Journal of Cleaner Production 294 (2021) 126341

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Effects of urban expansion on ecosystem health in Southwest China from a multi-perspective analysis

Weijie Li [a], Shiyou Xie [a], Yong Wang [a,*], Jing Huang [a], Xian Cheng [b]

[a] Chongqing Key Laboratory of Karst Environment, College of Geographical Sciences, Southwest University, Chongqing, 400715, China
[b] College of Resources and Environment Sciences, Southwest University, Chongqing, 400716, China

ARTICLE INFO

Article history:
Received 16 September 2020
Received in revised form
6 January 2021
Accepted 8 February 2021
Available online 10 February 2021

Handling editor: Dr Sandra Caeiro

Keywords:
Urban expansion
Ecosystem health
Multi-perspective analysis
Southwest China

ABSTRACT

Effectively exploring the impact of urban expansion on ecosystem health has become a hot topic for sustainable development of cities. However, analyzing the relationship between urban expansion and ecosystem health from a multi-perspective view is relatively rare. Here, taking 438 cities in Southwest China as the study area, we attempted to quantify the relationship between urban expansion and ecosystem health, taking into account population density, economic structure, urban area size, and geological environment. First, the urban ecosystem health was assessed based on the vigor-organization-resilience-services framework. Second, we quantified urban expansion from three aspects: the intensity of expansion, growth modes and urban forms. Finally, the panel data analysis was used to focus on which aspects of urban expansion effect on ecosystem health. The result showed that when the intensity of urban expansion increased and the growth mode changed from edge-expansion type to outlying type, the ecosystem health experienced a significant decline. In addition, there was significant negative correlation between urban size and ecosystem health within all types of cities, except for the mega-scale cities (>100 km^2). A regular and aggregated urban form was benefit for ecosystem health at the medium-sized (100–500 person·km^{-2}) and large-sized cities (500–1000 person·km^{-2}). Moreover, urban form complex had a significant negative impact on ecosystem health in industry cities (secondary industry accounts for more than 50%) than in the service cities (tertiary industry accounts for more than 50%). The ecosystem health of karst cities was more sensitive to the fragmentation of urban core than non-karst cities. These findings will help to further understand the influence mechanism of urban expansion on ecosystem health under different scenarios and could provide a scientific basis for formulating reasonable urban planning.

1. Introduction

Natural ecosystems provide both the material basis and ecosystem services for the survival and development of human society. A healthy ecosystem is fundamental to guarantee the subsistence of human beings and achieve the sustainable development of socioeconomic (Rapport and Maffi, 2011; Peng et al., 2015). However, with increased intensity and breadth of human activity, the natural patches in rapidly urbanizing areas have presented a remarkable, highly fragmented feature, which has significantly influenced the structure and function of regional ecosystem, resulting in a series of eco-environment problems, such as urban heat island effect, soil erosion, biodiversity loss and so on, Therefore, a systematic monitoring and evaluating the health status of ecosystem is necessary for regional sustainability. (Rapport and Hilén, 2013).

Ecosystem health is a comprehensive indicator that reflects the stability and sustainability of the ecosystem, that is to say, the ecosystems have the ability to maintain its organization, self-operation and resilience to external disturbance (Rapport et al., 1998; Costanza, 1992). Ecosystem health assessment is considered to be an effective method to measure the stability and vulnerability of ecosystems, which provides a scientific basis for integrating ecosystem assessment and management at multi-scales (He et al., 2019). In terms of evaluation methods, the indicator system method is widely applied to assess ecosystem health, which mainly includes vigor-organization-resilience (VOR) evaluation method, principal component method, Pressure-State-Response (PSR)

* Corresponding author.
E-mail address: wyong826@163.com (Y. Wang).

https://doi.org/10.1016/j.jclepro.2021.126341

model and Driving force-State-Response (DFSR) model (Fu et al., 2009; Peng et al., 2015). Among them, the assessment framework of vigor-organization-resilience was widely used in the previous studies. Costanza (1992) proposed that a healthy ecosystem can be defined by three features: vigor, organization, resilience. Vigor refers to the metabolism or primary productivity of a system; organization describes the diversity and quantity of interactions between the components of ecosystems; resilience refers to the ability of the ecosystem to maintain its structure and function under stress. Besides, as an important indicator, ecosystem services are also applied to ecosystem health assessment, which can make a comprehensive assessment of ecological effect with urban expansion (Peng et al., 2017). To date, ecosystem health research has made evident progress in various ecosystems, such as forests (Styers et al., 2010), grassland (Zhao et al., 2017), waters (Zhao et al., 2019a, 2019b), urban (Su et al., 2010) and wetland (Chi et al., 2018). However, most studies on ecosystem health assessment were conducted at national, provinces, or urban agglomerations, but not at smaller scales, such as the county scale. As the county is the basic unit of economic and social development in China, the evaluation of regional ecosystem health based on county scale can provide more spatially explicit support for the formulation of ecological protection policy than previous research at the provincial scale. Furthermore, previous studies mainly focused on the assessment of ecosystem health, while few studies have explored the driving mechanism of ecosystem health.

Human activities have been demonstrated to significantly affect the regional ecosystem health, such as population size, economic structure, and road network density (Shi et al., 2019; Peng and Wang, 2019). For instance, Kang et al. (2018) showed that the increase of artificial surface ratio would lead to the decline of ecosystem health. In recently years, many studies have gradually realized that urban expansion is the most crucial factor, which has resulted in various impacts on the structures, functions and dynamics of nature systems at multi-scales (Liu et al., 2010). For example, Xia et al. (2019) explored the relationship between urban size growth and carbon metabolism rate with land use change and found that urban size growth had a negative impact on carbon metabolism rate. Using Myanmar as a case study, Wang et al. (2018) analyzed the impact of urban expansion on the regional environment and confirmed that a 1% increase of built-up area could potentially lead to a decrease in NPP of 34.3 kg/m^2. However, previous studies have two main weakness. Firstly, most studies of these effects only focused on a single aspect (i.e., urban size and urban expansion intensity), might ignore other potential factors (i.e., urban form, urban expansion mode, transportation, urban industry level, and the spatial neighboring of mix land use) that could affect the interactions between urban expansion and ecosystem health (Ding and Li, 2017; Shen et al., 2020). For instance, Some studies have indicated that a compact urban form, characterized by highly dense development and roughly circular urban area, was beneficial to ecosystem health, such as reducing CO_2 emissions, reliving urban heat effect and promoting air quality (Peng et al., 2015; Shi et al., 2019). Conversely, a scattered urban form have a significant negative effect on ecosystem health. In addition, Yuan et al. (2019) indicated that the high-speed urban expansion and disordered growth mode will occupy a large number of ecological land, reduce the supply of ecosystem services, which will ultimately be detrimental to the health of regional ecosystem. Thus, characterizing the spatial pattern and expansion dynamic of the urban landscape is the fundamental first step to understand the relationship between urban expansion and ecological process (Li and Li, 2019). Secondly, due to regional difference, the potential effect of social-economic structure, ecological protection policy, geological environment and urban landscape structure also not be systematically considered, and the results might be biased (Shi et al., 2019). For example, Luo et al. (2019) indicated that although the urban land increased continuously from 2009 to 2016 in the Yangtze River Economic Belt, comparing the pre-ecological policies period, the ecosystem services value showed a steady increase trend after the implementation of the ecological policy. Tao et al. (2020) found that urban fragmentation and compactness had a relatively weaker influence on air pollution for large cities than for small and medium-sized cities. He et al. (2019) analyzed the driving factors of ecosystem health at the national scale, which found that ecological conservation project was the key factor impacting ecosystem health in Southwest China, while the ecosystem health changes in the southeastern coastal region and the North China Plain region mainly arose from socio-economic factors. Therefore, at the spatial-temporal scale, how to comprehensively explore the effects of urban expansion on ecosystem health from a multi-perspective is still poorly understood.

Southwest China, as the most important ecological barrier for the Yangtze River Basin, plays an important role in safeguarding ecological security and food security (Peng and Wang, 2019). In recently years, with the implementation of the Western China Development strategy, rapid and large-scale urbanization has resulted in fundamental changes in the structure and function of natural ecosystem, which in turn seriously threatened the sustainable development of regional socioeconomic (Peng et al., 2016). Therefore, in this study, the southwestern region was chosen for evaluating the status of ecosystem health that was critical to regional ecosystem management. Through the panel data analysis, the impact of urban expansion on ecosystem health from a multi-perspective view was explored. In detail, this study had two main objectives: 1) to analysis the impact of various aspects of urban expansion on regional ecosystem health; 2) to explore whether the relationships between urban expansion and ecosystem health change with different population density, economic structure, urban area size, and geological environment. The endpoints of this study were to provide a deep understanding of the relationship between urban expansion and ecosystem health and to find a scientific path to maintain the sustainable development of urban ecosystem.

2. Materials and methods

Based on spatial and statistical data, this study was conducted with three sections (Fig. 1). The first one was to assess the urban ecosystem health with the vigor-organization-resilience-services framework based on land use/cover data. The second section was to quantify urban expansion from three aspects (i.e., the intensity of expansion, growth modes and urban landscape metrics) based on urban built-up area dataset obtained from land use/cover data. The last section was to explore the relationship between urban expansion (based on urban landscape metrics) and ecosystem health using the panel data model from a multi-perspective view. The details were analyzed in the next sub-section.

2.1. Study area and data source

Southwest China lies between 97°21′-110°11′ E and 21°08′-33°41′ N, with an total area of about 250×10^4 km^2, accounting for approximately a quarter of China's land surface (Fig. 2). The region includes 1 municipality (Chongqing) and 3 provinces (Sichuan, Guizhou and Yunnan), with a total of 438 counties. In terms of topography, the region has a high percentage of mountains and hills except for the Sichuan Basin, with an elevation ranging from 77 to 6233 m. The climate is subtropical moist monsoon with abundant precipitation and high vegetation coverage. Due to

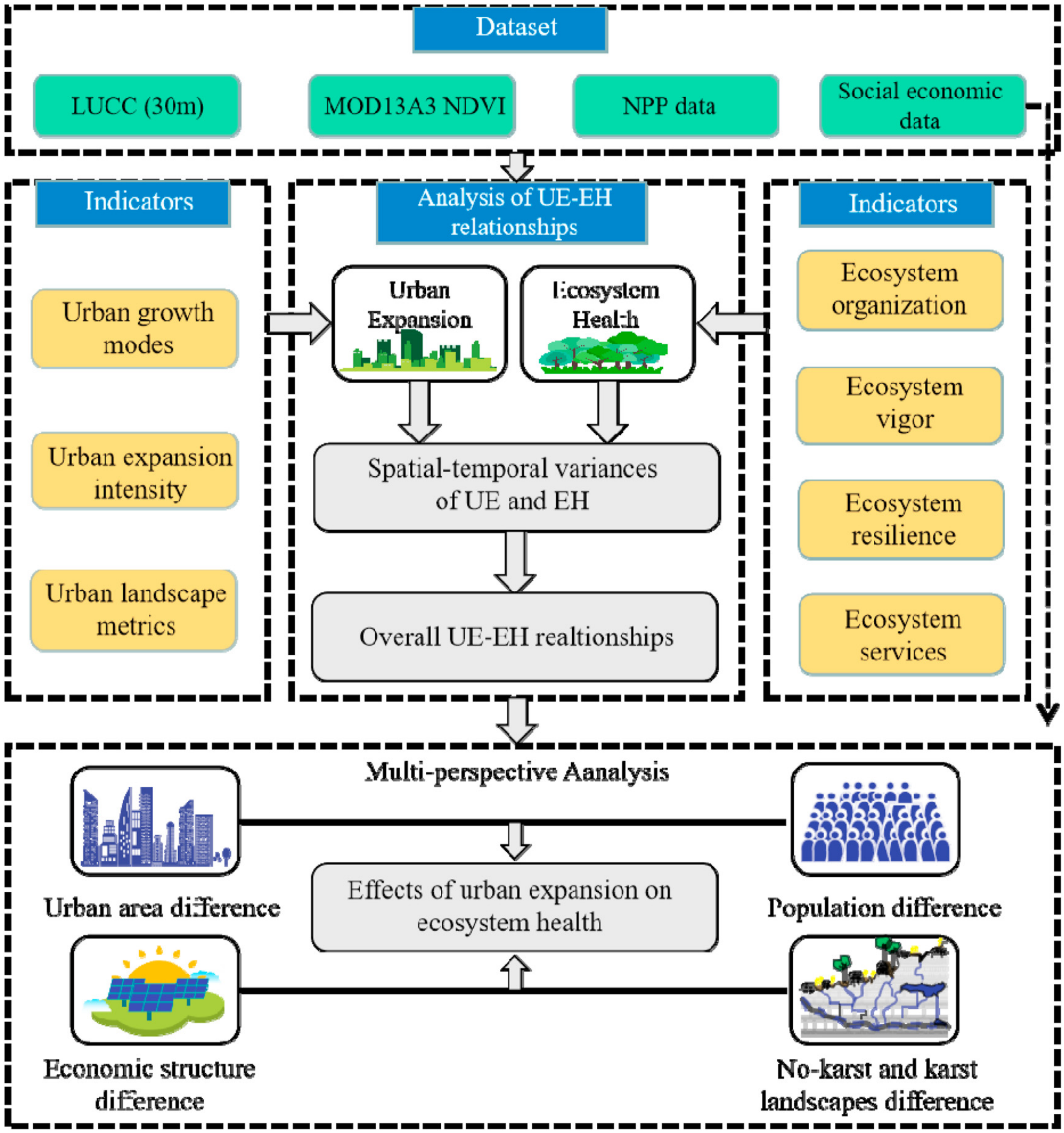


Fig. 1. Flowchart of the methodology.

complex natural environment and high biodiversity, the region is regarded as the most important ecological barrier in Western China. However, the regional ecosystem health is facing great challenges from the rapid urban expansion with the implementation of the Western China Development Strategy. Therefore, the urgent task for researchers and policymakers is to find a sustainable development path.

For this reason, we attempted to explore the impact of urban expansion on ecosystem health at the county scale in Southwest China from a multi-perspective view. In detail, to clarify the associations between urban expansion and ecosystem health under different scenarios (i.e., population density, economic structure, urban area size and geological environment), the 438 counties were divided into the following types: small-sized cities (<100 person$\cdot$km^{-2}), medium-sized cities (100–500 person$\cdot$km^{-2}), large-sized cities (500–1000 person$\cdot$km^{-2}), and mega-sized cities (>1000 person$\cdot$km^{-2}) based on the population density; small-scale cities (<10 km^2), medium-scale cities (10–50 km^2), large-scale cities (50–100 km^2), and mega-scale cities (>100 km^2) based on the urban area size; other cities (a relatively balanced proportion), service cities (secondary industry accounts for more than 50%) and industrial cities (tertiary industry accounts for more than 50%) based on the economic structure (Shi et al., 2019); non-karst cities, small-scale karst cities (carbonate rock accounts for less than 30%), medium-scale karst cities (carbonate rock accounts for 30%–60%), and large-scale karst cities (carbonate rock accounts for more than 60%) based on the geological environment.

In this study, the 30-m land use/cover data was generated from Landsat MSS/TM/ETM + images, which was obtained from Resources and Environmental Data Cloud Platform, Chinese Academy of Sciences (http://www.resdc.cn/). The land use data had an overall accuracy above 90%, and referring to the classification standard of Peng et al. (2015), which was classified into seven types: farmland, forest land, grass land, water body, wetland land, urban land, unused land. The 1-km Nighttime light index derived from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (https://ngdc.noaa.gov/eog/download.html). The 250-m Normalized Difference

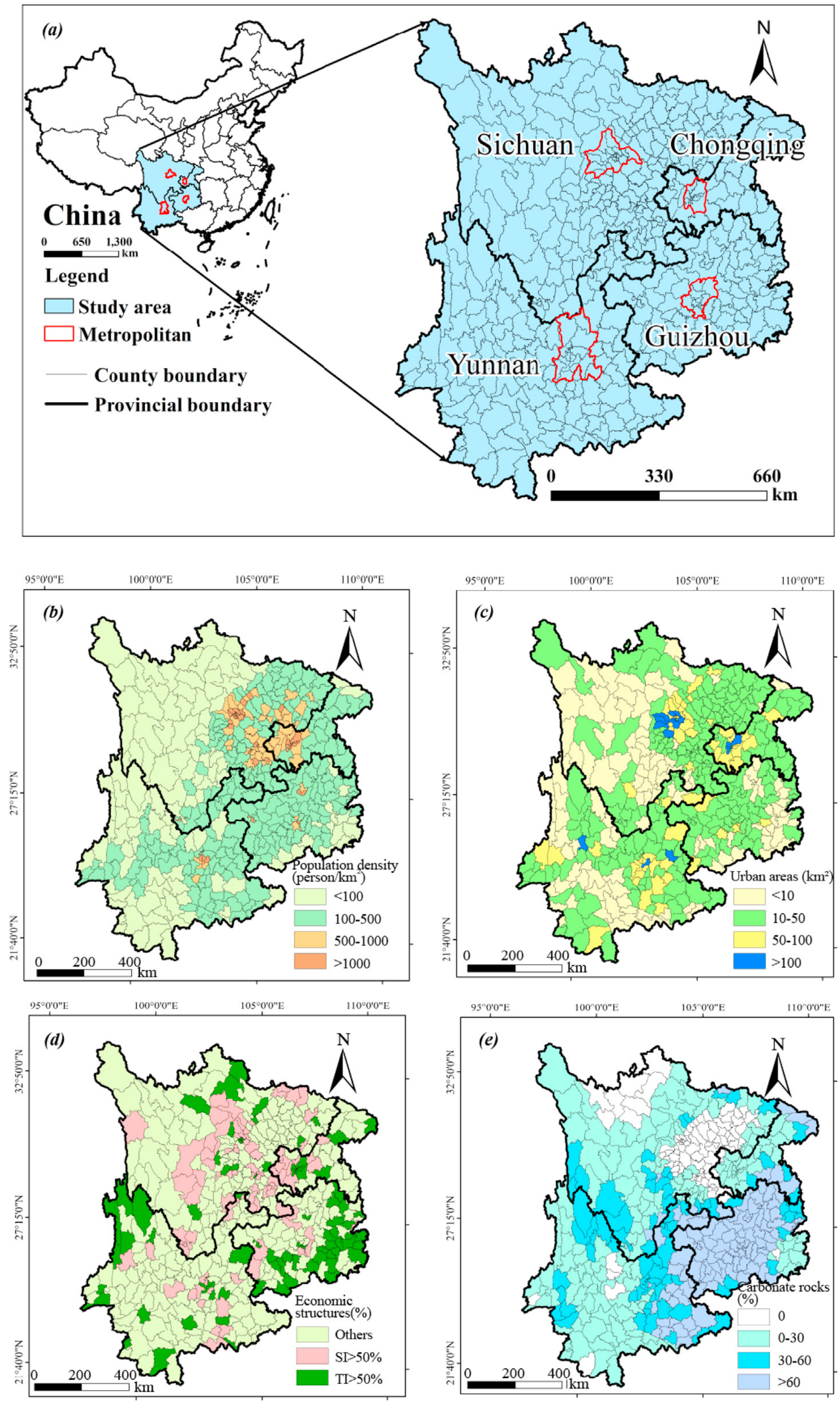


Fig. 2. Spatial distribution of the 438 districts and counties in this study. Note: SI is the proportion of secondary industry, and TI is the proportion of tertiary industry.

Vegetation Index (NDVI) was acquired from the Geospatial Data Cloud (http://www.gscloud.cn/). The geological data was derived from the Institute of Geochemistry, Chinese Academy of Sciences (http://www.gyig.ac.cn/). Daily temperature, precipitation, wind speed, humidity, and sunshine durations of 260 national stations were derived from Chinese Meteorological Data Sharing service System (http://data.cma.cn/). The population density and economic structure of 438 cities acquired from the Statistical Yearbook of counties in China.

2.2. Ecosystem health assessment

In this study, the health level of regional ecosystem mainly depends on the physical health of ecosystem itself and the supply capability of ecosystem services (Costanza, 1992; Peng et al., 2015). First, the physical health of ecosystems is usually quantified based on the traditional Vigor-Organization-Resilience assessment method, which reflects the health status of spatial entities. Second, to ensure that human and natural ecosystem are coupled, the supply capability of ecosystem services is integrated to the traditional ecosystem health assessment. It is known that human well-being can actually be enhanced by improving ecosystem services (Carpenter et al., 2009). Thus, when the ecosystem can maintain the stability of its own structure and function and the supply of ecosystem services can meet human demands, the regional ecosystem is in a healthy level. The general formula could be expressed as follows:

$$EH_{it} = \sqrt{PH_{it} \times ESV_{it}} \tag{1}$$

$$PH_{it} = \sqrt[3]{O_{it} \times V_{it} \times R_{it}} \tag{2}$$

where EH_{it} and PH_{it} refer to the regional ecosystem health and the physical health of ecosystem in the ith unit in year t; O_{it}, V_{it}, R_{it} and ESV_{it} donates ecosystem vigor, ecosystem organization, ecosystem resilience and ecosystem services in the ith unit in year t, respectively. Specifically, O_{it}, V_{it}, R_{it} and ESV_{it} needs to be normalized to the range of 0–1 before the assessment of ecosystem health. And urban ecosystem health is divided into five levels based on the fixed thresholds method: weak level (0–0.2), relatively weak level (0.2–0.4), ordinary level (0.4–0.6), relatively well level (0.6–0.8), and well level (0.8–1.0).

Ecosystem vigor is usually used to describe the metabolism and primary productivity of ecosystems. According to previous studies, NPP (net primary productivity) has widely been proven to be effective in the primary productivity of ecosystems (Kang et al., 2018). Thus, ecosystem vigor is assessed by using NPP in this study, which is estimated by using the Carnegie-Ames-Stanford Approach (CASA) (Potter et al., 1993).

Ecosystem organization characterizes the structural stability of ecosystems and reflects the interactions between the components of ecosystems, which are determined by landscape heterogeneity and landscape connectivity (Peterson, 2002). In detail, landscape heterogeneity can be quantified though the area-weighted mean patch fractal dimension (*AWMPFD*) and the Shannon diversity index (*SHDI*). Landscape connectivity is quantified with landscape contagion index (CONT) and landscape fragmentation index (FN). However, except the connectivity of the entire landscape, landscape connectivity also depends on the connectivity of the important ecological landscape, such as forest land and wetland. Therefore, a series of landscape pattern index were selected and set different weights to measure ecosystem organization, and the detail formula was expressed as follows:

$$\begin{aligned} O &= 0.35 \times LH + 0.35 \times LC + 0.3 \times IC \\ &= 0.25 \times SHDI + 0.1 \times AWMPFD + 0.25 \times FN_1 + 0.1 \times CONT_1 \\ &\quad + 0.1 \times FN_2 + 0.05 \times CONT_2 + 0.1 \times FN_3 + 0.05 \times CONT_3 \end{aligned} \tag{3}$$

where O is the organization of regional ecosystem; LH, LC, and IC refer to landscape heterogeneity, landscape connectivity of spatial entities, and landscape connectivity of important ecological patch (forest and wetland); *AWMPFD* is area-weighted mean patch fractal dimension; *SHDI* is Shannon diversity index; FN_1, FN_2, and FN_3 are the fragmentation index of spatial entities, forest land, and wetland, respectively; $CONT_1$, $CONT_2$, and $CONT_3$ are the contagion index of spatial entities, forest land, and wetland, respectively. All landscape pattern index were calculated by using FRAGSTATAS 4.2.

Ecosystem resilience reflects the ability of ecosystems to maintain its original functions and structures under the interference of natural and human factors (Peng et al., 2015). Based on previous studies, land use, to some extent, can reflects the information of ecosystem resilience (Peng et al., 2017). Thus, the ecosystem resilience of the study area is quantified through the summation of area-weighted ecosystem resilience coefficients for each land use types (Table 1). Specifically, the indicator for resilience coefficient (RC) were acquired based on expert knowledge and related references (He et al., 2019; Kang et al., 2018). The specific calculation formula is as follows:

$$R = \sum_{i=1}^{n} \frac{A_i}{A_t} \times RC_i \tag{4}$$

where R is the resilience of regional ecosystem; A_t is the total area of spatial entities; A_i is the area of land use type i; RC_i is the resilience coefficient of land use type i.

Ecosystem services refers to the ability of ecosystem to provide goods and services for human society (Costanza et al., 1997). Previous studies have indicated that the quantification of ecosystem services needed to be considered from two aspects: the ecosystem service value of spatial entities and the spatial neighboring of land use types (Kang et al., 2018). First, the ecosystem service value of spatial entities was generally quantified based on the equivalent factor method (Costanza, 1992). Referring to the revised ecosystem services assessment model Xie et al. (2015) for different land use types in China, the ecosystem service values of study area was obtained. Second, the services provision of specific ecosystem will be affected by the ecosystems of the neighboring area due to ecosystem services flow (Bagstad et al., 2013). In this study, the spatial neighboring coefficients of land use type effect on ecosystem services is calculated through the coefficient matrix according to expert score (Table 1). In summary, the ecosystem services of in a specific area are affected by their land use types and land use types of their neighboring area. The specific calculation formula is as follows:

$$ESV = \left(\sum A_j \times VC_j\right) \times \left(1 + \sum_{i=1}^{m} \frac{SNEC_i}{100}\right) \tag{5}$$

where ESV is the ecosystem services total values; A_j and VC_j are the area and value coefficient of land use types j; SNEC is the sum of spatial neighboring coefficient of the four adjoining pixels on the ecosystem services of pixel i; m is the number of pixels in the assessing units.

Table 1
The coefficient of spatial neighboring effect on ecosystem services.

	Farmland	Forest land	Grassland	Water body
RC	0.3	0.8	0.7	0.8
$SNEC_s$	4	5	5	4
$SNEC_d$	−2	4	3	3
	Built-up land	Unused land	Wetland	
RC	0.2	1.0	0.7	
$SNEC_s$	3	3	5	
$SNEC_d$	−4	−2	4	

Note: RC refers to resilience coefficient; $SNEC_s$ refers to the spatial neighboring effect on the same type of land use; $SNEC_d$ refers to the spatial neighboring effect on the different type of land use.

2.3. Measuring urban expansion

In this study, based on pattern-process analysis and spatial-temporal interdependences (Liu et al., 2010), the characteristics of urban expansion are mainly considered from three aspects: the scale and intensity of urban expansion (temporal process), urban growth modes (spatial process), and urban forms (urban landscape pattern). First, the scale and intensity of urban expansion was quantified through two index: overall urban expansion area (OEA) and annual urban expansion rate (AER) (Dou and Kang, 2019). OEA measures the changes of urban land areas, which reflects the scale of urban expansion over different periods. AER reflects the intensity of urban expansion and has been proved to be effective for comparing the urban expansion of various cities sizes in the same period. In addition, the modes of urban growth over different periods is identified by using landscape expansion index (LEI), which reflects the relationship between new urban patches and existing urban patches (Xu et al., 2019). Referring to the research of Liu et al. (2010), the modes of urban growth can be divided into three types, namely, outlying type (LEI = 0), edge-expansion type (0<LEI≤50), and infilling type (50<LEI≤100). Meanwhile, we also adopted the mean expansion index (MEI) and the area-weight mean expansion index (AWMEI) to characterize the aggregate degree and expansion degree of new urban patches as a whole, respectively (Liu et al., 2010). Finally, the composition and spatial pattern of urban landscape were characterized mainly through the landscape metric, which has been proven to be effective for representing urban forms (Peng et al., 2015; Shi et al., 2019). In this study, seven landscape pattern indices were chosen to represent urban forms, including the total urban area (TUA), percentage of like adjacencies (PLADJ), largest patch index (LPI), number of patches (NP), landscape shape index (LSI), percentage of landscape (PLAND), and patch cohesion index (COHESION). The selection of these metrics is mainly considered from two aspects: they have been widely used to characterize irregularity, sprawl, and the aggregation of urban forms (Wang et al., 2018). On the other hand, in order to facilitate comparison with other studies. Seven landscape metrics was calculated for each districts and counties using FRAGSTATAS 4.2. The specific formula and description of urban expansion indicators are shown in Table 2.

2.4. Econometric model

In this study, the relationship between urban expansion and ecosystem health was quantified based on the panel data model. Compared with the traditional statistic models, the panel data model has the following three main advantages. First, the panel data model has a high ability in controlling individual heterogeneity, reducing multicollinearity effect, and increasing the degrees of freedom (Shi et al., 2019). Second, the panel data model can solve the problem of insufficient sample size by considering more data points. Third, the panel data model can correctly explain the relationship between variables based on different research objectives (Chen et al., 2011).

In detail, urban landscape metrics were considered to analysis the associations between urban expansion and ecosystem health based on the following two reasons: 1. Those metrics have been proven to be effective for quantifying and characterizing various aspects (i.e., sprawl, irregularity, and aggregation) of urban landscape; 2. Landscape metrics could bridge between land-use pattern and governing process, improve our understanding of the ecological effects on urban expansion, and facilitate the characterization of heterogeneous urban landscape (Peng et al., 2015; Xia et al., 2019). Besides, the ecosystem health may also be impacted by other factors which are directly or indirectly related to urban expansion. Thus, based on previous studies (Shi et al., 2019), the Night light and NDVI were used to control the correlation analysis for better understanding the effects of urban expansion on ecosystem health from a multi-perspective view (Fig. S1). The Night light can effectively reflects the intensity of human activities and has been used as the most significant variable driving urban expansion. Meanwhile, due to the data scarcity, the Night light data from 2015 was replaced by the data from 2013. The NDVI can maintains the structure and function of ecosystems and guarantees the supply of ecosystem services to meet human demands, which is applied to analysis the effect of natural environment on ecosystem health associated with urban expansion.

Therefore, based on the seven landscape metrics and two control variable, we explored the associations between urban expansion and ecosystem health from a multi-perspective approach. Note that there are two points that need to be focused before the

Table 2
Description of urban expansion indicators.

	Indicators	Formula	Description
The scale and intensity of urban expansion	Overall urban expansion area (OEA)	$OEA = U_{end} - U_{start}$	U_{start} and U_{end} are the urban area of the start time and the urban area of the end time, respectively
	Annual urban expansion rate (AER)	$AER = (\sqrt[t]{\frac{U_{end}}{U_{start}}}) \times 100\% - 1$	t is the time span of the period in years.
The modes of urban growth	The landscape expansion index (LEI)	$LEI = \frac{U_{com}}{U_{buf}} \times 100\%$	U_{com} is the length of common edge of the buffer zone; U_{buf} is the perimeter of the urban buffer zone
	The mean expansion index (MEI)	$MEI = \sum_{i=1}^{N} \frac{LEI_i}{N}$	N is the total number of overall new patches
	The area-weight mean expansion index (AWMEI)	$AWMEI = \sum_{i=1}^{N} LEI_i \times (\frac{a_i}{A})$	a_i is the area of the new urban patch i; A is the total area of overall new patches
The urban landscape metrics	Total urban area (TUA)	$CA = \sum_{j=1}^{n} a_{ij}(1/10000)$	a_{ij} is the area of patch ij.
	Number of patches (NP)	$\mathrm{NP} = \mathrm{n}$	N is the number of patches.
	Largest patch index (LPI)	$LPI = \frac{\max_j^i(a_{ij})}{CA}(100)$	a_{ij} is the area of patch ij. CA is the total area of urban.
	Landscape shape index (LSI)	$LSI = \frac{0.25\sum_{k=1}^{m} e_{ik}^*}{\sqrt{CA}}$	CA is the total area of urban. eik* is the total length of edge in landscape between i and k.
	Percentage of like adjacencies (PLADJ)	$PLADJ = (\frac{\sum_{i=1}^{m} g_{ii}}{\sum_{i=1}^{m}\sum_{k=1}^{n} g_{ik}})(100)$	g_{ii} is the number of like adjacencies between pixel of i. g_{ij} is the number of adjacencies between class i and k.
	Patch cohesion index (COHESION)	$COHESION = (1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} p_{ij}^*}{\sum_{i=-1}^{m}\sum_{j=1}^{m} p_{ij}^* \sqrt{a_{ij}^*}})(1 - \frac{1}{\sqrt{z}})^{-1}(100)$	P_{ij}* is the perimeter of patch ij. a_{ij}* is the area of patch ij in terms of number of cells. Z is total number of cells.
	Percentage of landscape (PLAND)	$PLAND = \frac{a}{A}(100)$	a is the total area of urban. A is the total area of landscape.

implementation of the panel data model. First, in order to avoid the influence of nonstationarity and heteroscedasticity, all variables should be processed through natural logarithm transformation (Shi et al., 2019). Second, the validity of the panel data model need to be confirmed though the panel root unit test and panel cointegration test. The panel data model was formula as follows:

$$\begin{aligned} EH_{it} = {} & \alpha_i + \beta_1 CA_{it} + \beta_2 NP_{it} + \beta_3 PLAND_{it} + \beta_4 ED_{it} + \beta_5 LPI_{it} \\ & + \beta_6 LSI_{it} + \beta_7 PLADJ_{it} + \beta_8 COHESION_{it} + \beta_9 GDP_{it} + \beta_{10} NDVI_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

where EH_{it} is ecosystem health of cities i in year t; α is the intercepts of all individuals; β_1-β_{10} refers to regression parameters for each explanatory variable; and $\mathcal{E}$ is the random error.

3. Results and discussion

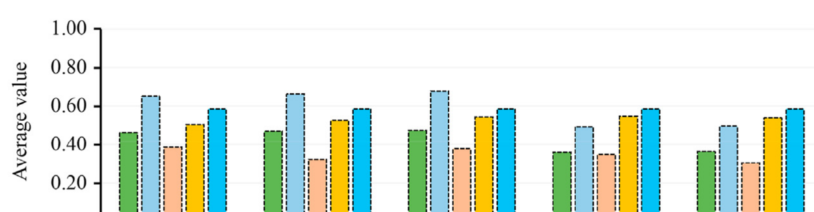
3.1. Spatial pattern and change of ecosystem health

3.1.1. Change of ecosystem health indicators

In this study, in order to clarify the overall change trend of each indicator and its contribution to urban ecosystem health, the average values of all indicators in Southwest China were calculated and compared (Fig. 3). The results showed that the change of ecosystem services were similar to ecosystem health, preforming a change trend of ascending firstly and then descending, with a peak in 2005. It was suggested that ecosystem services played a key role in urban ecosystem health, which was in accordance with previous studies (He et al., 2019; Peng et al., 2015). The other indicators varied differently; the highest values of ecosystem resilience and ecosystem vigor were in 2005, while the peak for ecosystem organization occurred in 1995. By contrast, the lowest value of all the indicators occurred in 2010 and 2015, indicating that the status of regional ecosystem health was gradually deteriorating after 2005. The reason for the improvement of ecosystem health before 2005 may be attributed to the implementation of a series of ecological projects (i.e., Natural Forest Protection Project and The Grain for Green Program), which was contributed to increase the ecosystem vigor and improve the supply of ecosystem services (Wang et al., 2019). Meanwhile, although urbanization had continued, there had been no significant changes in the urban landscape heterogeneity and connectivity in Southwest China throughout this period, which was beneficial to the ecosystem organization to maintain a stable state (Kang et al., 2018). However, the reason for the deterioration of ecosystem health after 2005 may be related to the increase in the scale and intensity of urban expansion. Consistent with our studies, Li and Li. (2019) found that the urban sprawl in Southwest China and Yangtze River Delta region was the most severe during 2006–2014, which would directly lead to the decline in ecosystem services and ecosystem resilience, and the low ecosystem organization due to the increase of landscape diversity and fragmentation. Therefore, the scale and intensity of urban expansion is an important factor affecting urban ecosystem health.

3.1.2. Change of ecosystem health

As shown in Fig. 4 and Table 3, there were significance difference in the spatial distribution and change trend of ecosystem health among the 438 counties. In terms of the spatial distribution of ecosystem health, counties with a well or relatively well health mainly distributed in the western mountainous areas with high vegetation coverage and ecological integrity, which was consistent with Kang et al. (2018). These areas were not only important ecological barrier of the Yangtze River Basin in China but also a restricted development area in China referring to Major Function-Oriented Zone Planning (Peng and Wang, 2019). In contrast, counties with a weak or relatively weak health mainly concentrated in Sichuan Basin and metropolitan areas with high urbanization and industrial development. Peng et al. (2015) indicated that rapid and large-scale urban expansion had significantly changed the land use/cover, and a large number of ecological land had been converted into farmland and construction land, which had altered the structure and function of regional ecosystem to some extent, thereby, led to the deterioration of ecosystem health. Meanwhile, counties with ordinary health were mainly concentrated in the Yunnan-Guizhou Plateau areas with various ecosystem types and relatively slow urbanization. The ecosystem health of these areas are more sensitive to human activities (especially farmland reclamation and urban expansion) than other areas, due to the widespread distribution of karst landscapes and fragile natural environment (Wang et al., 2019). In general, we found that ecosystem health exhibited different spatial pattern for counties with different population density, economic structure, urban area size, and geological environment in Southwest China. In addition, the number of counties with relatively weak level accounted for the largest proportion form 1995 to 2015 (He et al., 2019). Meanwhile, the number and area proportion of counties above the ordinary health level (well health and relatively well health) showed an ascending trend during from 1995 to 2005 and then decrease from 2005 to 2015, while the total number and area proportion of counties below the ordinary health level (weak health and relatively weak health) showed decreased from 1995 to 2005 and increased from 2005 to 2015. The resulted indicated that the deterioration of urban ecosystem health within Southwestern China mainly occurred between 2010 and 2015, which was may be attributed to the increase in the scale and intensity of urban expansion. He et al. (2019) indicated that urbanization rate



	1995	2000	2005	2010	2015
Ecosystem Health	0.46	0.47	0.48	0.36	0.36
Ecosystem Services	0.65	0.66	0.68	0.50	0.50
Ecosystem Organization	0.39	0.33	0.38	0.35	0.31
Ecosystem Vigor	0.51	0.53	0.55	0.54	0.54
Ecosystem Resilience	0.59	0.59	0.59	0.58	0.58

Fig. 3. Average value change of each indicator used in the assessment of urban ecosystem health within Southwest region during 1995–2015.

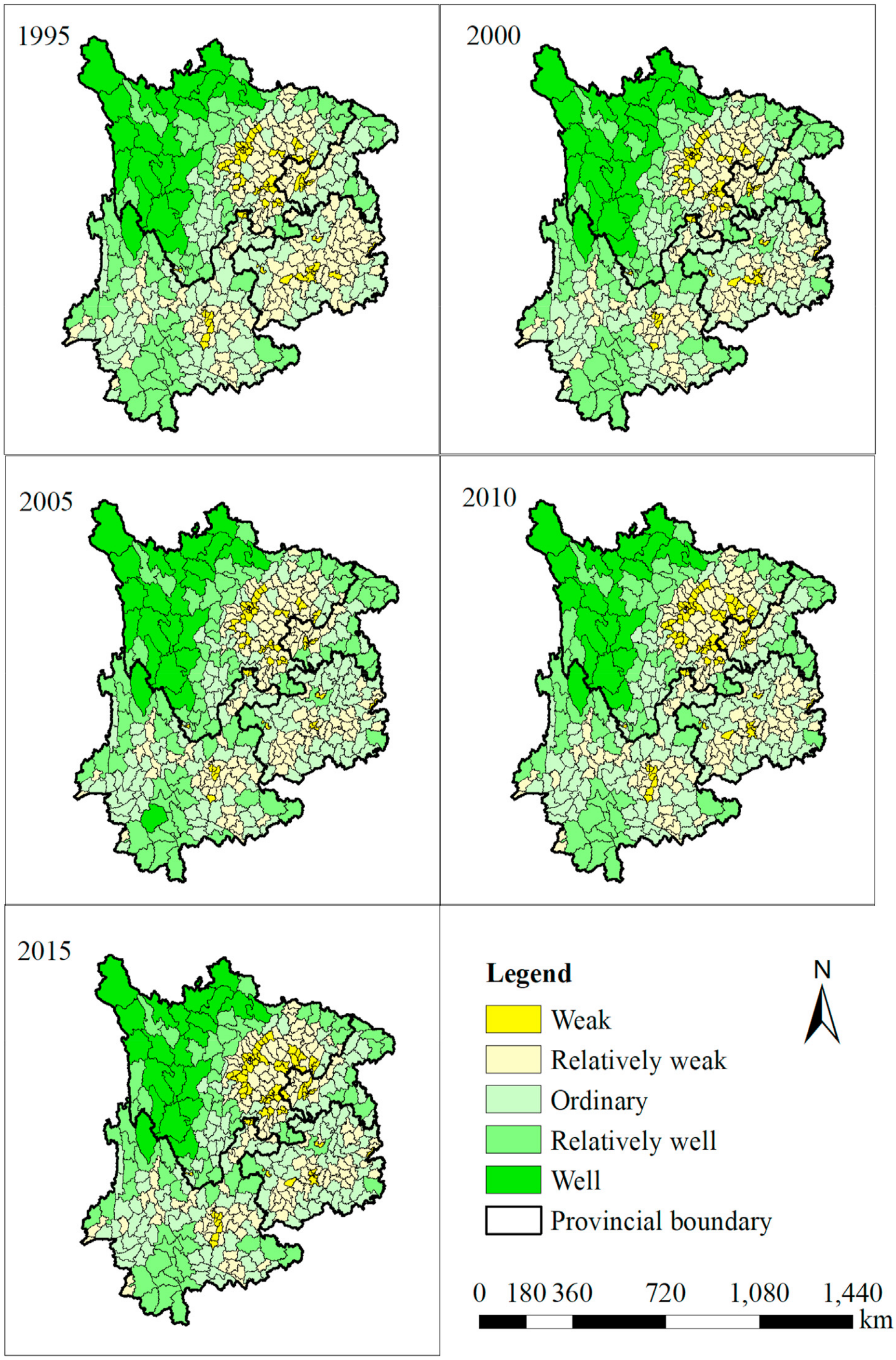


Fig. 4. Level of urban ecosystem health in all the assessed units from 1995 to 2015.

Table 3
Number of unit assessed and their area ratios in relation to urban ecosystem health levels.

Level	1995	2000	2005	2010	2015
Weak	70 (2.21%)	61 (2.22%)	57 (2.01%)	75 (2.65%)	77 (2.74%)
Relatively weak	158 (18.39%)	148 (16.86%)	145 (16.60%)	145 (18.07%)	140 (18.08%)
Ordinary	119 (25.94%)	125 (24.30%)	128 (23.28%)	125 (25.73%)	123 (24.89%)
Relatively well	68 (22.43%)	79 (20.55%)	83 (20.46%)	71 (22.33%)	75 (21.61%)
Well	23 (31.03%)	25 (36.07%)	25 (37.65%)	22 (31.22%)	23 (32.68%)

dominated the regional differences of ecosystem health in Southwest China, explaining 28.8% of the health variation.

3.2. Spatial pattern and change of urban expansion

3.2.1. Change of urban expansion intensity

In the period of 1995–2015, the urban area in Southwestern China increased continuously and rapidly (Fig. 5a–b). The urbanized area for the entire region increased from 2441.98 km^2 (3.98% of the total area) in 1995 to 9710.43 km^2 (8.53% of the total area) in 2015, with an average annual expansion percent of 6.84%, while the China average between 1995 and 2015 was about 4.37%, according to Dou and Kuang (2019). In terms of the urban expansion area, the total area of urban expansion during 2010–2015 was the largest, reaching 3224.70 km^2. The area of urban expansion in the other three periods (1995–2000, 2000–2005, and 2005–2010) was 319.18 km^2, 640.64 km^2, and 2543.93 km^2, respectively (Fig. 5c). In terms of the annual expansion rate, urban land in the entire region during 2005–2010 increased most rapidly, with an annual expansion rate of 11.81%. The annual urban expansion rate in the other three periods (1995–2000, 2000–2005, and 2010–2015) was 2.49%, 4.26%, and 9.05%, respectively. Meanwhile, we also found that the areas with the largest scale and speed of urban expansion in Southwest China were concentrated in large-cities (i.e., Chongqing and Chengdu), which was consistent with Li and Li.'s (2019) findings. The results further indicated that the degree of urban expansion was correlated with the city size.

3.2.2. Change of urban growth modes

The dramatic changes in the urban landscape have been observed during 1995–2015, while the urban landscape showed different expansion patterns in four periods. As is shown Fig. 6, the domination types of urban growth has gradually changed from edge-expansion to outlying during 1995–2015, which means that the spatial form of urban landscape has transformed from compact to scatter. In detail, in the period of 1995–2005, the edge-expansion was the domination types of urban growth in terms of patch proportion and area proportion, indicating that the urban form for the entire region was compact in this period (Fig. 6 b1-b2). In the period of 2005–2010, the area and patch proportion of outlying-type and infilling-type demonstrated an ascending trend, especially, the proportion of outlying patches increased to 40.01%. In the meantime, edge-expansion type experienced a significant decline in patch (83.26%) and area (47.22%), but it remained the main growth type. In the last period (2010–2015), edge-expansion and infilling showed a significant decline in patch and area, whereas the area proportion and patch proportion of outlying-type increased to 53.89% and 73.34%, respectively. This change indicated that the main types of urban growth has changed from edge-expansion to outlying and the urban form increasing dispersed, which was consistent with Liu et al. (2010). Furthermore, as is shown Fig. 6-b3, the changes trend of MEI and AWMEI also indicated that the urban form tended to scatted from 1995 to 2015. In detail, MEI fluctuated slightly (range from 46.01 to 48.74) in the period of 1995–2010, then significantly declined from 48.74 in 2005–2010 to 9.51 in 2010–2015. In contrast, AWMEI showed a gradual downward trend, and the value of the four periods was 24.25, 23.95, 22.19, and 11.12, respectively. Meanwhile, we also found that the edge-expansion was the domination types of cities (i.e., Chengdu) with relatively flat terrain and urban form tended to be compact, while the mountain cities (i.e., Guiyang) were mainly outlying-expansion type and urban form was relatively scattered (Fig. 6 a1-a4). The results indicated that the urban growth mode was related to the local topography. For example, Peng and Wang (2019) indicated that the topography had a long-term restraining effect on the urban expansion. Therefore, the topography was also taken into account when exploring the impact of geological environmental on the urban expansion-ecosystem health relationships.

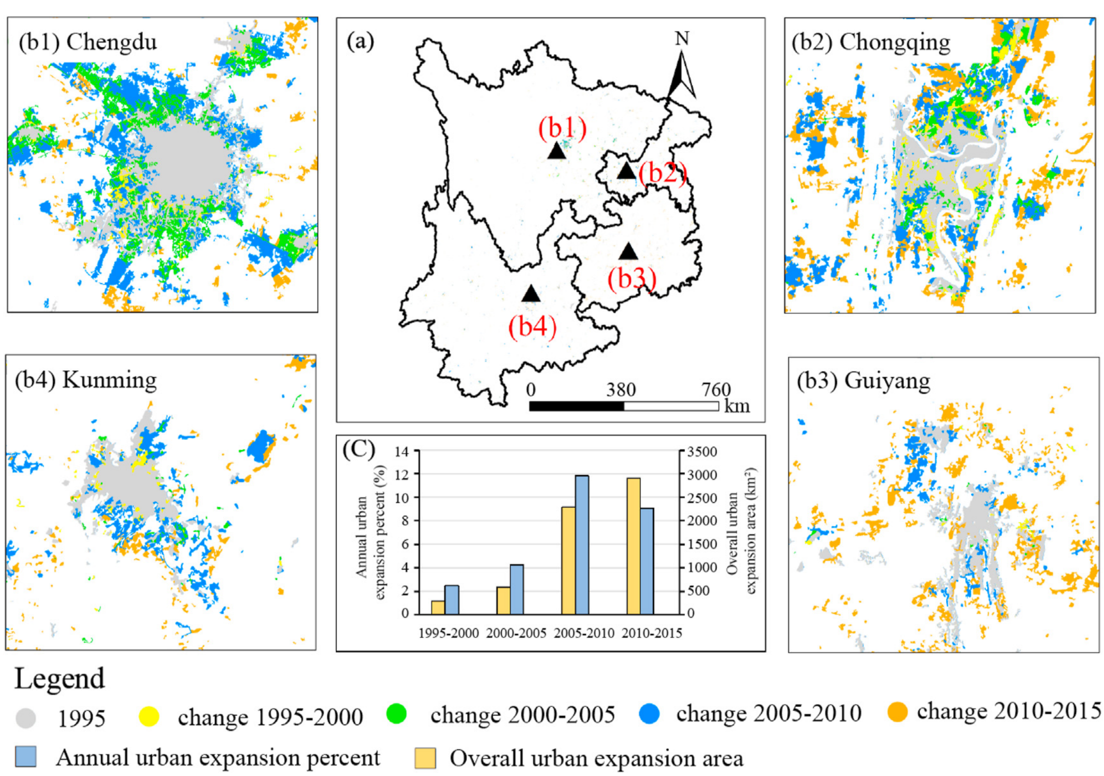


Fig. 5. Distribution of urban expansion in different cities during 1995–2015.

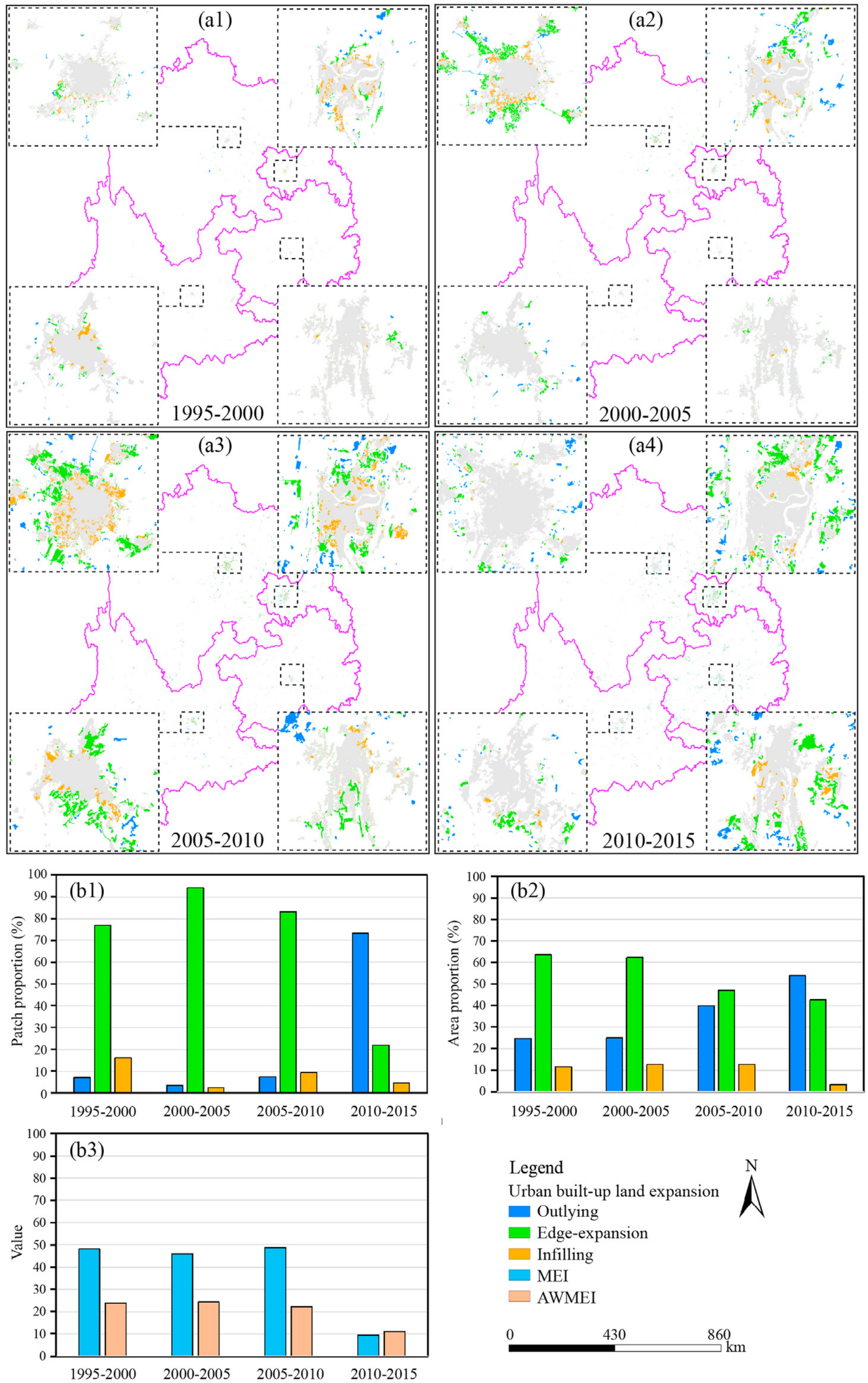


Fig. 6. Spatial distribution of three urban growth types in the four periods (a1-a4). Percentages of growth area and number of patches for the three urban types (b1). MEI and AWMEI of newly grown urban patches in the four periods (b2-b3).

3.2.3. Change of urban landscape metrics

Due to the acceleration of urbanization process from 1995 to 2015, the form of urban in Southwestern China become more and more complex (Table 4). In terms of the scale and sprawl degree of urban patches, the average TUA values of the entire region has rapidly increased from 5.01 km^2 in 1995 to 18.84 km^2 in 2015. It was remarkable that the maximum TUA values have increased from 141.09 km^2 in 1995 to 226.59 km^2 in 2015. Meanwhile, we also found that the maximum PLAND values and the mean LPI values increased by 26.22% and 99.04%, from 1995 to 2015. On one hand, these results indicated that the scale and proportion of urban land in Southwest China has significantly increased, and the expansion of big cities was the main trend (Peng et al., 2017; Li and Li, 2019). On the other hand, these results also showed that edge-expansion

Table 4
Statistics of independent variables at the regional scale.

Year	STA	TUA (km^2)	PLAND (%)	NP	LPI (%)	LSI	PLADJ (%)	COHESION	NSL (DN)	NDVI
1995	mean	4.68	1.28	3.73	1.04	3.42	91.29	94.94	1.24	0.71
	min	0.36	0.00	1.00	0.00	0.01	0.01	0.00	0.00	0.26
	max	54.11	69.22	51.00	69.22	16.17	98.46	99.87	38.44	0.83
	std	7.72	5.92	5.33	5.34	2.28	13.91	14.07	1.95	0.06
2000	mean	5.66	1.39	4.47	0.01	3.76	92.067	95.89	2.56	0.71
	min	0.36	0.00	1.00	0.00	0.01	0.01	0.00	0.03	0.29
	max	62.75	70.71	50.00	70.72	16.18	98.21	99.88	42.35	0.82
	std	8.45	6.19	5.78	5.65	2.15	11.61	11.65	2.41	0.06
2005	mean	6.97	1.69	5.38	1.39	4.14	92.40	96.38	3.89	0.75
	min	0.36	0.00	1.00	0.00	0.01	0.01	0.00	0.04	0.32
	max	90.34	73.00	52.00	70.75	16.46	97.98	99.91	46.01	0.85
	std	10.55	7.32	6.61	6.75	2.34	9.79	9.67	3.18	0.06
2010	mean	12.18	2.39	13.22	1.88	5.45	93.28	97.01	5.34	0.75
	min	14.31	0.00	1.00	0.00	0.01	0.01	0.00	0.08	0.39
	max	122.57	86.96	265.00	86.51	41.36	98.54	99.96	52.41	0.85
	std	16.50	9.14	.17.04	8.70	3.22	6.82	6.73	6.12	0.06
2015	mean	18.84	3.03	28.25	2.07	7.60	93.15	97.14	9.43	0.79
	min	19.89	0.00	1.00	0.00	0.01	0.01	0.00	0.12	0.39
	max	226.59	87.34	293.00	86.90	40.18	98.53	99.96	56.81	0.89
	std	21.98	9.57	25.07	8.72	3.52	5.01	4.87	6.33	0.07

and infilling growth, not outlying growth, were the dominant types of urban expansion in the period of 1995–2015. In terms of the aggregation degree of urban patches, the average COHESION and the average PLADJ showed a slight upward trend during 1995–2015, indicating that the urban patches were far away from each other and become less compacted. Specifically, the average PLADJ increased from 91.30 in 1995 to 93.15 in 2015, and the average COHESION increased from 94.94 in 1995 to 97.14 in 2015. In terms of the irregularity of urban form, the NP for urban landscape performed a rapid growth trend. In detail, the mean NP increased from 3.73 in 1995 to 28.26 in 2015, increased about 7.58 times, indicating that the spatial growth of urban landscape become more and more complicated and fragmented. Meanwhile, the mean LSI values also showed an ascending trend form 3.43 in 1995 to 7.60 in 2015, suggesting that the spatial heterogeneity of urban landscapes gradually increased due to the rapid urban expansion.

3.3. Correlations between urban expansion and ecosystem health

In order to eliminate the spurious regression caused by non-stationary data, panel cointegration and panel unit root tests needed to be performed to verify the feasibility of model before regression (Shi et al., 2019). As shown Table S1–S14, all variables were stationary and cointegrated with each other during the study period. Therefore, based on the above results, we were able to construct a panel model to explore the relationship between urban expansion and ecosystem health form a multi-perspective view. As shown in Table 5, the correlation coefficient (R^2) of the panel model is higher than 0.79, and the Prob (F-statistic) value is lower than 0.001, indicating that the model has a relatively high goodness of fit and can accurately explain the relationship between urban expansion and ecosystem health.

Table 5
The relationship between urban expansion and ecosystem health for the 438 selected cities (at the regional scale).

Independent variable	Coefficient	Independent variable	Coefficient
TUA	−0.509***	PLADJ	−0.807**
PLAND	−0.491***	Night light	−0.078***
NP	0.025	NDVI	2.325***
LPI	−0.045**	Adjusted R^2	0.799
LSI	−0.148***	F-statistic	847.450
COHESION	1.563	Prob (F-statistic)	0.000

Note: Significant at * 10% level, ** 5% level, *** 1% level.

Table 5 showed that most landscape metrics had a significant impact on urban ecosystem health. Specifically, the TUA was found to exert a significantly negatively correlated with ecosystem health in Southwest China. Thanks to the implementation of the Western China Development strategy, continuous expansion of urban land not only caused the change of urban structure but also the loss of ecological land, which directly resulting in the increase of landscape fragmentation and the decrease of ecosystem function, and thereby affecting the regional ecosystem health (He et al., 2019; Luo et al., 2019; Li and Li, 2019). Meanwhile, urban expansion is often accompanied by the migration of a large number of people from rural areas to cities (Peng et al., 2016). Due to lack of good public service systems, the increase of population density in urban areas might cause a series of eco-environment problems (i.e., air pollution, soil erosion, and green space degradation), which undoubtedly hinder the sustainable development of city (Xia et al., 2019; Song et al., 2020). In addition, the LPI and LSI had a significant negative impact on ecosystem health, indicating that a highly fragmented and complex urban form was not conducive to the health and sustainable development of urban ecosystem. Previous studies had indicated that with the irregularity of urban land increased, the expansion of infrastructure (i.e., road network) gradually become the most important factor affecting regional ecological environment (Shi et al., 2019; Tao et al., 2020). For example, Mo et al. (2017) found that road networks affected the spatial structure of urban landscapes, leading to the increase of regional ecological risk and a broader impact on the regional ecosystem health. Furthermore, the PLADJ was significantly negatively correlated with ecosystem health, suggesting that an aggregation urban growth mode, to some extent, could help to improve the regional ecosystem health. An extensive study has demonstrated that the decrease of landscape connectivity would hinder the spread of material and energy flow and change the regional material, energy and ecological process, resulting in the deterioration of regional eco-environment (Kang et al., 2018; Peng et al., 2016). Of the control variables, there was significant positive correlation between the NDVI and ecosystem health. The more the NDVI, the more vegetation coverage. The increase of vegetation coverage can improve the ability of ecosystems to maintain its own structure, function, and resilience to external disturb (Peng et al., 2017). However, the night light had a significant negative impact on ecosystem health. The Night light reflects the intensity of human activity to some extent, the more human activity will increase the demand for construction land and decrease the supply of ecosystem services, which is not benefit for the sustainable development of ecosystems.

3.3.1. Effects of the urban area size on the relationship between urban expansion and ecosystem health

As shown in Table 6, the correlation coefficient (R^2) for different urban area size scenarios ranging from 0.74 to 0.95, and the all Prob (F-statistic) values are lower than 0.001, indicating that the urban size affected the associations between urban expansion and ecosystem health to some extent (Li and Li, 2019). Four main findings were found in this study. First, the TUA was significantly negatively correlated with ecosystem health in all of the cities except for mega-scale cities, and the impact of the urban scale on ecosystem health was the most significant in small-scale cities, followed by medium-scale cities and large-scale cities. The results indicated that the environmental problems resulting from urbanization may be phasic, which was consistent with previous studies (Kang et al., 2018; Peng et al., 2017). For example, Peng et al. (2016) found that compared to highly developed urban zones, lowly and moderately developed urban zones had an obvious negative ecological effect on NPP. Note that there was significant positive association between urban expansion and ecosystem health in mega-scale cities, which may be attributed to the impact of local eco-environment management and urban planning. Many studies had indicated that urban land in mega-scale cities had experienced more greening than other size cities through urban land use management, which improved quality of life and urban sustainability within cities (Dou and Kuang. 2019; Peng et al., 2016). Second, the LSI except for small-scale cities was significantly negatively correlated with ecosystem in various types of cities, indicating that the impact of urban form irregularity on ecosystem health was relatively significant in the medium-scale, large-scale and mega-scale cities. Previous studies had found that during the rapid urbanization process, the appearance of more planer, irregular urban patches will directly lead to the low ecosystem organization due to the increase of landscape diversity and fragmentation (He et al., 2019; Liao et al., 2018; Kang et al., 2018). By contrast, it was not significant correlation between the LSI and ecosystem health for small-scale cities, which may be due to small cities have small areas and relatively good ecological environment so that they are insensitive to urban irregularity (Peng et al., 2015). Third, compared to small-scale and medium-scale cities, the impacts of the compact of urban form (PLADJ) on ecosystem health was more significant in mega-scale cities, which reason may be that compared with other types of cities, mega-scale cities are in the rapid development stage of urbanization, and urban forms is more scattered and complex, which reduces the landscape patches connectivity and increases the potential ecological risk to some extent. For example, Shi et al. (2019) demonstrated that a continuous and aggregated urban pattern was conducive to improving the efficiency of urban public service systems and reducing air pollution. Fourth, the NDVI had a significant benefit for ecosystem health within various types of cities, indicating that increasing vegetation coverage could improve the vigor, resilience, and function of ecosystems (Luo et al., 2019; Song et al., 2020). However, the impact of the Night light on ecosystem health in the small-scale and medium-scale cities were more significant than that of large-scale and mega-scale cities, which reason may be that the economic development of small-sized and medium-sized cities mainly depend on resource exploitation and energy consumption (Li and Li, 2019).

3.3.2. Effects of the population density on the relationship between urban expansion and ecosystem health

As shown in Table 7, all models are statistically significant at Prob <0.001 and have adjusted R^2 values ranging from 0.66 to 0.86, which indicated that the impacts of urban expansion on ecosystem health varied between cities with different population density. Many studies have demonstrated that the urban population density was the most important factor driving urban sprawl, to some extent, which also resulted in the imbalance of ecosystem health between different regions (Xia et al., 2019; He et al., 2019). Four main findings emerged for population density effects on the urban expansion-ecosystem health relationship. First, the TUA was found to exert a significant negative impact on ecosystem health within all of the cities except for small-sized cities, and the impacts of urban expansion on ecosystem health was more significant with the increase of population density. Undoubtedly, an increase in population density inevitably resulted in increases in the housing demand, transportation and energy consumption, thereby, resulting in an increase in eco-environment pressure and decline in ecological function (Shi et al., 2019; Song et al., 2020). By contrast, the TUA had a significant positive impact on ecosystem health for small-sized cities, which may be due to the relatively small population density, the urban scale of small-sized cities might be more conducive to maintain the vigor of ecosystems and guarantee the sustainable supply of ecosystem services (Li and Li., 2019; Dou and Kuang. 2019). For instance, Peng et al. (2015) found that the urban population increased several times without a degradation of ecosystem health at the early stage of urbanization in Shenzhen, on

Table 6
The relationship between urban expansion and ecosystem health with different urban area size.

Independent variable	Coefficient (UA<10 km^2)	Coefficient (10 km^2<UA<50 km^2)	Coefficient (50 km^2<UA<100 km^2)	Coefficient (100 km^2<UA
TUA	−0.449***	−0.390**	−0.321**	0.251*
PLAND	−0.547*	−0.285*	−1.169*	−0.794
NP	−0.028**	−0.019*	−0.081	0.535
LPI	−0.052*	−0.213*	−0.244*	−0.151
LSI	−0.250	−0.131**	−2.836**	−1.535*
PLADJ	−2.047**	−1.293*	26.810	−5.868***
COHESION	−0.147*	2.690	8.429	32.782
Night light	−0.113*	−0.084*	−0.044*	−0.012*
NDVI	0.562**	3.604**	3.499*	1.744**
Adjusted R^2	0.911	0.741	0.839	0.954
F-statistic	852.230	323.400	81.630	18.450
Prob (F-statistic)	0.000	0.000	0.000	0.000

Note: Significant at * 10% level, ** 5% level, *** 1% level, UA represents the urban area size.

Table 7
The relationship between urban expansion and ecosystem health under different population density.

Independent variable	Coefficient (PD < 100)	Coefficient (100 <PD < 500)	Coefficient (500 <PD < 1000)	Coefficient (1000 <PD)
TUA	0.468	−0.519**	−0.575*	−0.841**
PLAND	−0.512*	−0.428***	−0.446**	0.255
NP	0.031	−0.017	0.055	0.139
LPI	−0.063*	−0.105***	−0.011	−0.612
LSI	0.184	−0.012*	−0.102**	−0.823*
PLADJ	−0.288*	−0.412*	−2.281**	−3.953
COHESION	0.211	1.416	−1.125**	3.682**
Night light	−0.011	−0.028***	−0.066*	−0.204**
NDVI	0.056**	0.908**	0.687**	0.629*
Adjusted R^2	0.863	0.822	0.781	0.662
F-statistic	446.350	590.310	96.250	33.700
Prob (F-statistic)	0.000	0.000	0.000	0.000

Note: Significant at * 10% level, ** 5% level, *** 1% level, PD represents the population density (person/km^2).

the contrary, which brought a win-win effect for sustainable development. These results suggested that regulation of population is the preferred means of realizing the coordinated development of urban expansion and ecosystem health. Second, the impact of urban form complex (NP, LPI, and LSI) on ecosystem health were more significant in the small-sized and medium-sized cities than of large-sized and mega-sized cities. These results indicated that cities with small population density and relatively regular urban form were favorable to maintain the organization and self-operation of ecosystems. On the contrary, cities with high population density and irregular urban form would reduce the connectivity between landscapes and the supply capacity of ecosystem services (Peng et al., 2015; Wang et al., 2019). For example, Tao et al. (2020) found that the irregularity of urban form had a relatively stronger impact on air pollution in small and medium cities, whereas urban land use composition was the dominant factor influencing air pollution in large cities. Third, the PLADJ was significantly negatively associated with ecosystem health within all of the cities except for mega-sized cities, indicating that a compact urban form was benefit for maintaining the structure and function of ecosystem and improving the quality of eco-environment (Peng et al., 2015; Kang et al., 2018). Many studies indicated that with the migration increase of rural-urban population in the process of urbanization, the intensity of urban expansion would further strength for meeting the people's demands of work and live, thereby, resulting in the increase of landscape fragmentation and the loss of ecological land (Song et al., 2020; Liao et al., 2018). Note that the COHESION was significantly positively associated with ecosystem health in mega-sized cities, which may be attributed to the changes in human life styles and the positive demand for urban green space (Xia et al., 2019; Peng et al., 2016). For example, Shi et al. (2019) indicated that due to the overcrowded traffic system, people preferred to walk and use public transportation, which reduced air pollution and improved the living environment quality. Fourth, the NDVI was positively correlated with ecosystem health in all of cities, whereas the Night light was negatively associated with ecosystem health in all of cities except for small-sized cities. On the hand, these results suggested that only when population density reaches a certain scale, socioeconomic factors and natural environment would had a significant impact on ecosystem health. On the other hand, these results also indicated that the impact of natural environment on ecosystem health was more significant than socioeconomic when taking the population density into consideration.

3.3.3. Effects of the economic structure on the relationship between urban expansion and ecosystem health

As shown in Table 8, both the Prob (<0.001) values and adjusted R^2 (>0.75) indicated that the panel data model can effectively be applied to analyze the relationship between urban expansion and ecosystem health with different economic structure. Four main findings emerged for economic structure effects on the urban expansion-ecosystem health relationship. First, the TUA was significantly negatively correlated with ecosystem health in the industrial cities and other cities, rather than in the service cities. Indicating that the impact of the proportion of tertiary industry on urban expansion was relatively weaker than the proportion of secondary industry, which was consistent with the results of previous studies (Xu et al., 2019; Li and Li., 2019). After all, the separation between residence and work caused by industrial manufacturing is more likely to lead to urban expansion, thus optimizing the structure of industry is conducive to improve the utilization effective of urban land (Shi et al., 2019; Yuan et al., 2019). Meanwhile, the irregularity of urban forms (i.e., LSI and LPI) had a negative impact on ecosystem health, which may be due to a complex urban form often caused an increase in the use of transportation land, thereby resulting in the increase of landscape fragmentation and the decline of ecological function (Song et al., 2020). For example, Xia et al. (2019) found that the highest carbon transitions were largely from the transformation from natural components to artificial components, especially from cultivated land to industrial and transportation land. In addition, the COHESION was found to exhibit a significant positive impact on ecosystem health, suggesting that an urban form with high agglomeration may result in congested urban operations, in turn leading to a decrease in ecosystem connectivity (Yuan et al., 2019). Overall, urban forms had a more significant impact on ecosystem health in industrial cities. Second, for the service cities, the urban sprawl metric (i.e., TUA, NP, and LPI) were insignificant correlated with ecosystem health, which may be attributed to the industry structure and local government management (He et al., 2019). These cities have many environment-friendly industries (i.e., high-tech and light industries with high utilization efficiency), which not need too much land resources and have less damage to the environment. Using Lijiang as a case study, Peng et al. (2017) found that the status of ecosystem health showed an increase trend by optimizing the regional land use. Furthermore, the COHESION was significantly negatively correlated with ecosystem health, indicating that a compact urban form was benefit for maintaining the structure and function of ecosystem and improving the quality of eco-environment (Tao et al., 2020). Third, for other cities, all urban irregularity and compactness metrics were significantly negatively correlated with ecosystem health. On the hand, cities with the highly complexity of urban form usually result in the increase of transportation demand. On the other hand, cities with the highly fragmentation of urban form would directly result in the low ecosystem organization. Fourth, of the control variables, Night light and NDVI were found to exert significant impact on ecosystem

Table 8
The relationship between urban expansion and ecosystem health under different economic structure.

Independent variable	Coefficient (Others)	Coefficient (The proportion of secondary industry >50%)	Coefficient (The proportion of tertiary industry >50%)
TUA	−0.501**	−0.551***	−0.132
PLAND	−0.509*	−0.363**	−0.707
NP	−0.006*	−0.057**	0.033
LPI	0.036	−0.187**	0.152
LSI	−0.058*	−0.046***	−0.015
PLADJ	−0.025**	−0.396	−3.578
COHESION	−0.514*	0.793*	−0.474***
Night light	−0.056*	−0.046***	−0.092*
NDVI	0.428**	0.653**	1.286***
Adjusted R^2	0.923	0.918	0.755
F-statistic	1672.060	542.050	145.890
Prob (F-statistic)	0.000	0.000	0.000

Note: Significant at * 10% level, ** 5% level, *** 1% level.

health within various types of cities. Note that from other cities to second cities to industry cities, the impact of the natural environment gradually strength. In general, the urban expansion-ecosystem health relationship changed gradually with various economic structure.

3.3.4. Effects of the geological environment on the relationship between urban expansion and ecosystem health

As shown in Table 9, the adjusted R^2 and Prob-values indicated that the geological environment could affected the associations between urban expansion and ecosystem health to some extent. Most studies have demonstrated that difference in geological environment was also an important factor affecting the relationships between urban expansion and ecosystem health (Wang et al., 2019). The results showed that the relationships between urban forms and ecosystem health between cities with different geological environment existed significant differences. In terms of the urban sprawl scale, the TUA and PLAND were found to exhibit a significant negative impact on ecosystem health within all types of cities, and the impact of urban sprawl metrics on ecosystem health was more significant in the non-karst cities than the karst cities. These results may be due to differences in the effects of topography and human activity intensity on ecosystem health (He et al., 2019). For non-karst cities, the urban scale was relatively large and continuous due to it was mainly located in the basin area, and the development of socio-economic further accelerated the intensity of urban expansion, thereby resulting in the loss of ecological land and the decline of ecosystem services (Xu et al., 2019). By contrast, the topography had a long-term restraining effect on the urban scale in the karst cities, and economic and technological conditions were not good enough, leading to the impact of urban scale on ecosystem health was relatively small (Han et al., 2020). For instance, Dou and Kuang. (2019) found that the impact of urban expansion on green space in low altitude areas (below 500 m) was more significant than high altitude areas (above 2000 m). In addition, the significant negative correlations between the LSI and ecosystem health was found in karst cities, rather than non-karst cities. These results indicated that the ecological environmental in karst area was more sensitive to the irregular of urban form, which was consistent with previous studies (Peng and Wang, 2019; Shi et al., 2019). For example, Wang et al. (2019) indicated that karst landscapes were more fragile than non-karst landscape due to the unique geological setting and soil properties. The complex of urban form usually lead to the increase of potential traffic demand, which increases the number of patches, heterogeneity and decreased landscape stability. Furthermore, the PLADJ had a significant negative effect on ecosystem health with all types of cities, and the impact of urban form compactness on ecosystem health was more significant in the medium-scale and large-scale karst cities. The reason may be that the landscape was relatively fragmented in the high-proportion karst area (i.e., high percentage of rock outcrop and large slope variation), a compact and continuous urban form could improve the stability of ecosystem structure and maintain the sustainable health of ecosystems. For instance, Hou and Gao (2020) found that landscape fragmentation was more severe in karst cities than non-karst cities, especially the most serious fragmentation areas was mainly distributed in the karst areas with steeper slope. Furthermore, the NDVI and Night light were significant associated with ecosystem health within various types of cities. Note that the impact of the NDVI on ecosystem health was more significant in the karst cities than non-karst cities, which may be related to the implementation of a series of ecological engineering projects aimed at rocky desertification in karst areas (Wang et al., 2019). For example, Liao et al. (2018) found that 74% of the

Table 9
The relationship between urban expansion and ecosystem health under different geological environment.

Independent variable	Coefficient (Non-karst area)	Coefficient (The proportion of karst area >30%)	Coefficient (30%<The proportion of karst area <60%)	Coefficient (The proportion of karst area >60%)
TUA	−0.544***	−0.308**	−0.263*	−0.165**
PLAND	−0.546*	−0.201**	−0.379**	−0.369*
NP	−0.064	−0.014**	0.031	0.003
LPI	0.543	−0.047**	−0.147**	−0.072
LSI	0.102	−0.452***	−0.044**	−0.195***
PLADJ	−0.373**	−2.276***	−3.186*	−0.693***
COHESION	4.088	−0.581**	−0.994***	2.526
Night light	−0.091***	−0.024*	−0.021*	−0.006**
NDVI	0.271**	0.309*	0.316**	1.073***
Adjusted R^2	0.785	0.904	0.905	0.943
F-statistic	172.450	924.370	392.810	911.530
Prob (F-statistic)	0.000	0.000	0.000	0.000

Note: Significant at * 10% level, ** 5% level, *** 1% level.

study area showed an increasing trend of ecosystem health through the ecological restoration project, and the increase in karst areas was more obvious than non-karst areas. Thus, improving the effectiveness of ecological protection is conductive to achieve the coordination between urban expansion and ecosystem health.

3.3.5. Limitation and future directions

In this study, there are several limitations that are worth mentioning. First, the health of urban ecosystem was affected by a series of urban form metrics (i.e., the size and shape of urban patches), since only seven landscape metrics in this study were chosen to assess the impacts of urban expansion on ecosystem health, future studies should emphasize the selection and quantification of urban form metric to accurately describe the influence mechanism of urban expansion-ecosystem health relationship. Second, using coefficient matrix score measuring the spatial neighboring effect on ecosystem services existed serious constrains when considering the broad temporal and spatial scales. An improved method should be adopted to obtain more accurate at the pixel level in the following studies. Third, Although the panel data model have been proven to be effective for evaluating the relationship between explanatory variables and the independent variables (Chen et al., 2011), it is difficult to quantify the spatial dependence and heterogeneity of the relationship between urban expansion and ecosystem health. Thus, the relationship needs to be further analyzed using spatial regression models (i.e., the spatial lag model, the geographically weighted regression model, and the spatial Durbin model) in the following studies. Finally, the relationship between urban expansion and ecosystem health were explored only at the county scale in this study, future studies need to quantify and compare the impact of urban expansion on ecosystem health form a multi-scale view (i.e., county, city, and provincial scales).

4. Conclusions and policy implications

In recently years, exploring the impact of urban expansion on ecosystem health has gradually become a hot topic. However, analyzing the relationship between urban expansion and ecosystem health from a multi-perspective view is relatively rare, which limits the understanding of the urban expansion-ecosystem health relationship when considering different scenarios. Thus, taking 438 cities in Southwest China as the study area, this study attempted to explore the impact of urban expansion on ecosystem health from a multi-perspective view (population density, economic structure, urban area size, and geological environment). The results were as follows: First, regional ecosystem was relatively health when urban expansion was slow and dominated by edge-expansion type, but regional ecosystem was relatively weak when urban expansion was rapid and dominated by outlying type. Second, at the region scale, a regular and aggregated urban form had a significant positive impact on ecosystem health. Third, the TUA except for mega-sized cities had significant positive impact on ecosystem health within all types of cities. Fourth, the relationship between urban form and ecosystem health between cities with various population size showed significant difference. A regular urban form was benefit for ecosystem health at the medium-sized and large-sized cities. Fifth, the scale and irregular of urban land had a significant negative impact on ecosystem health within industry cities than the service cities, indicating that optimizing the industry structure was conducive to improve the health of urban ecosystem. Sixth, the significant negative correlations between the LSI and ecosystem health was found in karst cities, rather than non-karst cities, suggesting that the ecological environmental in karst cities was more sensitive to the irregular of urban core than non-karst cities. These findings would help to further understand which aspects of urban expansion affect ecosystem health under different scenarios and could provide a scientific basis for formulating reasonable urban planning. First, at the regional scale, policy-maker should avoid excessively irregular and scattered urban forms, since a complex and less aggregated urban forms could increase the fragmentation of landscape and decrease the connectivity of landscape, which ultimately lead to the decline of ecosystem stability. Second, the TUA except for mega-scale cities was significantly negatively correlated with ecosystem health with all types of cities. Thus, policy-maker should control the scale of urban expansion and optimize urban expansion mode for small-scale, medium-scale, and large-scale cities, in order to maintain the regional ecosystem health. Third, the urban planning should be adjusted when taking different population density into consideration. The results of our study proved that cities with small population density and relatively regular urban form were conductive to maintain the organization and self-operation of ecosystems. On the contrary, cities with high population density and irregular urban form would reduce the connectivity between landscapes and the supply capacity of ecosystem services. Fourth, it is necessary to optimize the structure of industry for achieving the intensive utilization of urban land and the sustainable health of ecosystems. Because the irregular and fragmentation of urban forms had been found to exert a significant negative impact on ecosystem health in the industrial cities. Fifth, due to unique geological environment, policy-maker should control the scale and number of urban core and improve the effectiveness of ecological protection as much as possible for karst cities.

CRediT authorship contribution statement

Weijie Li: Data curation, Writing - original draft. **Shiyou Xie:** Supervision. **Yong Wang:** Writing - review & editing. **Jing Huang:** Software. **Xian Cheng:** Conceptualization, Methodology.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.126341.

References

Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., DeFries, R.S., Diaz, S., et al., 2009. Science for managing ecosystem services: beyond the Millennium Ecosystem Assessment. In: Proceedings of the National Academy of Sciences., vol. 106, pp. 1305–1312, 5.

Chen, Y., Li, X., Zheng, Y., Guan, Y., Liu, X., 2011. Estimating the relationship between urban forms and energy consumption: a case study in the Pearl River Delta, 2005- 2008. Landsc. Urban Plann. 102, 33–42.

Chi, Y., Zheng, W., Shi, H., et al., 2018. Spatial heterogeneity of estuarine wetland ecosystem health influenced by complex natural and anthropogenic factors. Sci. Total Environ. 634, 1445–1462.

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., et al., 1997. The value of the world's ecosystem services and natural capital. Nature 387 (6630), 253–260.

Costanza, R., 1992. Toward an Operational Defifinition of Ecosystem Health. Ecosystem Health: New Goals for Environmental Management. Island Press.

Ding, Y., Li, F., 2017. Examining the effects of urbanization and industrialization on carbon dioxide emission: evidence from China's provincial regions. Energy 125, 533–542.

Dou, Y., Kuang, W., 2019. A comparative analysis of urban impervious surface and green space and their dynamics among 318 different size cities in China in the past 25 years. Sci. Total Environ. 706, 135828.

Fu, A., Chen, Y., Li, W., 2009. Ecosystem health assessment in the tarim River Basin by using analytical hierarchy process. Resour. Sci. 31, 1535–1544 (in Chinese with English abstract).

Han, R., Feng, C.C., Xu, N., Guo, L., 2020. Spatial heterogeneous relationship between ecosystem services and human disturbances: a case study in Chuandong, China. Sci. Total Environ. 721, 137818.

He, J., Pan, Z., Liu, D., Guo, X., 2019. Exploring the regional differences of ecosystem health and its driving factors in China. Sci. Total Environ. 673.

Hou, W., Gao, J., 2020. Spatially variable relationships between karst landscape pattern and vegetation activities. Rem. Sens. 12 (7), 1134.

Kang, P., Chen, W., Hou, Y., Li, Y., 2018. Linking ecosystem services and ecosystem health to ecological risk assessment: a case study of the Beijing-Tianjin-Hebei urban agglomeration. Sci. Total Environ. 636, 1442–1454.

Li, G., Li, F., 2019. Urban sprawl in China: differences and socioeconomic drivers. Sci. Total Environ. 673, 367–377.

Liao, C., Yue, Y., Wang, K., Fensholt, R., Tong, X., Brandt, M., 2018. Ecological restoration enhances ecosystem health in the karst regions of southwest China. Ecol. Indicat. 90, 416–425.

Liu, X., Li, X., Chen, Y., Tan, Z., Li, S., Ai, B., 2010. A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. Landsc. Ecol. 25, 671–682.

Luo, Q., Luo, Y., Zhou, Q., Song, Y., 2019. Does China's Yangtze River Economic Belt policy impact on local ecosystem services? Sci. Total Environ. 676, 231–241.

Mo, W., Wang, Y., Zhang, Y., Zhuang, D., 2017. Impacts of road network expansion on landscape ecological risk in a megacity, China: a case study of Beijing. Sci. Total Environ. 574, 1000–1011.

Peterson, G.D., 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. Ecosystems 5 (4), 329–338.

Peng, L., Wang, X., 2019. What is the relationship between ecosystem services and urbanization? A case study of the mountainous areas in Southwest China. J. Mt. Sci. 16 (12).

Peng, J., Liu, Y., Wu, J., Lv, H., Hu, X., 2015. Linking ecosystem services and landscape patterns to assess urban ecosystem health: a case study in Shenzhen City, China. Landsc. Urban Plann. 143, 56–68.

Peng, J., Shen, H., Wu, W., Liu, Y., Wang, Y., 2016. Net primary productivity (NPP) dynamics and associated urbanization driving forces in metropolitan areas: a case study in Beijing City, China. Landsc. Ecol. 31 (5), 1077–1092.

Peng, J., Liu, Y., Li, T., Wu, J., 2017. Regional ecosystem health response to rural land use change: a case study in Lijiang City, China. Ecol. Indicat. 72, 399–410.

Potter, C.S., Randerson, J.T., Field, C.B., Matson, P.A., Vitousek, P.M., Mooney, H.A., Klooster, S.A., 1993. Terrestrial ecosystem production: a process model based on global satellite and surface data. Global Biogeochem. Cycles 7, 811–841.

Rapport, D.J., Costanza, R., McMichael, A.J., 1998. Assessing ecosystem health. Trends Ecol. Evol. 13 (10), 397–402.

Rapport, D.J., Maffi, L., 2011. Eco-cultural health, global health, and sustainability. Ecol. Res. 26 (6), 1039–1049.

Rapport, D.J., Hildén, M., 2013. An evolving role for ecological indicators: from documenting ecological conditions to monitoring drivers and policy responses. Ecol. Indicat. 28, 10–15.

Styers, D.M., Chappelka, A.H., Marzen, & L.J., et al., 2010. Developing a land-cover classification to select indicators of forest ecosystem health in a rapidly urbanizing landscape. Landsc. Urban Plann. 94 (3–4), 158–165.

Shen, Y.-S., Lung, S.-C., 2020. Multiple impacts and pathways of urban form and environmental factors on cardiovascular mortality. Sci. Total Environ. 738, 139512.

Shi, K., Wang, H., Yang, Q., Wang, L., Sun, X., Li, Y., 2019. Exploring the relationship between urban forms and fine particulate (PM2.5) concentration in China: a multi-perspective study. J. Clean. Prod. 231, 990–1004.

Song, Y., Chen, B., Kwan, M.P., 2020. How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities. J. Clean. Prod. 246, 119018.

Su, M., Fath, B.D., Yang, Z., 2010. Urban ecosystem health assessment: a review. Sci. Total Environ. 408, 2425–2434.

Tao, Y., Zhang, Z., Ou, W., Guo, J., Pueppke, S.G., 2020. How does urban form influence pm2.5 concentrations: insights from 350 different-sized cities in the rapidly urbanizing Yangtze river delta region of China, 1998–2015. Cities 98, 102581.

Wang, C., Myint, S.W., Fan, P., Stuhlmacher, M., Yang, J., 2018. The impact of urban expansion on the regional environment in Myanmar: a case study of two capital cities. Landsc. Ecol. 33 (5), 765–782.

Wang, K., Zhang, C., Chen, H., Yue, Y., Zhang, W., Zhang, M., Qi, X., Fu, Z., 2019. Karst landscapes of China: patterns, ecosystem processes and services. Landsc. Ecol. 34, 2743–2763.

Xu, G., Jiao, L., Liu, J., Shi, Z., Zeng, C., Liu, Y., 2019. Understanding urban expansion combining macro patterns and micro dynamics in Southeast Asian megacities from 1990 to 2014: Bangkok, Ho Chi Minh City, and Manila. Sci. Total Environ. 660, 375–383.

Xia, C., Li, Y., Xu, T., Chen, Q., Ye, Y., Shi, Z., Liu, J., Ding, Q., Li, X., 2019. Analyzing spatial patterns of urban carbon metabolism and its response to change of urban size: a case of the Yangtze River Delta, China. Ecol. Indicat. 104, 615–625.

Xie, G.D., Zhang, C.X., Zhang, L.M., et al., 2015. Improvement of the evaluation method for ecosystem service value based on per unit area. J. Nat. Resour. 30 (8), 1243–1254 (In Chinese).

Yuan, Y., Chen, D., Wu, S., Mo, L., Tong, G., Yan, D., 2019. Urban sprawl decreases the value of ecosystem services and intensifies the supply scarcity of ecosystem services in China. Sci. Total Environ. 697, 134170.

Zhao, Y.T., Li, W.L., Chen, D., Yu, C., Zhao, X.L., Xu, J., Guo, X.L., 2017. Dynamic assessment of alpine pasture grassland ecosystem health—a case study from the Gannan region. Pratacult. Sci. 34 (1), 16–29.

Zhao, C.S., Yang, Y., Yang, S.T., Xiang, H., Wang, F., Chen, X., et al., 2019a. Impact of spatial variations in water quality and hydrological factors on the food-web structure in urban aquatic environments. Water Res. 153 (APR.15), 121–133.

Zhao, C., Pan, T., Dou, T., Liu, J., Liu, C., Ge, Y., Zhang, Y., Yu, X., Mitrovic, S., Lim, R., 2019b. Making global river ecosystem health assessments objective, quantitative and comparable. Sci. Total Environ. 667, 500–510.