area (Fig. 6 a). In each cluster, socio-ecological factors were supplied with the same magnitude and type. The results of overlay analysis suggested that ES bundle 2 mainly overlapped with socio-ecological cluster 1, characterized by high slope and elevation and low humidity. ES bundle 3 mainly overlapped with cluster 6 characterized by high NDVI, high proximity to artificial facilities and rather flat terrain, and with cluster 2 characterized by high per capita cropland and low humidity. ES bundle 1 overlapped mainly with cluster 4 characterized by high humidity and temperature and low vegetation coverage and population density, and with cluster 3 characterized by large distance to artificial facilities, high elevation and low temperature.

4. Discussion

This study provides a comprehensive analysis of ES associations and their relationships with socio-ecological factors in CBYN, where humans often underestimate ESs due to intensive cultivation and human activities (Chen & Zhang, 2000). Such analysis is critical to the understanding of how to minimize trade-offs among ESs, and enhance their synergies (Bennett et al., 2009). In this approach, the spatial distribution and co-occurrence of ESs was quantified to illustrate the abundance or deficiency of ESs in different regions (see Fig. 4). Likewise, the effects of common socio-ecological factors on individual ES (see Fig. 5) and the spatial congruence of ES bundles and socio-economic clusters (see Fig. 6) were assessed to understand the underlying driving mechanisms of ES associations.

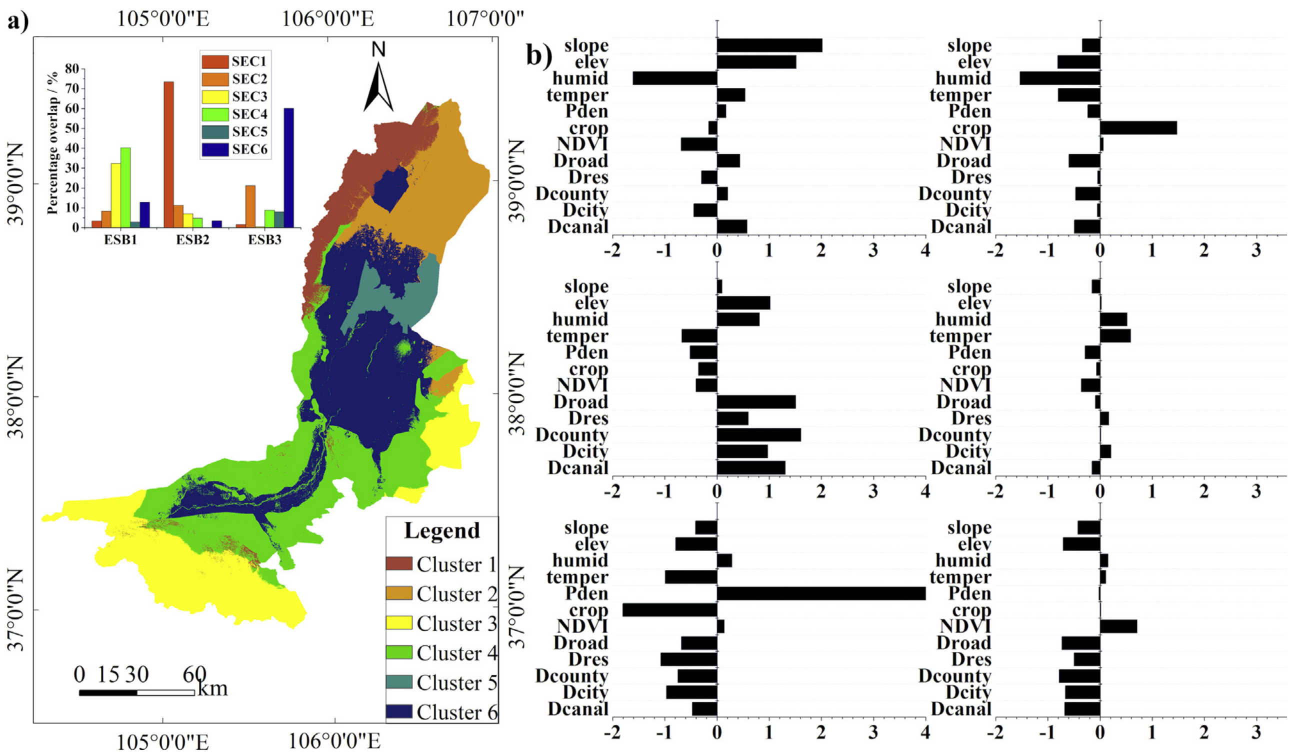

Fig. 6. Socio-ecological cluster (SEC) mapped in CBYN (panel a) spatial distribution of each cluster with the indicator of spatial overlap area percentage of each cluster per ES bundle in the left-top corner; panel b) contribution of each driving factor to the cluster).

4.1. ES correlations with driving mechanisms

Quantification and mapping of ESs are the foundation of integrating ecosystem services into management planning and decision making (de Groot et al., 2010; Grêt-Regamey, Altwegg, Sirén, van Strien, & Weibel, 2017). The calculation method of ESs is applicable to other areas, thus this analysis result is comparable with those presented in previous studies, i.e., carbon sequestration evaluated for the Guanzhong-Tianshui economic region (Zhou et al., 2017), sand fixation in Yinchuan Plain (Li & Wang, 2018), and food production in the Three Parallel Rivers Region (Lin et al., 2018).

Significant correlations have been detected among the selected ESs, which present both similarities to and differences from patterns found in previous studies (Maes, Paracchini, Zulian, Dunbar, & Alkemade, 2012). A general trade-off relation has been suggested between provision services and regulating services, especially between crop production and regulating services of carbon storage, water interception and soil retention (Jopke et al., 2015; Zhou et al., 2017). However, synergy relations between service provision of food production and regulating services of carbon storage, carbon sequestration and nutrient retention at the regional scale were observed in this study. This might be explained by the similarities in their driving mechanisms—vegetation with high positive impact, elevation for the second, proximity and socio-economic with moderate impact and climate factors with low impact. Thus the unique vegetation structure in CBYN, where intensive cropland occupies the dominant vegetation type, forest land is only a small part, and other land use types have sparse or no vegetation coverage, results in different synergies among the four ESs compared with other studies. Particularly, the impacts of NDVI and elevation decrease on carbon storage, which results in the weaker correlations between carbon storage and the other three services at a regional scale, and this synergy changes to trade-off in ES bundle 2 located in the mountain area. Therefore, the synergy and trade-off relations among ESs are not only caused by the differences in their calculation methods, but also largely impacted by their socio-ecological environment.

Sand fixation and recreation opportunity are positively correlated with each other, while both are negatively correlated with the other four ESs at the regional scale. However, significant differences exist in their driving mechanisms, that is, sand fixation is highly impacted by humidity, population density and slope, but recreational opportunity by proximity and elevation. The similarities in these driving factors generally cause similar distributions in the ESs and their synergy relations, while the differences could also cause trade-offs among ESs. Despite the fact that the six ESs can be classified into two groups due to their spatial correlations, three ES bundles have been detected in CBYN through the use of SOM, which is consistent with the results of driving mechanisms. Thus driving analysis can be used to predict the correlations and bundles among ESs. Positive (negative) correlations among ESs do not indicate synergies (trade-offs) in all of the areas (Lin et al., 2018; Qiu & Turner, 2013). Thus, it is not enough to analyze the whole set of correlations for ES management, and it is important to further map the spatial distribution of ES bundles to investigate the trade-off or synergy relations among ESs for specific socio-ecological systems.

4.2. ES bundles corresponding to socio-ecological clusters

SOM is a widely used method for clustering in the environmental sciences (Václavík, Lautenbach, Kuemmerle, & Seppelt, 2013). It has also been described as one of the most promising approaches in ES association analysis due to its advantage of considering the topology of the input data (Cord et al., 2017). The clustering algorithm in SOM can delineate ES bundles, and visualize ES co-occurrences based on the similarity of different geographic locations in supplying ESs (Renard et al., 2015). Thus, this method allows an exploration of the spatial distribution of the supply level of selected ESs, and the abundance of ESs within regions. Based on the spatial distribution and associations among ESs, the whole region can generally be classified into three subregions: central plain, mountain area, and their transition zones. Specific management strategies should be proposed for each region due to their different driving mechanisms.

The irrigated cropland in the central plain has a high level of food production, a medium supply of regulating services (nutrient retention, carbon sequestration and carbon storage), and a limited supply of recreational opportunity and sand fixation. It is mainly overlapped with socio-ecological clusters characterized by high vegetation, low elevation and high proximity to artificial facilities, and by high per capita cropland and low humidity. Thus vegetation coverage and socio-economic factors have larger impacts on ES bundles with high provision and medium regulating services, while the former is highly impacted by human activities, e.g. irrigation and cultivation. This differs from the results of Dittrich et al. (2017) in Germany, which suggests that provision services are mainly determined by environmental factors. It can be explained by the fact that human activities can partly overcome the limitations of ecological conditions, thus cultivation with high vegetation coverage has been highly promoted in the central plain. More efforts should be made to reduce abandoned cropland, promote technical development and build artificial facilities which are beneficial for vegetation coverage growth in the central area.

A hot spot for recreation opportunity has been identified in the area in the transition region between central irrigated cropland and the mountain area, where other provision and regulating services are limited. This bundle mainly overlaps with driving clusters characterized by climate and proximity factors, which is consistent with the preference of human beings for tourism in distant natural and cultural landscapes, e.g. deserts, Sand Lake and the Western Xia Imperial Tombs, while the natural landscape generally requires specific climate conditions. Thus more attention should be paid to the improvement of recreational opportunity in the transition area, e.g. protecting native habitat from human disturbance, and reducing the impact of climate change.

The northern and southern mountains had the largest supply of sand fixation due to the steep terrain and higher humidity, which is critical in northwestern China (Li & Wang, 2018). It also maintains large areas of native vegetation and intact natural environment with high forest biomass, high biodiversity, valuable scenery (Lin et al., 2016), and high carbon density (Buczko et al., 2017) and has moderate potential for recreational opportunity and carbon storage, which is consistent with the results in an Alpine region (Zoderer, Tasser, Erb, Lupo Stanghellini, & Tappeiner, 2016), and in the Three Parallel Rivers Region (Lin et al., 2018). Meanwhile, this area was limited in the ESs of nutrient retention, carbon sequestration, and food production. It mainly overlaps with driving clusters characterized by geography and climate factors, indicating that ecological conditions, e.g. topography and climate, have larger impacts on ESs in areas far away from human residents. Future global climate change would threat the ES supply, especially in the mountain area in CBYN, which can be partly addressed by human activities.

5. Conclusions

This study has assessed spatial correlations (trade-off, synergy and bundle) among multiple ESs, and investigated their underlying driving mechanisms. All of the selected ESs had significant spatial patterns, and moderate to low levels of correlations existed among them. At the regional scale, food production, carbon sequestration, carbon storage and nutrient retention were synergistically correlated with each other, and driven by similar mechanisms—vegetation coverage the highest, elevation the second and proximity the least. Sand fixation and recreational opportunity had a synergy relation, while the former was highly driven by humidity, population and slope, and the latter by proximity to artificial facilities and elevation. Specially, the first four ESs had trade-off relations with the latter two services.

Correlations and bundles among ESs can be predicted by their driving mechanisms. Three ES bundles have been detected among the six ESs. In the central plain, the ecosystem provided a high supply of food and regulating services of nutrient retention, carbon sequestration and carbon storage, which was highly impacted by vegetation coverage and proximity to artificial facilities. In the northwestern and southern mountains, the ecosystem was characterized by a high supply of sand fixation, medium carbon storage and recreation opportunity and limited other services, mainly impacted by ecological factors, e.g. topography and climate. In the transitional region, the ecosystem provided a high supply of recreational opportunity and a limited supply of other services, mainly driven by both ecological factors (climate) and socio-economic factors (proximity to artificial facilities). Further study should pay more attention to sustainable development strategies to address the challenges of future climate change for ES management.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.apgeog.2019.05.003.

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