Ecosystem Health in the Southwest China Hybrid Geomorphologic Region: Evolution Characteristics and Driving Factors

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Abstract

The ecosystem health of the Chishui River Basin (CRB)—a crucial ecological barrier in the upper reaches of the Yangtze River—is vital for the ecological security and socioeconomic sustainability of the Yangtze River Basin. However, the evolution of the ecosystem health in various CRB areas of different geomorphologic types and its driving factors remain unclear. This study combined the Revised Universal Soil Loss Equation (RUSLE) and Soil and Water Assessment Tool (SWAT) models to construct a VORES framework–based ecosystem health assessment for the CRB and evaluated the spatiotemporal evolution characteristics in the CRB in 2010–2020, and then explore the driving factors of ecosystem health based on geographical detectors. The results were as follows: (1) In 2010–2020, ecosystem service function in the CRB decreased and then increased; the overall trend was downward, and the overall ecosystem service function was higher in the Danxia area than it was in the karst area. (2) The ecosystem was generally subhealthy; the Danxia area was mostly extremely healthy, whereas the karst area was mostly subhealthy and unhealthy. (3) In the CRB, strong explanatory power for healthy spatial distribution of ecosystems was demonstrated by vegetation, precipitation, and the bedrock bareness rate in the karst area, whereas it was demonstrated by vegetation, land use, and precipitation in the Danxia area. All influencing factors demonstrated increased explanatory power after interaction, and the combinations of the dominant interaction factors of different geomorphologic types demonstrated considerable differences. These results may provide scientific support for CRB ecosystem health maintenance and conservation.

Introduction

Ecosystems are the foundation of human survival and development, and the integrity of their structures and functions are related to the sustainable development of human society (Fu et al. 2001). With the intensification of climate change and human activities, increasingly serious issues related to the ecological environment have gradually engendered concerns regarding health and ecosystem security, and the concept of health has gradually been extended to include ecosystems (Liu et al. 2015). Ecosystem health reflects the comprehensive characteristics of ecosystems (Rapport et al. 1999); conducting ecosystem health research is a major means of understanding the state of ecosystems and serves as a critical foundation for environmental protection and sustainable development (Zhang et al. 2016).

Karst ecosystems are crucial parts of terrestrial ecosystems; they are fragile systems with a low environmental capacity and weak anti-interference ability (Hu et al. 2020). Southwest China is one of the three areas with the highest concentrations of karst in the world and has strong karst development and large areas with exposed carbonate, special geological backgrounds, and karstification. However, in these areas, soil erosion and land productivity loss make vegetation vulnerable to damage and difficult to restore in addition to other prominent environmental issues (Jiang et al. 2014). This results in the allowance of considerable reductions in karst ecosystems to provide services for humans (Boesch et al. 1981). As such, karst area resource utilization, ecological protection, and sustainable social economic development appear to be correlated. To resolve the aforementioned problems, starting in the 1980s, China began investing heavily in ecological construction projects and implementing ecological restoration projects involving, for example, returning farmlands to forest land or grasslands, closing hillsides for afforestation, and comprehensively controlling rocky desertification and ecological migration. The implementation of these projects has protected and restored ecosystems and ensured their safety (Ouyang et al. 2016). Many studies with focuses on karst landscape vulnerability, human activity impact, and ecosystem degradation have revealed changes in landscapes, vegetation cover, and ecosystems resulting from ecological restoration programs (Zhou et al. 2019; Gao et al. 2020; Hou et al. 2016). However, only a few studies on ecosystem health in karst area have been reported. Karsts in southern China have alternating distributions of karst and nonkarst landforms (Lin 2001). Considerable differences are present in the ecosystem health, impact factors, and prevention and control strategies of different landform areas. However, research has often ignored these differences. Few studies have employed a perspective of ecological restoration and focused on the changes in ecosystem health in karst areas; in particular, how the ecosystem health of different landform types evolves and what its main driving factors are remain unclear. Therefore, on the basis of the differences of different geomorphologic types, an exploration of the spatiotemporal differentiation and driving factors of ecosystem health under ecological restoration measures is warranted.

The Chishui River Basin (CRB) is a first-class tributary of the upper reaches of the Yangtze River. Moreover, the upper and middle reaches of the Yangtze River are typical karst landforms with acute topographic undulation, and the lower reaches belong to the Danxia (nonkarst) landform and a less undulating topography. Over the years, due to the special geomorphic environment and the influence of human activities, the CRB has experienced serious soil erosion, making the CRB a national key soil erosion control area in China. The CRB is also a strategic area for the construction of ecological barriers in the Yangtze River Basin as a means of ensuring ecological security and socioeconomic development in the area (Li et al. 2021). Considering the importance of the ecological functions of the CRB, China aims to continue strengthening its comprehensive treatment of the ecological environment and scientifically implement ecological restoration projects. For such projects to be completed, the state of the ecosystem health must be determined, the leading factors that affect the ecosystem health must be clarified, and a reference for the formulation of ecosystem protection measures in the CRB must be developed.

Ecosystem health assessment methods mainly involve the indicator species method and indicator system method (Yang et al. 2010). Compared with the indicator species method, the indicator system method is more widely used because it highlights the evolutionary relationship between
ecological health, human services, and the regional environment and more accurately reflects the load capacity and recovery capacity of the ecosystem under stress (Li et al. 2021). In terms of its research content, the indicator system method explores the impact of external disturbances on the spatiotemporal differentiation of ecosystem health, such as the impact of engineering measures and economic urbanization development on the health and spatiotemporal evolution of urban agglomerations (Chen et al. 2022), wetlands (Xu et al. 2020), rivers (Su et al. 2019), and grasslands (Yin et al. 2019). It also analyzes improvements in ecosystems through application of ecosystem health assessment frameworks, such as the Vigor–Organization–Resilience–Ecosystem Services (VORES) assessment and Pressure–State–Response (PSR) frameworks (Wang et al. 2020), or a single measurement of the natural state or external perturbations of ecosystems. Although the aforementioned studies have analyzed the spatial differences and influencing factors of ecosystem health, they have focused on the influence of only a single factor; studies on the interactions of a combination of factors are lacking. Because ecosystem health is often affected by the interaction of multiple factors under natural conditions, an exploration of the impact of a combination of factors on the ecosystem is warranted.

To study ecosystem health and its driving factors in the CRB from 2010 to 2020, this study used Net Primary Productivity (NPP) data and the RULSE and SWAT models to measure three typical ecosystem service functions: carbon sequestration, soil conservation, and water supply. In addition, this study combined Fragstats4.2 and multisource data to construct an ecosystem health assessment theoretical framework based on the VORES framework and used a theoretical framework and the geographical detector model to explore CRB ecosystem health and its driving factors.

The primary objectives of this study were (1) to explore the ecosystem health status and its spatiotemporal distribution characteristics of the karst and Danxia landforms in the CRB from 2010 to 2020, (2) to investigate the main driving factors affecting the ecosystem health of the CRB in karst and Danxia landforms, and (3) to analyze the ecosystem health characteristics in the CRB to provide a crucial basis for the implementation of differentiated ecological protection measures as well as a theoretical reference for the ecological barrier area of the upper reaches of the Yangtze River to facilitate ecosystem protection and maintenance according to local conditions.

**Materials And Methods**

**Study area**

The Chishui River (26°49′–28°54′N, 104°09′–107°10′E) originates in Chuxiong County, Yunnan, along the border between Sichuan and Guizhou, and joins the Yangtze River in Hejiang County, Sichuan (Fig. 1). The main stream is 436.5 km long, and it flows through Yunnan, Guizhou, and Sichuan—with a watershed area of 18,932.2 km² and average elevation of 1077m. The middle and upper reaches of the Chishui River are part of the Yunnan–Guizhou Plateau, a typical karst landform, accounting for approximately 74% of the total area of the basin, and are mainly in plateau mountains. The river's lower reaches are located in the Sichuan Basin, which is part of the Danxia landform and accounts for approximately 26% of the total area, and are mainly in hilly plains. The climate of the CRB is subtropical monsoon, with annual average precipitation of 749–1286mm. Because of special physical and geographical factors and considerably humans’ activities, the aforementioned areas have encountered serious ecological issues, such as soil erosion and rocky desertification.

**Data**

The main data sources and descriptions are listed in Table 1. Of these data, the NPP data were used to characterize the ecosystem carbon sequestration services, and the DEM and hydrological data were mainly used for the SWAT model to simulate surface and underground runoff in the CRB to represent water supply services. Meteorological and soil data were mainly used to calculate soil conservation services in the CRB by using the RULSE model. Normalized difference vegetation index (NDVI) data were combined with land-use data to calculate the natural health index of the watershed ecosystem. Landsat remote-sensing images were processed using ENVI5.3 to obtain NDRI data. On the basis of these data, the bedrock exposure rate was inverted in a pixel dichotomy model. By using the Create Fishnet tool of ArcGIS10.2 to generate sampling points, the average annual precipitation, elevation, land use, NDVI, and bedrock bareness rate were classified using natural breaks, which were extracted to the sampling points and input into the geographical detector, which was used to analyze the ecosystem health–environmental factor relationship in the watershed.
### Table 1
Data sources.

<table>
<thead>
<tr>
<th>Data</th>
<th>Spatial resolution</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPP</td>
<td>500m</td>
<td>National Aeronautics and Space Administration (NASA) (<a href="https://earthengine.google.com/">https://earthengine.google.com/</a>)</td>
</tr>
<tr>
<td>NDVI</td>
<td>250m</td>
<td>National Aeronautics and Space Administration (NASA) (<a href="https://earthengine.google.com/">https://earthengine.google.com/</a>) with a spatial resolution of 250m</td>
</tr>
<tr>
<td>DEM</td>
<td>30 m</td>
<td>Resource and Environment Science and Data Center, Chinese Academy of Sciences (<a href="http://www.resdc.cn/">http://www.resdc.cn/</a>)</td>
</tr>
<tr>
<td>Land use data</td>
<td>30 m</td>
<td>Resource and Environment Science and Data Center, Chinese Academy of Sciences (<a href="http://www.resdc.cn/">http://www.resdc.cn/</a>)</td>
</tr>
<tr>
<td>Climate data</td>
<td>–</td>
<td>China Meteorological Data Sharing Network (<a href="http://data.cma.cn">http://data.cma.cn</a>)</td>
</tr>
<tr>
<td>Landsat images</td>
<td>30 m</td>
<td>Geographic Data Cloud (<a href="http://www.gscloud.cn/">http://www.gscloud.cn/</a>)</td>
</tr>
<tr>
<td>Hydrological data</td>
<td>–</td>
<td>Guizhou Hydrology and Water Resources Bureau</td>
</tr>
</tbody>
</table>

### Methods

#### Ecosystem Health Assessment

On the basis of the VORES framework, the theoretical framework for ecosystem health assessment in the CRB was constructed. Then, the comprehensive ecosystem service index and the ecosystem physical health index were measured separately, and finally, the ecosystem health of the CRB was assessed (Fig. 2). With reference to the literature (Pan et al. 2020), we mainly quantified ecosystem health through two aspects: the ecosystem physical health index and ecosystem service index. Because health is a relative concept, we referred to a previously developed method of dividing ecosystem health into several levels and considered the average ecosystem health to be a general state of ecosystem health (Ou et al. 2018); we divided the results into five levels: pathogenic (0–0.55), unhealthy (0.55–0.7), subhealthy (0.7–0.8), healthy (0.8–0.9), and extremely healthy (0.9–1). Here, we used the following formula:

\[
EHI = \sqrt{PH \times ES}
\]

where \(EHI\) is the ecosystem health index, \(PH\) is the ecosystem physical health index, and \(ES\) is the ecosystem service index. To eliminate the impacts of dimensional and quantitative differences, we adopted the extreme value normalization method to uniformly treat each index for its value to be in the range of \([0,1]\).

#### Ecosystem Service Index Measurement

The three typical ecological service functions of carbon sequestration, soil conservation, and water supply were selected, and the spatiotemporal variation characteristics of the three ecological service functions in the CRB were quantitatively estimated by using NPP data, the RULSE model, and the SWAT model, which can be expressed as:

\[
ES = \sum_{j=1}^{m} ES_{sj}
\]

where \(ES\) is the ecosystem service index, \(m\) is the number of ES supply types (\(m = 3\)), and \(ES_{sj}\) is the normalized value of ES supply type \(j\).

1. Carbon sequestration
NPP reflects vegetation productivity and plays a major role in the global carbon balance. NPP can be used to accurately evaluate the quality of total carbon sequestration services in ecosystems, which is a key factor for evaluating the health status of terrestrial ecosystems (Feng et al. 2020; Jiang et al. 2020).

(2) Soil conservation

In view of the successful application of the RULSE model in the measurement of soil conservation services in karst areas (Feng et al. 2016), we used the RULSE model to estimate the function of soil conservation services with the following formula:

\[ SCA = R \times K \times LS \times (1 - C \times P) \]

where \( SCA \) is the soil conservation amount, \( R \) is the rainfall erosivity factor, \( K \) is the soil erodibility factor, \( LS \) is the slope aspect factor, \( C \) is the land cover and management factor, and \( P \) is the conservation measure factor.

Zhu et al. (2021) found that the R model proposed by Yu and Rosewell (1996) is more suitable for calculating R factors in karst areas; 12mm was determined to be the best threshold for the erosive daily rainfall amounts in the southwest karst areas of China. This study adopted this model and threshold. The equation is as follows:

\[ R_i = 0.2686 \left[ 1 + 0.5412 \cos \left( \frac{\pi}{6} j - \frac{7\pi}{6} \right) \right] P_d^{[1.7265]} \]

where \( R_i \) denotes the monthly rainfall erosivity (MJ mm ha\(^{-1}\) h\(^{-1}\)), \( i \) is from January to December, and \( P_d \) is the daily rainfall (mm).

On the basis of the soil texture and soil organic matter, the K factor was estimated using the EPIC model proposed by Williams et al. (1989). The equation used is as follows:

\[ K = \left\{ 0.2 + 0.3 e^{-0.0256 W_s(1-W_i/100)} \right\} \times \left( \frac{W_i}{W_i + W_t} \right)^{0.3} \times \left[ 1 - \frac{0.25 W_c}{W_c + e^{(3.72 - 2.95 W_i)}} \right] \times \left[ 1 - \frac{0.7 W_n}{W_n + e^{(-5.51 + 22.9 W_s)}} \right] \]

where \( W_d \) is the sand content(%), \( W_i \) is the silt content(%), \( W_j \) is the clay content(%), and \( W_c \) is the organic carbon content (%).

The LS factor was computed using the modified version of McCool McCool et al. (1989) method proposed by Zhang et al. (2013), the expression of which is as follows:

\[ L = \left( \frac{\lambda}{22.13} \right)^\alpha \]

\[ \alpha = \frac{\beta}{\beta + 1} \]

\[ \beta = \frac{\sin \theta / 0.0896}{3(\sin \theta)^{0.8} + 0.56} \]

\[ S = \begin{cases} \ 10.8 \sin \theta + 0.03 & \theta < 5^\circ \\ \ 16.8 \sin \theta - 0.05 & 5^\circ \leq \theta < 10^\circ \\ \ 3(\sin \theta)^{0.8} + 0.56 & \theta \geq 10^\circ \end{cases} \]
where $\lambda$ is the slope length, $\alpha$ is the variable slope length exponent, $\beta$ is the factor related to the slope value, and $\theta$ is the slope value.

The factors C and P (Table 2) were acquired from previous studies on karst areas in southwest China (Xu et al. 2010).

<table>
<thead>
<tr>
<th>Land use type</th>
<th>Paddy field</th>
<th>Dry land</th>
<th>Forest</th>
<th>Shrub</th>
<th>Open forest</th>
<th>Grass land</th>
<th>Wates</th>
<th>Construction land</th>
<th>Unused land</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.15</td>
<td>0.4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>0.1</td>
<td>0.22</td>
<td>0.006</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

(3) Water supply

In the present study, the hydrological process submodel in the SWAT model was used to estimate the water yield; the simulation mainly included the water cycle processes of the production flow and slope confluence and the water cycle processes related to the river confluence. First, the SWAT model based on the DEM data of the CRB was used to generate a river network distribution map of the basin, to automatically determine the topological relationship between subwatersheds, and to divide the whole basin into multiple subwatersheds. Next, each subwatershed was divided into multiple units—referred to as hydrologic response units (HRUs)—with same land use, soil, and slope. Finally, by coupling meteorological data and the model, relevant simulations were performed using the SWAT model.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{deep} - Q_{gw})$$

where $SW_t$ is the final soil water content (mm), $SW_0$ is the initial soil water content (mm), $t$ is the number of days, $R_{day}$ is the amount of precipitation on day $i$ (mm), $Q_{surf}$ is the amount of surface runoff on day $i$ (mm), $E_a$ is the amount of evaporation on day $i$ (mm), $W_{deep}$ is the amount of percolation and bypass flow exiting the soil profile bottom on day $i$ (mm), and $Q_{gw}$ is the groundwater content on day $i$ (mm).

In the present study, the Sequential Uncertainty Fitting Version 2 algorithm of the SWAT-CUP tool was used to calibrate and validate the simulation results. The measured data comprised the monthly average flow at the Maotai, Erlangba, and Chishui hydrological stations in the CRB from 2008 to 2015. The period of 2016–2020 was set as the calibration period, whereas that of 2014–2018 was set as the validation period. The Nash efficiency coefficient (NSE) and determination coefficient (R2) were used as evaluation indexes for evaluating the adaptability of the SWAT model in the study area. The following equation was used (Yuan et al. 2022):

$$R^2 = \frac{\sum_{i=1}^{n} (Q_{mi} - Q_{oi})^2}{\sum_{i=1}^{n} (Q_{mi} - Q_{o})^2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{mi} - Q_{oi})^2}{\sum_{i=1}^{n} (Q_{oi} - Q_{o})^2}$$

where $Q_{mi}$ is the simulated value, $Q_{oi}$ is the observed value, $Q_{o}$ is the average value of measured runoff, $Q_{mi}$ is the average value of simulated value, and $n$ is the number of samples.

**Ecosystem physical health index measurement**

The ecosystem physical health index reflects the ability of an ecosystem to maintain a healthy structure, self-regulate, and recover under pressure; it can be divided into vigor, organization, and elasticity and calculated as follows (Ou et al. 2018):

$$PH = \sqrt[3]{V \times O \times E}$$

where $PH$ is the ecosystem physical health index and $V$, $O$, and $E$ are the vigor, organization, and elasticity respectively.

(1) Ecosystem vigor

Based on the NDVI, ecosystem vigor can generally be characterized through the vegetation coverage index calculated according to the weight of each region in the Technical Criterion for Ecosystem Status Evaluation (HJ 192–2015) as follows Meng et al. (2018).
\[ V = A_{bio} \times (0.35 \times A_1 + 0.21 \times A_2 + 0.11 \times A_3 + 0.04 \times A_4 + 0.01 \times A_5) / A_{total} \]

where \( V \) is index of ecosystem vigor; \( A_{bio} \) is the NDVI; \( A_{total} \) is the total area of the basin; and \( A_1 - A_6 \) are the woodland, grassland, cultivated land, construction land, and unused land, respectively.

(2) Ecosystem organization

Ecosystem organization is mainly characterized by ecosystem stability, which can be quantitatively evaluated through landscape heterogeneity and landscape connectivity. On the basis of the research of Ou et al. (2018) and Peng et al. (2018), we selected the Shannon diversity index (SHDI) and area-weighted mean patch fractal dimension (AWMPFD) to represent landscape heterogeneity; landscape fragmentation (FN1) and landscape contag (CONT) to represent whole landscape connectivity; and forest land fragmentation (FN2), patch cohesion of forest land (COHESION1), water fragmentation (FN3), and patch cohesion of water (COHESION2) to represent habitat connectivity. The following formula was used:

\[ O = 0.25 \times SHDI + 0.1 \times AWMPFD + 0.25 \times FN1 + 0.1 \times CONT + 0.1 \times FN2 + 0.05 \times COHESION1 + 0.1 \times FN3 + 0.05 \times COHESION2 \]

(3) Ecosystem elasticity

Elasticity refers to the ability of the structure and behavioral patterns of an ecosystem to rebound after the initial stages of human or natural disturbances; it can be characterized through resistance and resilience to external disturbances. In this study, the elasticity of different land-use types were first assigned on the basis of the indications provided by Peng et al. (2017), and then the elasticity of the regional ecosystem was calculated on the basis of the area weighting of the land-use types (Table 3). Therefore, elasticity was calculated as follows:

\[ E = 0.3 \times R_{esi} + 0.7 \times R_{exist} \]

where \( E \) is the ecosystem elasticity index, \( R_{esi} \) is the ecosystem resilience, and \( R_{exist} \) is the ecosystem resistance.

<table>
<thead>
<tr>
<th>Land use type</th>
<th>Dryland</th>
<th>Cultivated land</th>
<th>Forest land</th>
<th>Grassland</th>
<th>Bare land</th>
<th>Waterbody</th>
<th>Construction land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resilience coefficient</td>
<td>0.4</td>
<td>0.3</td>
<td>0.5</td>
<td>0.8</td>
<td>1</td>
<td>0.7</td>
<td>0.2</td>
</tr>
<tr>
<td>Resistance coefficient</td>
<td>0.5</td>
<td>0.6</td>
<td>1</td>
<td>0.7</td>
<td>0.2</td>
<td>0.8</td>
<td>0.3</td>
</tr>
<tr>
<td>Elasticity coefficient</td>
<td>0.47</td>
<td>0.51</td>
<td>0.85</td>
<td>0.73</td>
<td>0.44</td>
<td>0.77</td>
<td>0.27</td>
</tr>
</tbody>
</table>

Geographical Detector

Geographical detector is a spatial variance analysis method developed to detect spatial heterogeneity and its driving forces (Wang et al. 2010). In this study, factor and interactive detection are used to determine the impact of each influencing factor on ecosystem health.

(1) Factor detection

We determined the contribution of control factors to ecosystem health, measured as the \( q \) value, by using the following expression:

\[ q = 1 - \frac{1}{N} \sum_{h=1}^{L} \frac{n_h \sigma_h^2}{\sigma^2} = \frac{SSW}{SST} \]

\[ SSW = \sum_{h=1}^{L} n_h \sigma_h^2 \]
where \( h = 1, 2, \ldots; L \) is the stratification of independent variable \( X \); \( N_h \) and \( N \) are the numbers of units in the \( h \) layer and the whole area, respectively; \( \sigma^2 \) and \( \sigma \) are the variances of the layer \( H \) and \( Y \) values of the whole region, respectively; \( SSW \) is the intra-layer variance sum; \( SST \) is the total regional variance; and \( q \) is the explanatory power of the independent variable to the dependent variable within the range of \([0,1]\). Here, the closer the \( q \) value is to 1, the stronger the explanatory power of the independent variable is to the dependent variable.

(2) Interaction detection

We evaluated the influence of the interactions between two environmental variables on ecosystem health and whether the influences of multiple environmental variables on ecosystem health are independent of each other; the bases of judgment are presented in Table 4.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q(X_1 \cap X_2) &lt; \min(q(X_1), q(X_2)) )</td>
<td>Nonlinear weakening</td>
</tr>
<tr>
<td>( \min(q(X_1), q(X_2)) &lt; q(X_1 \cap X_2) &lt; \max(q(X_1), q(X_2)) )</td>
<td>Single factor nonlinear weakening</td>
</tr>
<tr>
<td>( q(X_1 \cap X_2) &gt; \max(q(X_1), q(X_2)) )</td>
<td>Two-way enhancement</td>
</tr>
<tr>
<td>( q(X_1 \cap X_2) = q(X_1) + q(X_2) )</td>
<td>Independent</td>
</tr>
<tr>
<td>( q(X_1 \cap X_2) &gt; q(X_1) + q(X_2) )</td>
<td>Nonlinear enhancement</td>
</tr>
</tbody>
</table>

Note: \( X_1 \) and \( X_2 \) represent different independent variables.

Results

Land-Use and Land Cover Changes in the CRB

As illustrated in Fig. 3, forestlands and cultivated lands are the main land-use types in the CRB. In 2010, 2015, and 2020, 54.03%, 52.29%, and 54.89% of the area was woodland, respectively, and 34.29%, 33.07%, and 34.29% of the area was cultivated land, respectively. From 2010 to 2020, the forestland area in the CRB increased at a 1.59% rate, whereas the cultivated land area remained unchanged. Because of construction for land expansion engendered by economic development, much of CRB’s land have been transformed into construction land; the construction land area increased from 73.21km\(^2\) in 2010 to 138.53km\(^2\) in 2020, with a growth rate of 47.15%. The areas of other land-use types, such as wetlands and grasslands, also increased, whereas the growth rate of woodland and cultivated land areas was far lower than that of construction land; in other words, a large amount of land in the CRB has been converted to construction land.

Spatiotemporal Evolution Characteristics of Ecosystem Service Functions in Different Landform Types

Spatiotemporal distribution characteristics of carbon sequestration services

From 2010 to 2015, NPP in the CRB was generally low in the northwest and high in the southeast (Fig. 4). The high-value areas were mostly karst areas with relatively high altitudes, high vegetation coverages, and few human activities upstream, and the low-value areas were distributed in the Danxia area, with relatively frequent human activities and considerable economic development downstream. During the study period, the mean NPP values of the karst and Danxia areas of the CRB were 597.07 and 588.60gC·m\(^{-2}\)a\(^{-1}\), respectively; in other words, the carbon sequestration function was slightly higher in the karst area than it was in the Danxia area. In 2010, 2015, and 2020, the average annual NPP values of the CRB were 530.02, 639.73, and 588.15gC·m\(^{-2}\)a\(^{-1}\), respectively; in other words, from 2010 to 2020, NPP first increased and then decreased, with a generally slight upward trend. The NPP value in the karst area increased from 540.41gC·m\(^{-2}\)a\(^{-1}\) in 2010 to 599.62gC·m\(^{-2}\)a\(^{-1}\) in 2020 at a 9.87% rate, and that in Danxia area increased from 504.28gC·m\(^{-2}\)a\(^{-1}\) in 2010 to 559.93gC·m\(^{-2}\)a\(^{-1}\) in 2020 at a 9.9% rate. This result indicates that the carbon sequestration function of both the landforms demonstrates a slow upward trend, indicating China’s efforts toward comprehensive management of the ecological environment have had desirable results.
Spatiotemporal distribution characteristics of water supply services

The calibration and validation results of monthly runoff at the Erlangba, Maotai, and Chishui stations in the study area are presented in Fig. 5. According to the parameter evaluation standard for model simulation results, when $R^2 > 0.6$ and NSE $> 0.5$, a SWAT model can be considered suitable for a study area (Schuol et al. 2008). The results of the present study demonstrated that the monthly runoff simulation results from the SWAT model had good agreement with the runoff values measured at the hydrological stations; the $R^2$ and NSE of the calibration and validation periods were all $> 0.6$, meeting the evaluation standards and indicating the SWAT model has good applicability for the Chishui River.

The SWAT model simulation results for the subbasin division of the CRB and the spatiotemporal distribution of water yield are presented in Fig. 6. From 2010 to 2015, the average annual water yield of the CRB was generally high in the northwest and low in the southeast. The high-yield areas were mainly concentrated in the subbasins of the Danxia area in the lower reaches of the Chishui River, and the low-yield areas were mainly distributed in subbasins No.15, 16, 18, 23, and 24 in the southeast of the karst area. The average annual water yields in the karst and Danxia areas were 554.75 and 664.28 mm, respectively. In 2010, 2015, and 2020, the average annual water yield of the CRB was 437.52, 630.00, and 675.65 mm, respectively. Compared with that in 2010, the water yield of the entire CRB in 2020 was generally $> 600$ mm, demonstrating a 34.61% increase; the water volume, therefore, exhibited a significantly increasing trend.

Spatiotemporal distribution characteristics of soil conservation services

In 2010–2020, the overall soil conservation in the CRB showed an increasing trend, with high-value areas mainly distributed in karst mountainous areas with low human activity and low-value areas mainly distributed in the hilly areas of Danxia with relatively flat terrain (Fig. 7). During the study period, the average soil conservation values in the karst and Danxia areas of the CRB were 48.51 and 43.38 t·ha$^{-1}$·a$^{-1}$, respectively. In other words, soil conservation in the karst area was slightly higher than that in the Danxia area. The average soil conservation in the CRB in 2010, 2015, and 2020 was 34.22, 47.18, and 65.16 t·ha$^{-1}$·a$^{-1}$, respectively—with a general 47.48% increase in soil conservation. In areas with high soil conservation, mountain slopes were steep, the altitude and surface vegetation coverage were high, and human activity was low. Although the soil erosion intensity gradually increased with an increase in slope, vegetation inhibited soil erosion (Zhang. 2021). The areas with low soil conservation values were mostly areas with little topographic relief; they were mostly construction and cultivated lands, had low altitudes, and had frequent human activity.

Spatiotemporal distribution characteristics of comprehensive ecosystem service index for different geomorphologic types

As illustrated in Fig. 8, in the CRB, the average comprehensive ecosystem service index in 2010, 2015, and 2020 was 0.57, 0.47, and 0.55, respectively. Moreover, the average comprehensive ecosystem service indexes of the karst and Danxia areas were 0.51 and 0.59, respectively. In general, the CRB’s comprehensive ecosystem service index demonstrated a downward trend followed by an upward trend. Overall, the trend remained downward. The comprehensive ecosystem service index was higher in the Danxia area than in the karst area, with the high-value areas mainly located in the hilly areas of Danxia and the low-value areas mainly located in the southeast karst mountain areas.

Spatiotemporal Distribution Characteristics of Ecosystem Physical Health for Different Geomorphologic Types

The spatiotemporal distribution of ecosystem physical health in the CRB from 2010 to 2020 is illustrated in Fig. 9. In 2010, 2015, and 2020, the average ecosystem physical health level was 0.92, 0.92, and 0.93 respectively. The ecosystem physical health index in the central valley area was mostly $< 0.89$, and that in the surrounding mountains was $> 0.93$. The ecosystem physical health level was considerably lower in the central valley area than in the surrounding mountains. The ecosystem physical health level was slightly higher in the Danxia area than in the karst area. In 2010, 2015, and 2020, the ecosystem physical health index of the karst area was 0.92, 0.92, and 0.94, respectively, whereas that of the Danxia area was 0.93 in this decade. Thus, the ecosystem physical health level in the CRB did not change considerably, with the exception of a few local changes.

Spatiotemporal Distribution Characteristics of Ecosystem Health Index for Different Geomorphologic Types

As illustrated in Fig. 10, in 2010–2020, the overall ecosystem health level of the CRB was subhealthy and healthy although a few areas were unhealthy. From a spatial perspective, the ecosystem health level of the Danxia area in the northwest was high, that is, mostly healthy and subhealthy, whereas that of the karst area in the southeast was mostly unhealthy. From a temporal perspective, in 2010, 2015, and 2020, the
overall ecosystem health index of the CRB was 0.77, 0.79, and 0.70, respectively, demonstrating a general reduction. From 2010 to 2015, the ecosystem health improved considerably, with a decrease occurring in areas where ecosystem health levels were unhealthy but a significant increase occurring in areas where ecosystem health levels were extremely healthy and subhealthy. In 2015–2020, the overall decline in ecosystem health and the number of areas in the pathological karst area increased significantly, with the health status of ecosystems demonstrating a decreasing trend.

**Factor Analysis of Healthy Ecosystem Evolution in Different Landform Types in the CRB**

The effects of different environmental factors on the spatial distribution of ecosystem health in the karst and Danxia areas were explored; the q values of the driving factors are listed in Table 5. The results of factor detection demonstrated that the environmental factors and their explanatory powers, which affected the health levels of the ecosystem in the watersheds, were different for different landform types. In 2010–2020, the magnitude of the explanatory power of the factors in the karst area was in the following order: NDVI > bedrock bareness rate > precipitation > LUCC; by contrast, the magnitude of the explanatory power of the factors in the Danxia area in 2010–2020 was in the following order: NDVI > DEM > vegetation type > LUCC > precipitation. In general, vegetation, the bedrock bareness rate, precipitation, and LUCC had a strong impact on ecosystem health in the karst area, whereas vegetation, DEM, vegetation type, LUCC, and precipitation had a strong impact on ecosystem health in the Danxia area.

<table>
<thead>
<tr>
<th>Environmental factors</th>
<th>LUCC Karst area</th>
<th>precipitation Karst area</th>
<th>DEM Karst area</th>
<th>NDVI Karst area</th>
<th>Bedrock bareness rate Karst area</th>
<th>Vegetation types Karst area</th>
<th>q statistic 2010</th>
<th>LUCC Danxia area</th>
<th>precipitation Danxia area</th>
<th>DEM Danxia area</th>
<th>NDVI Danxia area</th>
<th>Bedrock bareness rate Danxia area</th>
<th>Vegetation types Danxia area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.026</td>
<td>0.249</td>
<td>0.031</td>
<td>0.133</td>
<td>0.023</td>
<td>0.303</td>
<td>0.084</td>
<td>0.350</td>
<td>0.038</td>
<td>-</td>
<td>-</td>
<td>0.261</td>
<td></td>
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<tr>
<td>q statistic 2015</td>
<td>-</td>
<td>-</td>
<td>0.064</td>
<td>0.046</td>
<td>0.122</td>
<td>0.036</td>
<td>0.123</td>
<td>0.077</td>
<td>0.031</td>
<td>-</td>
<td>0.055</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>q statistic 2020</td>
<td>0.021</td>
<td>0.209</td>
<td>0.180</td>
<td>0.057</td>
<td>0.024</td>
<td>0.236</td>
<td>0.033</td>
<td>0.350</td>
<td>0.022</td>
<td>0.054</td>
<td>0.019</td>
<td>0.150</td>
<td></td>
</tr>
</tbody>
</table>

As illustrated in Fig. 11, the explanatory power of factor interaction on different landform types demonstrated enhancements at varying degrees for different factors, and the explanatory power of factor interactions was stronger than that of single factors. The dominant factor interactions in the spatial distribution of ecosystem health in different geomorphologic type areas demonstrated considerable differences; these interactions included NDVI×precipitation, NDVI×vegetation type, NDVI×LUCC, and NDVI×DEM in the Danxia area, whereas they included precipitation×NDVI, precipitation×DEM, precipitation×vegetation type, and precipitation×bedrock bareness rate in the karst area.

**Discussions**

**Analysis of Spatiotemporal Evolution Characteristics of Ecosystem Health in the CRB**

Since 2000, a series of ecological restoration projects have been implemented in southwest China; they include returning farmlands to forestlands or grasslands, ecological migration and comprehensive treatment of rocky desertification, and improvement of ecology(Li et al. 2021). In 2010–2015, China carried out large-scale comprehensive treatment of rocky desertification, and the effects of this treatment were remarkable: it effectively alleviated soil erosion, reduced the bedrock bareness rate, accelerated alleviation of rocky desertification, and gradually improved the ecological environment(Yu et al. 2022). The soil conservation effect of vegetation and the alleviation of plant coverage have also improved soil and water conservation and NPP in the area(Ding et al. 2020). Moreover, the quality of the CRB ecosystem has significantly improved, which is reflected in the finding of an increase in the ecosystem health index of the CRB from 2010 to 2015 of the present study; this indicates that ecological restoration has led to considerable benefits. The soil conservation effects of vegetation and improvements in plant coverage have also increased soil and water conservation and NPP in the area, and the quality of the ecosystems has been significantly improved, corroborating the current result that the ecosystem health index in the CRB increased from 2010 to 2015. This indicates that the ecological restoration projects have led to significant benefits. The decline in ecosystem health in the CRB between 2015 and 2020 may be mainly correlated with LUCC and national policy preferences. China’s sprint to build a well-off society in an all-round way; after a series of rocky desertification treatment projects in the early stage, during this period, the southwest china rocky desertification of the area has remained relatively stable, and its development areas and degrees have been small and in a slow decline. Therefore, Chinese national policy has been...
influenced more toward socioeconomic construction. However, in the CRB, forest and cultivated land areas have not change considerably; the construction land area in the CRB increased at a rate of 47.15%, from 73,211 km² in 2010 to 138,531 km² in 2020. In other words, a large amount of land has been converted to construction land. Since 2015, the conversion from urban and rural construction land to other land-use types in the CRB has increased significantly; however, land-use efficiency has been low, land resource shortages have become notable, a large amount of land has been converted to construction land, vegetation has decreased, surface runoff has increased, and ecosystem health has been affected (Ma et al. 2021).

From the perspective of spatial distribution, the areas with high ecosystem health in the CRB are mostly distributed in the humid evergreen and broad-leaved forest areas of the downstream Danxia area and in the evergreen coniferous and broad-leaved forest areas in the middle reaches and the evergreen coniferous and deciduous broad-leaved forest areas in the upper reaches of the high mountains, which have a relatively flat terrain, thick soil layers, appropriate hydrothermal conditions, and are suitable for the growth of forests and grasses. Therefore, these areas have a high ecological health level. Areas with poor health statuses are mainly distributed in the upper karst area of Wumeng contiguous special hardship areas, with complex geomorphic conditions, prominent rocky desertification, fragile ecologies, and susceptibility to human activity; therefore, the level of ecosystem health in such areas is low (Chen et al. 2021).

Analysis of Influencing Factors of Ecosystem Health Level in CRB

The karst and Danxia landforms have different ecological characteristics; therefore, the environmental factors affecting their ecosystem health vary with their landform type areas. The results of the factor detection analysis reveal that strong explanatory power for ecosystem health is demonstrated by environmental factors such as vegetation, bedrock bareness rate, and precipitation in the karst area and vegetation, altitude, and vegetation type in the Danxia area. Vegetation has a larger impact on the spatial distribution of ecosystem health in the whole CRB because vegetation can effectively prevent precipitation erosion on the surface and has a stabilizing effect on the surface soil, thereby enhancing the erosion resistance and water storage capacity of the soil. Therefore, the soil maintenance function is better in areas with high vegetation coverage (Gao et al. 2019). However, vegetation is susceptible to changes resulting from natural and human interference, which can in turn affect CRB ecosystem health (Geng et al. 2022). In the CRB karst area, the large amount of exposed bedrock increased surface runoff and sediment production by increasing the amount of impervious surface area and interception of rainfall, which greatly affected the regional hydrology, soil, and ecology and resulted in frequent geological disasters, such as drought, flood, landslide, and subsidence, which ultimately affected the ecosystem health in the karst area (Ding et al. 2019). In contrast to the karst area, the Danxia area was less affected by the bedrock bareness rate. However, the overall terrain of the Danxia area is flat, and the area has frequent human activity; slight fluctuations in the Danxia area surface led to changes in other environmental factors, such as the transformation of vegetation and land-use types, which in turn affected the carbon source/carbon sink of the ecosystem and the affected carbon sequestration service function of the watershed (Zhang et al. 2022).

In addition, compared with the karst area, the Danxia area has a thicker soil layer, and it is located in the lower reaches of the Chishui River. Because of erosion caused by the upstream water flow, rainfall, and human activity, soil retention is lower in the Danxia area than it is in the karst area, reducing its soil conservation service function and ultimately causing damage to its ecosystem health.

The factor interaction detection results demonstrate that the explanatory power of environmental factor interactions was stronger than that of single factors; moreover, the explanatory power of precipitation×vegetation was greater than that of the other factors. This is because environmental factors affecting ecosystem health often act in combination and vegetation can greatly reduce the erosion of rainfall runoff on land surfaces and the splashing of raindrops on land surfaces, which is crucial for soil erosion control (Jiang et al. 2021). However, the CRB has a complex terrain and a large population along with rapid industrialization and urbanization. Economic growth occurs at the expense of consumption and destruction of the ecological environment, and the CRB ecosystem is fragile and more sensitive to vegetation changes (Li et al. 2021). Under extreme precipitation conditions, vegetation changes exacerbate soil and nutrient loss in the CRB, resulting in soil depletion, which in turn further increases the fragility of the ecosystem; therefore, vegetation and rainfall have considerable combined effects on CRB ecosystem health.

In the CRB karst area, precipitation×DEM, precipitation×vegetation type, and precipitation×bedrock bareness rate had a considerable impact on ecosystem health. Altitude is a crucial indicator of surface undulation. Terrain undulation changes often lead to increased air mass and adiabatic expansion and cooling, which thereby increases precipitation, and altitude by controlling soil and hydrothermal conditions affect the vertical distribution of vegetation, and then affect the distribution of vegetation. Therefore, the surface environment changes in karst areas are easily influenced by the terrain. In the karst area, when a large area of bedrock is exposed, surface soil and nutrient loss due to rainfall increase and destroy surface vegetation growth (Peng et al. 2016); therefore, the ecosystem health of the karst area is easily affected by the interaction of natural factors such as precipitation×DEM, precipitation×vegetation type, and precipitation×bedrock bareness rate.

Recommendations for Ecological Restoration in the CRB
The current results demonstrate that in the CRB, ecosystem health is lower in the karst area than it is in the Danxia area. The combinations of the dominant factors and their interactions considerably affect the health of the ecosystem but to varying degrees in different landform type areas. Ecological restoration projects have significantly improved ecosystem health levels in the CRB; however, from 2015 to 2020, China's policy was more inclined toward economic construction. Therefore, the CRB's ecosystem health, particularly in the karst area, declined. This result demonstrates that ecological restoration is a long-term, continuous process; that human intervention considerably affects the ecological restoration of ecologically fragile areas; and that watershed protection and restoration warrants continual attention. Vegetation, a crucial factor affecting CRB health, is particularly crucial for moderately strengthening vegetation restoration in the CRB, particularly in the karst area, and limiting irrational landscape development. However, vegetation restoration often involves returning farmland to forestland or grassland. Because the livelihood of farmers is mainly dependent on agriculture, implementing land ecological compensation schemes to improve land quality and increase farmer income is warranted. Furthermore, because the CRB karst and Danxia areas have different ecological characteristics, differences in their ecosystem health levels and the factors influencing them should be considered comprehensively; differentiated treatment should be implemented on the basis of local conditions. The Danxia area, which has less topography and undulation, is the main distribution area of cities, cultivated land, and other infrastructure and is the main implementation area of new urbanization construction. Therefore, in future urban and economic development processes, special attention should be paid to preventing intensive landuse and rational planning (Lu et al. 2015). Because karst areas have a special natural ecological environment, natural vegetation does not grow easily there. Human intervention is crucial for ecological restoration in areas with high-intensity economic development activities as the main driving force of ecosystem degradation due to irrational exploitation, such as the Wumeng contiguous special hardship area in the upper reaches of the Chishui River and the ecological environmental degradation area in the middle reaches of the Chishui River. Reducing the impact of development and construction activities by setting ecological redlines is essential for the karst area of the CRB (where natural factors mainly drive ecosystem degradation) (Kong et al. 2019). This should be followed by an appropriate increase in artificial ecological engineering interventions.

Include a Discussion that summarizes (but does not merely repeat) your conclusions, elaborates on their implications or significance, and compares with previously published results. If applicable, there should be a paragraph outlining the limitations of your results and interpretation, as well as a discussion of the steps that need to be taken for the findings to be applied. Please avoid claims of priority.

**Conclusion**

Based on an ecosystem service assessment measured using the RULSE and SWAT models and NPP data, we constructed a theoretical VORES framework for ecosystem health assessment, evaluated the spatiotemporal distribution characteristics of ecosystem health in the karst and Danxia areas of the CRB in 2010–2020, and explored the factors affecting ecosystem health in the CRB during the study period in combination with employing a geographical detector.

The main conclusions of the current study are as follows:

1. During the study period, the forest land area in the CRB demonstrated a slow increasing trend, and the cultivated land area remained unchanged. The construction land area increased significantly, at a growth rate of 47.15%.

2. The comprehensive ecosystem service index of the CRB exhibited a trend of first decreasing and then increasing. However, in general, it demonstrated a downward trend. The composite ecosystem service index was generally higher in the karst region than in the nonkarst region. Similarly, the overall ecosystem health index of the CRB increased and then decreased; the ecosystem health in the Danxia area was mostly in a healthy and subhealthy state, whereas that in the karst area was mostly in a subhealthy and unhealthy state.

3. The geographical detector results demonstrate that the environmental factors affecting the ecosystem health level and their explanatory power differ significantly in different landform type areas. The explanatory power was stronger for environmental factor interactions than it was for any single factor, and the combinations of dominant interaction factors affecting ecosystem health levels in different landform type areas demonstrated considerable differences.

**Declarations**

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**Conflict of 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.

**References**


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Location of the study area.

Figure 2

Conceptual framework for ecosystem health assessment.
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Spatiotemporal distribution patterns of NPP in the CRB
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Figure 6
Spatiotemporal distribution patterns of annual water yield
Figure 7
Spatiotemporal distribution patterns of soil conservation service

Figure 8
Spatiotemporal distribution patterns of ecosystem services index

Figure 9
Spatiotemporal distribution patterns of ecosystem physical health level
Figure 10
Spatiotemporal distribution patterns of ecosystem comprehensive health index

Figure 11
The interactive detection explanatory (q) of various environmental factor