Ecological Indicators 138 (2022) 108860

Contents lists available at ScienceDirect

Ecological Indicators

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

Original Articles

Exploring ecosystem responses to coastal exploitation and identifying their spatial determinants: Re-orienting ecosystem conservation strategies for landscape management

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ARTICLE INFO

Keywords:
Coastal ecosystem
Ecosystem services
Driving factors
Sustainable management

ABSTRACT

Coastal ecosystems provide important ecosystem services (ESs) and have been subject to conservation and restoration efforts in China for decades. However, ecosystem responses to coastal exploitation activity and their spatial determinants have not been sufficiently evaluated, which limits the efficacy of ecosystem restoration efforts. To fill these gaps, this study assessed the dominant change trends in ESs in southeastern China since the 1980s using an integrated biophysical model. Moreover, we explored the determinants of ESs, their spatial heterogeneity, and spillover effects via spatial econometrics and geospatial analysis approaches. The results indicate that coastal exploitation, particularly rapid urbanization and land reclamation, profoundly altered landscape composition and further affected ESs. In urbanization hotspots, rapid land use/cover conversion (i.e., wetland, woodland, and grassland losses) and increasingly intensive human activities have substantially lowered carbon stock, soil retention, and habitat quality services while increasing water yield and nitrogen export. Environmental, socioeconomic, and landscape variables were identified as important determinants of ES changes and exhibit significant spatial heterogeneity and spillover effects. Our findings indicate that such indicators are highly useful for ecosystem assessments, modeling, and forecasting for ES management and conservation efforts. The identified spatial determinants and their spillover effects demonstrate that regional landscape planning and ecosystem management must consider environmental, socioeconomic, and landscape indicators from a regionally integrated perspective and coordinate cross-border collaborations from neighboring areas to improve the efficacy of ecological projects. Our findings provide important references for scheme optimization and strategy adjustment for ES management, both in the study region and globally.

1. Introduction

Ecosystem services (ESs) refer to the goods and benefits derived from natural ecosystems (Nelson et al., 2009), which are now among the most important indicators for assessing global and regional ecosystem health, quality, and sustainability since the Millennium Ecosystem Assessment (2005). Because more than 60% of the world's natural ecosystem and subsequent ESs are threatened by land degradation (UNCCD, 2016, 2017), understanding ecosystem responses and ES dynamics as well as their determinants has become increasingly emphasized by academic organizations, international communities, government agents, and other stakeholders in policy making and strategy formulations (Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES),

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https://doi.org/10.1016/j.ecolind.2022.108860
Received 18 September 2021; Received in revised form 6 April 2022; Accepted 9 April 2022
Available online 15 April 2022

Nomenclature

Abbreviations	Full names
Ecosystem service assessment	
ESs	Ecosystem services
CS	Carbon stock
WY	Water yield
AP	Aquatic purification
SR	Soil retention
HQ	Habitat quality
NE	Nitrogen export
InVEST	Integrated Valuation of Ecosystem Services and Trade-offs
RUSLE	Revised universal soil loss equation
Landscape, environmental, and socioeconomic variables	
LUC	Land use/cover
COHESION	Patch cohesion index
DIVISION	Landscape division index
ENN	Mean Euclidian nearest-neighbor distance
IJI	Interspersion and Juxtaposition index
LSI	Landscape shape index
NP	Number of patches
PD	Patch density
PLADJ	Proportion of like adjacency
SHAPE	Mean shape index
SHDI	Shannon's diversity index
SPLIT	Splitting index
GDP	Gross domestic productivity
POPD	Population density
NDVI	Normalized Difference Vegetation Index
RF	Rainfall
TEM	Temperature
Others	
SPMs	Spatial panel models
SLM	Spatial lag model
SEM	Spatial error model
SDM	Spatial Durbin model
GWR	Geographically weighted regression
SWCPs	Soil and water conservation projects
ERPs	Ecosystem restoration projects

2015; UNCCD, 2016). Several studies have made great achievements in terms of ES evaluation methods, such as material assessment (Costanza et al., 2017; Schirpke et al., 2019), valuation accounting (Burkhard et al., 2014; Congreve and Cross, 2019), spatiotemporal change analysis (Castillo-Eguskitza et al., 2018), assessment of (non–)linear interactions (synergies and trade-offs) between ESs (Jiang et al., 2018; Aryal et al., 2019), identification of the dominant determinants of ES variations (Baró et al., 2017), and further practical applications of ES theory (Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), 2015). In addition, several sophisticated independent and integrated biophysical models have been developed for ES assessment, such as Integrated Valuation of Ecosystem Services and Trade-offs (InVEST; Sharp et al., 2018), the land utilization and capability indicator (Jackson et al., 2013), and artificial intelligence for environment and sustainability (Villa et al., 2014).

Previous studies in China have focused on quantifying, mapping, and monitoring ESs and their supply–demand dynamics as well as their driving mechanisms (Mao et al., 2019; Hou et al., 2020; Peng et al., 2020; Zhang et al., 2021). However, contributing factors that have been considered mainly include direct biophysical and anthropogenic factors such as temperature, rainfall, vegetation cover, and land use/cover (LUC), while other indirect factors that profoundly determine ES availability (e.g., landscape structure and socioeconomic change) have not received sufficient attention (Chen et al., 2019b, 2020b; Li et al., 2019; Jiang et al., 2021). Intensive human activities such as agricultural reclamation, urbanization, and industrial exploitation directly alter LUC and landscape composition, resulting in heterogeneous, discontinuous, and fragmented landscapes (Mitchell et al., 2015; Zhu et al., 2020; Meng et al., 2021). Moreover, landscape fragmentation substantially influences ES supply and demand capacity (Peng et al., 2020; Hou et al., 2020; Zhang et al., 2021). In addition, economic development and population growth brought about by urbanization and industrial exploitation also indirectly accelerate LUC transformations (Chen et al., 2019b).

To optimize landscape allocation and promote ecosystem sustainability, it is essential to reveal the driving mechanisms and spatial determinants of ESs (Chen et al., 2019b, 2020b; Jiang et al., 2021). The circulation and transportation of material and energy in ecosystems within a given unit (e.g., community, catchment, or region) generate spillover effects that impact surrounding areas because landscape composition and biophysical processes within and among each unit are interconnected (Chi and Ho, 2018; Meng et al., 2021). For instance, neighboring districts are more likely to be physically, socially, and economically connected than distant and non-adjacent districts (Chi and Ho, 2018). Similarly, ESs within an individual unit are not only influenced by local (internal) variables but also by external factors in neighboring units. Ecosystem degradation in an individual unit is likely to result in the deterioration of neighboring units (Chen et al., 2019b, 2020b). Thus, spatial information and spillover effects should be thoroughly investigated and considered in landscape planning and environmental conservation (Liu et al., 2021; Meng et al., 2021). Existing studies have not sufficiently identified geographic variations and determinants of ES spatial dependence and spillover effects (Chi and Ho, 2018; Jiang et al., 2021). Extant studies have typically concentrated on specific areas or local scales and ignored the spatial heterogeneity of critical determinants from a regional perspective, and the spillover effects of determinants and their consequences on strategy formulation and decisions regarding practical landscape planning have not been thoroughly examined (Chen et al., 2019b, 2020b; Wang et al., 2021). Considering the spatial autocorrelation and spillover effects in ESs and their drivers, which are necessary for understanding the driving mechanisms of ESs, the commonly applied statistical approaches in previous studies, such as gray correlation degree analysis (Yang et al., 2021), logistic regression (Cao et al., 2020), the partial least squares method (Li et al., 2019), the random forest approach (Xie et al., 2021), and multiple regression models (Xie et al., 2021), are not sufficient. The limitations of statistical approaches constrain the identification of spatial determinants of ESs and their practical applications (Jiang et al., 2021; Meng et al., 2021).

Southeastern China has experienced rapid coastal exploitation (such as industrial development, land reclamation, and mangrove deforestation for aquaculture) and urban expansion since the 1980s, accelerating the transformation of LUC from wetland, cropland, woodland, and grassland to built-up areas (Jia et al., 2018; Ren et al., 2019). These changes have subsequently caused or exacerbated agricultural pond loss (pond abandonment), landscape fragmentation, ecosystem degradation, environmental pollution, and other negative ecological consequences (Mao et al., 2018; Chen, et al., 2019c; Peng et al., 2020). For instance, frequent agricultural cultivation on steep croplands accelerates soil loss, which is the main source of river sediment (Chen et al., 2019a, 2020a, 2021). To alleviate soil loss and enhance ecosystem functions, several large-scale ecosystem restoration projects (ERPs), soil and water conservation projects (SWCPs), and catchment management projects have been initiated since the 1980s, particularly after 1990 (Ouyang et al., 2016; Li et al., 2020; Wang et al., 2020). Previous studies have reported that these projects achieved great progress in land degradation neutrality and ecosystem restoration, but the efficacy of these approaches should be further improved by coordinating ecosystem conservation and residents' livelihoods and reconciling trade-offs between dimensions (Cao et al., 2017, 2021; Chen et al., 2019a, 2020a; Li et al., 2020; Wang et al., 2020; Cai et al., 2021).

This study was designed to explore the responses of ESs to climate variation and landscape change via biophysical models and identify the spatial associations between ESs and determinants using spatial econometric approaches (LeSage et al., 2009). The main objectives were to (i) quantify the spatiotemporal changes of dominant ESs in the context of climate variability and human disturbances; (ii) explore spatial associations between multiple ESs and environmental, socioeconomic, and landscape variables, including their spatial variability and spillover effects; and (iii) discuss the practical implications of ES responses and their spatial determinants on ecosystem and land use management. Our findings are expected to contribute to policy formulations for designing and optimizing landscape planning and ecosystem conservation efforts, which will eventually facilitate win–win outcomes of sustainable

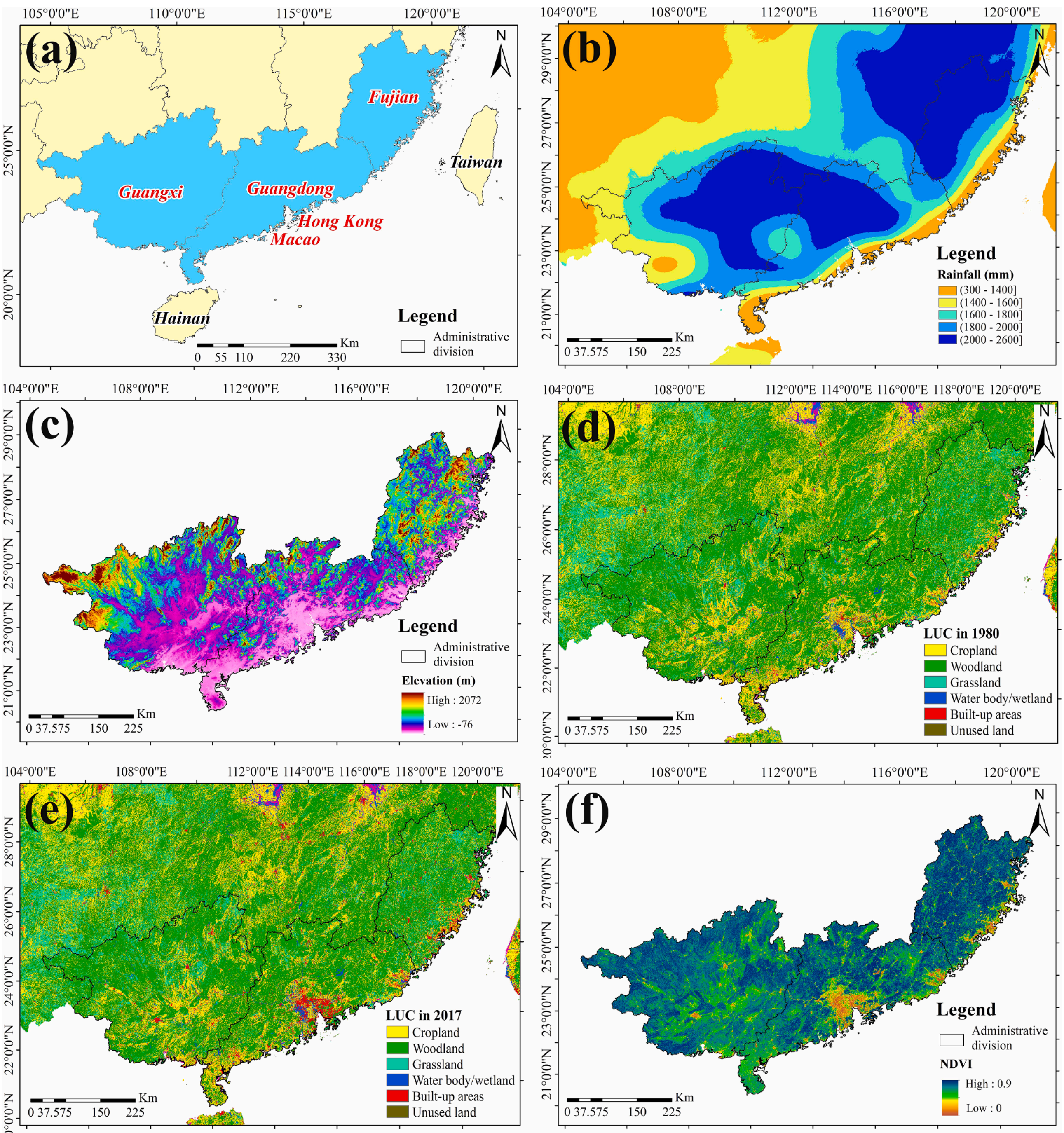

Fig. 1. (a) Geographic location of study area; spatial patterns of (b) rainfall for annual mean level, (c) elevation, LUC maps in (d) 1980 and (e) 2017, and (f) vegetation cover for annual mean level.

socioeconomic development and ecosystem management.

2. Materials and methods

2.1. Research area

The coastal regions in southeastern China (106°13′–121°15′E, 21°11′–29°17′N), including the Guangdong, Guangxi, and Fujian provinces, cover a total area of 54.13 km^2, approximately 5.6% of the total area of China (Fig. 1). This region has a humid subtropical monsoon climate, with an annual mean rainfall of approximately 1800 mm and strong spatial and temporal variability. The overall pattern of rainfall declines from northeast to southwest (from coast to inland), and more than 70% of the rainfall is concentrated between April and September. The annual mean temperature ranges from 14 °C to 25 °C. Because of the relatively high heat conditions and abundant water resources, the vegetation cover for this area is much higher than the national average; in particular, the forest coverage rate of subtropical evergreen broad-leaved forests and coniferous forests exceeds 50% (Chen et al., 2019a, 2020a). The regional landform is dominated by low mountains and hills. The main soil types are red soil and paddy soil, but the soil layer is shallow and soil nutrient content was relatively low (Chen et al., 2019a; Chen et al., 2020a). The population in the three provinces is approximately 200 million, accounting for one-seventh of the total population of China. To meet the demands of food and economic development, this area underwent extensive agricultural reclamation and rapid socioeconomic development, specifically in the coastal zone, since the implementation of "Reform and Opening Up" policy in the late 1970s. The study area has developed into one of the most important production areas for grain, industrial crops, and marketable fruits globally (Wang et al., 2020). In addition, rapid urbanization and economic development have attracted international talent, capital, and trade to this area, and the regional total GDP accounted for approximately 17.4% of China's total GDP in 2019. However, extensive agricultural reclamation, rapid urbanization, and other unsustainable activities have accelerated soil erosion (Wang et al., 2020), ecosystem degradation (Ouyang et al., 2016), and environmental deterioration (Peng et al., 2020) and caused other ecological consequences, such as water and soil pollution, carbon loss, and biodiversity degradation (Cai et al., 2021; Zhang et al., 2021). To mitigate and reverse land degradation and promote ecosystem restoration, massive ERPs and SWCPs were implemented including the SWCPs in the Pearl River and Min River, converting cropland to woodland and grassland projects in the red soil hilly region, and multiple urban landscape projects in the Pearl River Delta (Li et al., 2020). The dominant measures are afforestation, reforestation, and forest restoration via artificial and natural approaches, which are implemented to improve vegetation cover and mitigate soil loss (Chen et al., 2019a; Chen et al., 2020a).

2.2. Conceptual framework and workflow

Five ESs, including soil, water, carbon, and biodiversity sectors, which are important for environmental sustainability and human well-being, were selected for analysis (Ma et al., 2015; Ouyang et al., 2016). In general, ESs are closely interconnected and exhibit complex interaction and feedback mechanisms (such as trade-offs and synergism); they are often concurrently driven by landscape composition and structure, environmental conditions (such as vegetation cover, temperature, and rainfall), and socioeconomic indicators such as GDP and population density. Specifically, climate conditions are mostly controlled by the monsoon system (IPCC, 2019), while other factors are substantially influenced by human disturbances and interventions, such as urbanization, coastal exploitation, agricultural reclamation, and ecosystem conservation projects (Mao et al., 2018). For instance, urban construction and industrial exploitation convert (semi-)natural ecosystems (i.e., woodlands, grasslands, wetlands, and croplands) to built-up areas, which alter LUC, landscape structure, and vegetation cover and further result in profound ES changes. Therefore, landscape patterns, ecological processes, and functions, which are key aspects of ESs, are interconnected, and land use managers and stakeholders should maintain and improve ecosystem stability and functions by optimizing landscape composition and appropriately reconciling and balancing contradictions, conflicts, and trade-offs among cross-sectoral interests in strategy formulations for land use planning and governance.

As shown in the workflow of this study (refer to Fig. 2), three study phases were carried out: data preparation and pre-processing, ES quantification, and spatial association analysis. Multiple datasets were re-projected and resampled before inputting into biophysical models, and then, the ESs were quantified and analyzed in terms of spatiotemporal dimensions. The spatial associations between ESs and related environmental, socioeconomic, and landscape variables were identified via spatial econometrics and geographically weighted regression, which revealed the global regression relationship and its spatial variability, respectively. Determining these associations and their variability is expected to support strategy formulations for landscape planning and ecosystem conservation.

2.3. Data collection and processing

Summaries of the research data, including data source, spatial resolution, timespan, and usages, are shown in Table S1. LUC maps were interpreted from middle-resolution remote sensing images, derived by Landsat instruments based on manual visual interpretation with the assistance of machine learning techniques (Liu et al., 2005a,b, 2014). The overall accuracy of interpretation results reached more than 90% after field validation and further correction, and they met the requirements for middle-scale spatial analysis and ES assessment (Liu et al., 2014). As LUC maps are used as important input parameters for InVEST models and other ES assessment tools, we further verified the dataset accuracy using the Google Earth Engine. Cross-validations between samples (n = 400) from Google Earth maps (i.e., considered as observed results) and interpreted LUC maps demonstrated that consistency for LUC categories was higher than 93%. More details about dataset generation, accuracy verification, and potential applications are provided in Liu et al. (2005a,b, 2014). In this study, the fine-resolution LUC maps were used to calculate landscape metrics, and the associated definitions, abbreviations, and calculation processes are provided in McGarigal et al. (2012). To maintain scale consistency for ES assessments, the LUC maps were resampled to a 1 km × 1 km grid with the aim of matching the resolution of other input parameters. In addition to the LUC maps, vegetation, soil properties, and road/railway maps and the digital elevation model were also collected to estimate vegetation, soil, and topography factors in the SR assessment and support CS and HQ assessments (Table S1). Meteorological records, including those of temperature, rainfall, radiation, and wind speed, were collected from more than 100 stations in the research area and surrounding areas to assess WY and AP functions. The missing data only accounted for<5% of the total data, thus indicating that the data used in this study were of good quality and could be used as inputs for interpolation modeling. In the WY assessment, the estimated WY was compared with the observed runoff to verify the accuracy of the results. Thus, annual runoff records at eight gauging stations were collected from the catchment governance departments.

Since this study assessed the long-term ES over the period 1980–2017, which did not match the time period of even a single Normalized Difference Vegetation Index (NDVI) dataset, this study applied two NDVI datasets, i.e., the long-term data record (LTDR) AVH13C1 product (Pedelty et al., 2007) and the Moderate-resolution Imaging Spectroradiometer (MODIS) MOD13Q1 dataset (Huete et al., 2011), to reflect vegetation cover conditions and quantify vegetation factors for SR assessment over multiple periods. The goal of the LTDR AVH13C1 dataset was to produce a consistent dataset from the

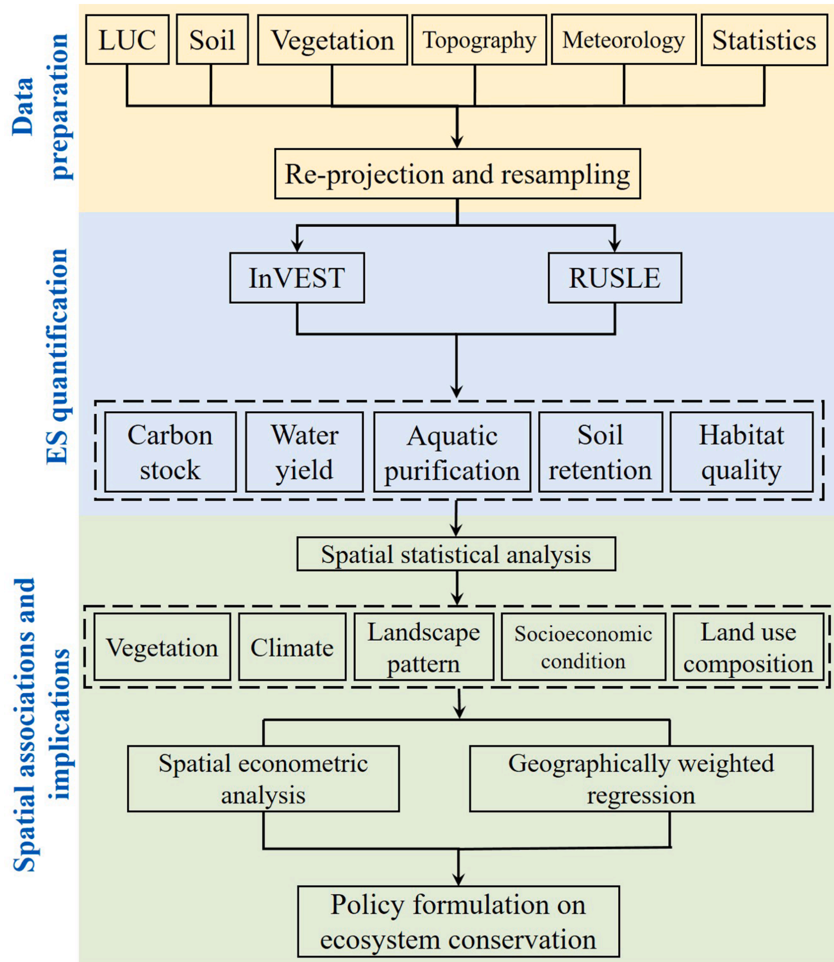

Fig. 2. Workflow of this study.

Advanced Very High Resolution Radiometer (AVHRR) and MODIS instruments to aid long-term ecological studies (Pedelty et al., 2007; Beck and Goetz, 2011). Although all datasets were subjected to radiometric calibration and geometric and atmospheric corrections, further consistency testing was conducted by cross-comparing three datasets. The cloud effects were removed according to the approach given by Sun et al. (2015). To identify the socioeconomic drivers of the spatial variability of ESs, this study adopted population density and GDP as indicators. The night light intensity dataset (Elvidge et al., 2013) was used to indicate the intensity of human activities and further estimate grid-scale GDP and population density based on spatial regression between image lightness and the measured statistical records (Jiang et al., 2002; Liu et al., 2005a, b; Huang et al., 2014). All datasets, except for NDVI datasets, were first re-projected to unify the projection systems and then resampled to a resolution of 1 km × 1 km before further analysis to reduce uncertainties arising from different datasets.

2.4. ES selection and quantification

According to the Common International Classification for ESs scheme (Czúcz et al., 2018) and the Millennium Ecosystem Assessment (Ma et al., 2015), ESs are normally divided into four categories—provision, regulation, support, and cultural services. Among them, provisioning and regulating services play fundamental roles in maintaining and enhancing human well-being (Ma et al., 2015). However, only a few ESs can be assessed by widely recognized biophysical models under the condition of limited data availability, with reliable results previously reported (Ouyang et al., 2016). Previous studies conducting ES assessments at the national and regional scales in China (e.g., Ouyang et al., 2016; Peng et al., 2020; Hou et al., 2020; Zhang et al., 2021), particularly in the coastal areas in southern China, have mostly chosen dominant ESs that are closely associated with landscape dynamics as indicators in the assessment framework (Chen et al., 2019b, 2020b; Wang et al., 2021). Therefore, considering the regional natural environment, data availability, assessment feasibility, and existing cases, we selected five dominant ESs—carbon stock (CS), water yield (WY), aquatic purification (AP), soil retention (SR), and habitat quality (HQ)—as indicators to assess ecosystems' response to land dynamics caused by ecosystem conservation and restoration measures as well as by coastal exploitation, including urbanization and reclamation. Specifically, the AP service was indicated by nitrogen export (NE) in this study. Due to the water-related ESs including WY, AP, and SR are normally affected by rainfall variability, which further alters ES evaluation conclusion (Ouyang et al., 2016), this study separately quantifies WY, AP, and SR in real rainfall and annual mean rainfall scenarios. The former scenario refers to the assessment result using real rainfalls in eight time nodes as input parameters, while the latter one reflects the ESs under period average level of rainfall from 1980 to 2017. The specific assessment methods and fundamental equations for each ES are provided in the Appendix.

2.5. Statistical approaches

2.5.1. Identifying spatial autocorrelations within spatial units

Global spatial autocorrelation indicated by Moran's I coefficient (Dall'erba, 2009) was applied to reveal the overall spatial correlation of

ESs within the study unit (i.e., county and other districts). Moran's I ranges between − 1 and 1, which reflects the positive and negative spatial correlations (i.e., spatial agglomeration) via positive and negative values, respectively (Dall'erba, 2009). However, a value of zero indicates that no spatial correlation was observed between the study units. The calculation equations are as follows:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j\neq 1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (1)$$

where n denotes the number of spatial units; x_i and x_j represent the zonal average values of ESs in units i and j, respectively; and w_{ij} represents the spatial matrix.

2.5.2. Investigating global associations via spatial econometric models

This study adopted three spatial econometric models to explore the associations and spillover effects of ESs. In contrast to traditional econometric models (e.g., logistic regression and multiple regression models), which are built on the unrealistic assumption that all explanatory variables are independent, stationary, or structurally stable (LeSage et al., 2009), spatial econometric models allow for spatial associations between specific and other variables because many socioeconomic and environmental indicators are spatially related and highly interconnected (Chaurasia et al. 2020; Cai et al., 2021). Previous traditional econometric models did not sufficiently consider the spatial correlations of regression variables, thereby leading to inaccurate results (Chen et al., 2019b, 2020b; Meng et al., 2021). As demonstrated in Fig. 3 and Tables S2–S6, the Moran's I scatterplots for the ESs presented close correlations with spatial aggregations of high and low values, and most of the points fell within the first and third quadrants, indicating that ESs tended to be adjacent and spatially autocorrelated. Thus, traditional econometric models are not applicable in this case. Accordingly, three spatial panel models (SPMs), namely, the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) (LeSage et al., 2009), were adopted to reveal the spatial spillover effects of landscape, environmental, and socioeconomic variables on ESs. The fundamental equations of SLM, SEM, and the general form of the two models, SDM, are expressed by Eqs. (2), (3), and (4), respectively:

$$LnY_{it} = \rho wLnY_{it} + \alpha_i LnX + \alpha_0 + \delta_{it}, \delta_{it}\ N\left(0, \mu_{it}^2\right) \quad (2)$$

$$LnY_{it} = \alpha_0 + \alpha_i LnX + \delta_{it}, \delta_{it} = \tau w\delta + \varphi_{it}, \varphi_{it}\ N\left(0, \mu_{it}^2\right) \quad (3)$$

$$LnY_{it} = \rho wLnY_{it} + \alpha_0 + \alpha_i LnX + \gamma_i wLnX + \delta_{it} \quad (4)$$

where ρ reflects the significance of the spatial autocorrelation of ESs between specific and neighboring counties. LnX denotes the socioeconomic, environmental, and landscape determinants that influence ESs, and $wLnY_{it}$ and $wLnX$ reflect the spatial lag term of the dependent and independent variables, respectively (i.e., the spatial spillover effect from surrounding counties). τ, φ_{it}, and δ_{it} represent the spatial

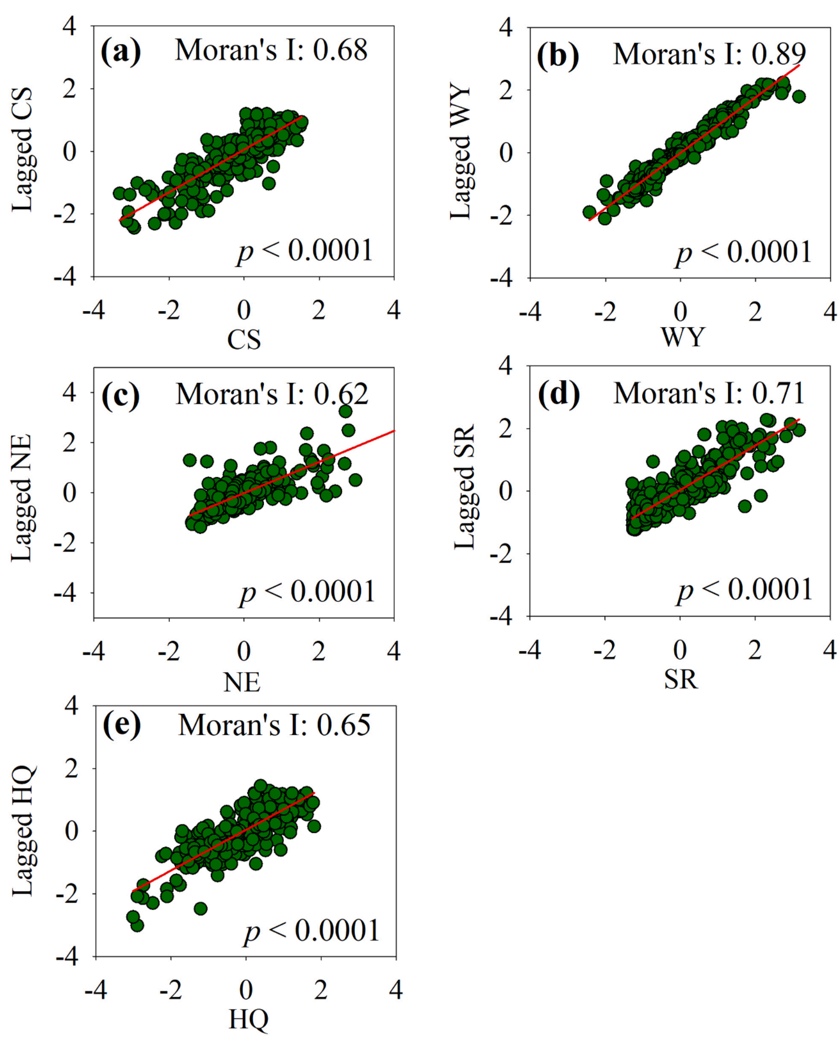

Fig. 3. Moran's I scatterplots of ecosystem services (ESs): (a) carbon stock (CS), (b) water yield (WY), (c) aquatic purification (AP), (d) soil retention (SR), and (e) habitat quality (HQ).

autocorrelation, random error, and disturbance terms, respectively. γ_i is the coefficient of the parameter $wLnX$ that must be determined, and w is the spatial weight matrix.

Considering the spatial spillover effect, the partial differential approach (Elhorst, 2014) was applied to estimate the direct and indirect effects of the environmental, socioeconomic, and landscape variables on ESs by decomposing the coefficients of the spatial model (LeSage et al., 2009).

2.5.3. Revealing the spatial variability of associations between variables

To quantify the effects of landscape metrics and environmental and socioeconomic variables on ESs, the GWR approach was applied to investigate the spatial heterogeneity of associations between two or more variables. GWR is widely applied in geospatial analysis because it allows for the non-stationarity of spatial variables, which potentially influences the spatial variability of associations between related variables (Zhu et al., 2020; Jiang et al., 2021). The principle equations of GWR are expressed as follows:

$$y = \eta_0 + \sum_{m=1}^{M} \eta_m x_m + \epsilon \tag{5}$$

$$y_a = \eta_0(o_a, p_a) + \sum_{b=1}^{N} \eta_b(o_a, p_a) x_{ba} + \sigma_a \tag{6}$$

where y_a represents the value of a specific ES, x_{ba} denotes the identified landscape metrics and environmental and socioeconomic variables that influence ESs, and N is the number of spatial units involved in spatial analysis. (o_a, p_a) represents the location of sample a, $\eta_0(o_a, p_a)$is the intercept at location a, and $\eta_b(o_a, p_a)$ represents the local estimated coefficient of the independent variable x_{ba}. σ_a is the random error term in the analysis. This study applied the Gaussian function to determine the weight and Akaike information criterion method to determine the optimal bandwidth (Zhu et al., 2020).

3. Results

3.1. Spatiotemporal changes in ESs

The spatial patterns of ESs presented significant spatial similarity and homogeneity for adjacent units, as indicated by the high Moran's indexes shown in Fig. 3 and Tables S2–S6. High and low values of ESs tend to be adjacent, and the scatter diagrams of ESs are mainly distributed in the first and third quadrants, which illustrates that ES patterns are characterized by high–high and low–low aggregations. As shown in Figs. 4 and 5, the spatial patterns of CS and HQ services have declined from inland to the coast, and they have maintained a stable pattern over the past four decades. Similarly, the SR services remained stable, but the high and low values were located in the inland and coastal areas, respectively. However, the LUC changes at the local scale caused by urbanization (Fig. 2(d–e)) resulted in significant declines in CS and HQ, particularly in the southeastern Guangdong Province (i.e., the Pearl River Delta). In terms of the WY and AP services, both presented a large fluctuation in accordance with rainfall variability, and

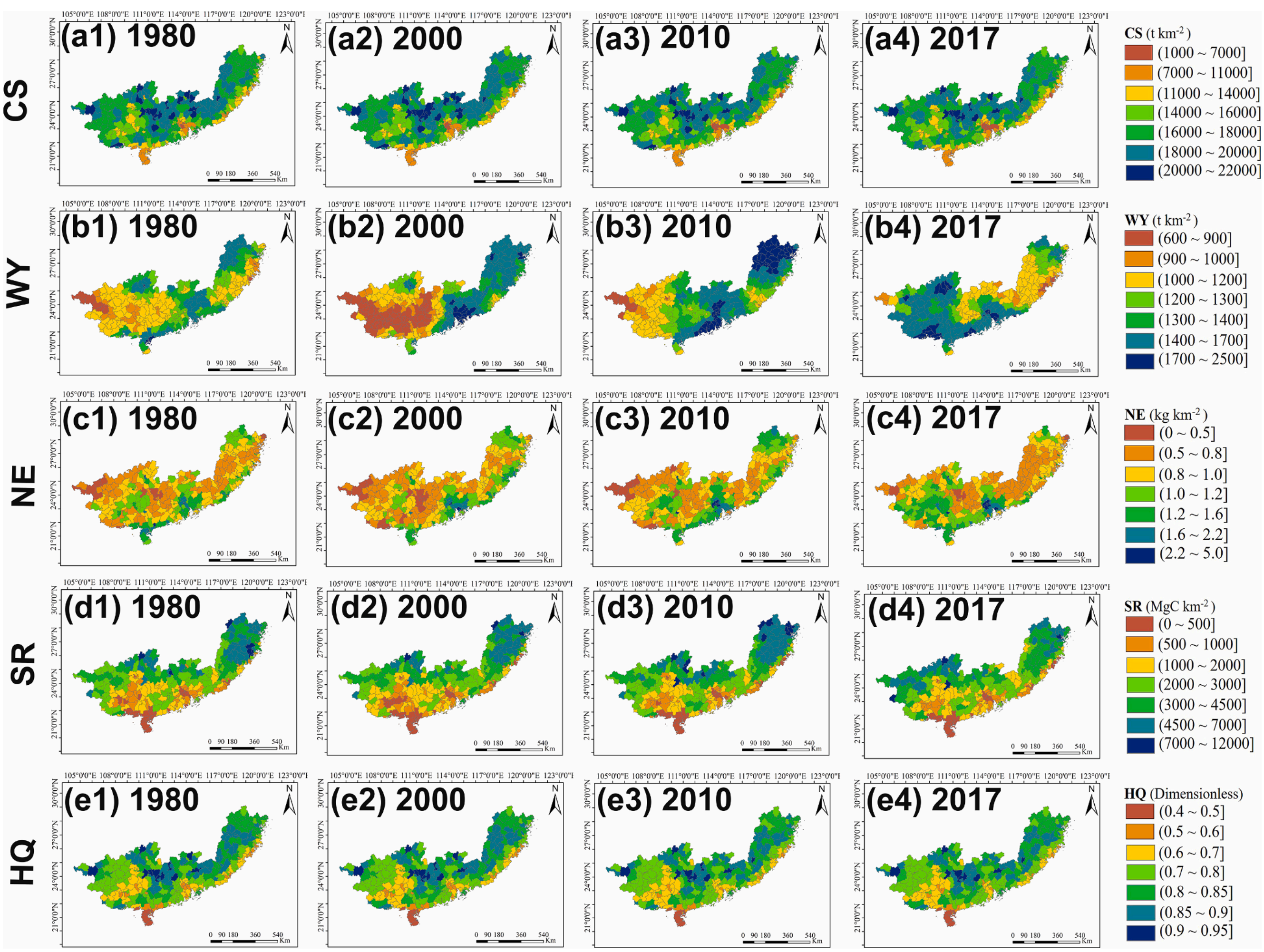

Fig. 4. Spatial patterns of ESs in 1980, 2000, 2010, and 2017: (a) CS, (b) WY, (c) AP, (d) SR, and (e) HQ.

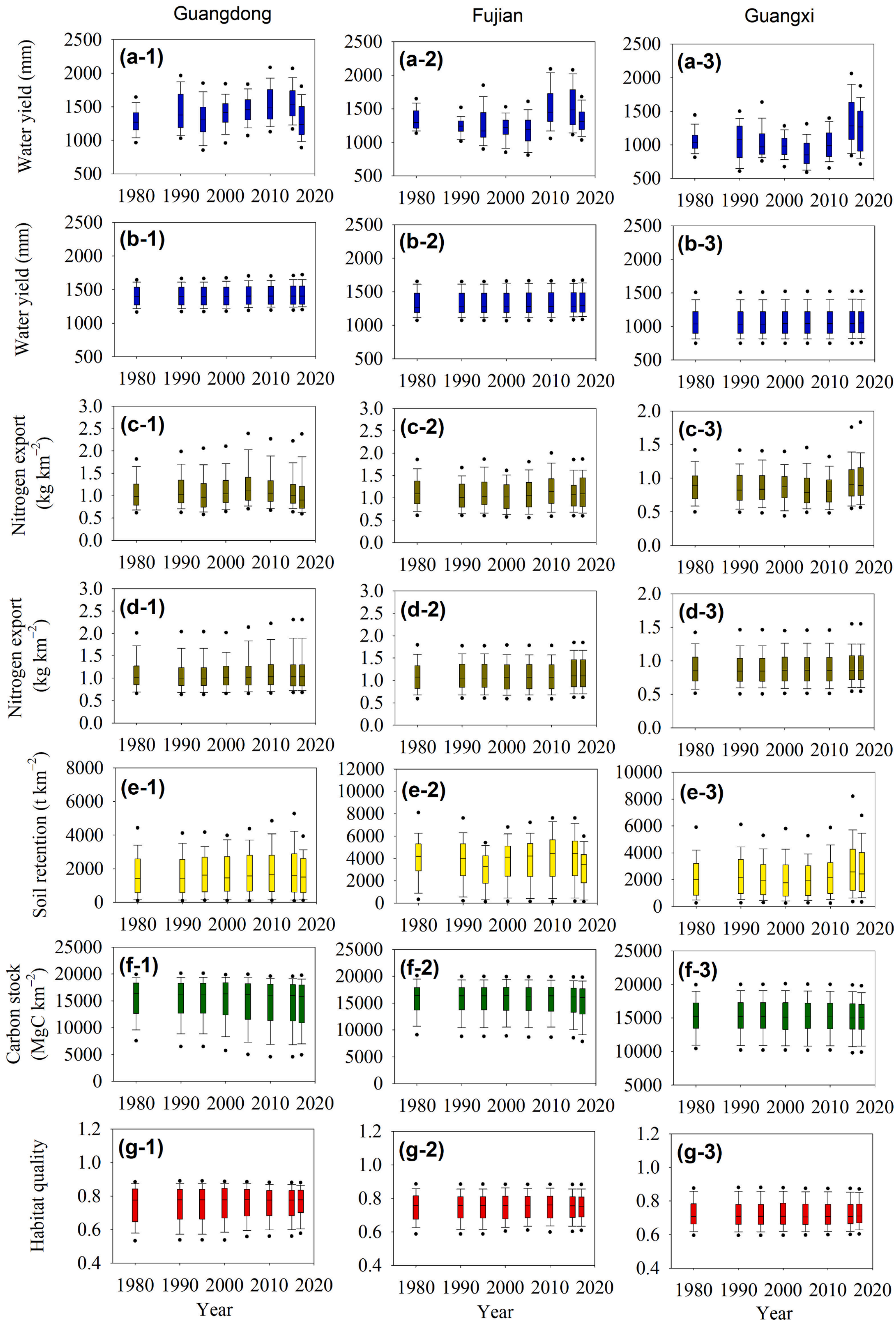

Fig. 5. Temporal changes in ESs from 1980 to 2017: (a) and (b) WYs under real rainfall and annual mean rainfall scenarios, respectively. (c) and (d) NEs under real rainfall and annual mean rainfall scenarios, respectively. (e) SR under real rainfall scenario. (f) CS (g) HQ.

their spatial patterns were not stable from 1980 to 2017. In the scenario of removing the effect of rainfall variability (i.e., annual mean rainfall scenario), the spatial patterns of WY and NE exhibited relatively stable patterns.

3.2. Spatial determinants of ESs

The correlation analyses between multiple ESs demonstrated that five categories of ESs were closely correlated, with some reaching significance ($p < 0.01$; Fig. 6). In Fujian Province, the correlations among CS, HQ, SR, and WY were found to be significant ($p = 0.001$), while those for NE and WY were not. Regarding the Guangdong and Guangxi provinces, the correlations among multiple ESs were not as significant as those in Fujian Province, although significant relationships ($p < 0.0001$) were also identified in NE versus WY. No significant trade-offs were identified between several ESs because the negative correlations did not pass the significance test. In contrast, the synergies were presented among CS, HQ, SR, and WY in Fujian Province as well as WY versus NE in Guangdong and Guangxi.

Correlation analyses (Fig. 7) and SPMs (Tables 1 and 2) showed that GDP and population density were negatively correlated with CS, HQ, and SR, while positively associated with NE and WY. This demonstrated that intensive human activities weakened CS, HQ, and SR services and increased WY and NE, which could be attributed to the increase in the area of the impermeable layer and the discharge of anthropogenic pollutants (Peng et al., 2020; Zhang et al., 2021). Rapid urbanization processes negatively impact natural vegetation (e.g., wetlands, woodlands, and grasslands) and weaken their services, such as CS, HQ, and SR. In contrast, increases in built-up and construction areas reduce rainfall infiltration and increase land surface runoff. Additionally, the increase in chemical substance usage and pollutant discharges inevitably increases NE. SPMs (i.e., LPM, EPM, and DPM) (Tables 1 and 2) also show that ESs are associated with other environmental and landscape variables, such as temperature, rainfall, vegetation cover, and multiple landscape metrics. In addition, the spatial determinants of ESs exhibited significant direct and indirect effects (Table 3). Changes in determinants in local areas not only influence ESs in local units but also profoundly alter ESs in the surrounding areas. For instance, GDP and population density not only negatively contribute to the CS and SR of local units but also exhibit negative effects on CS and SR in surrounding areas. However, these negative effects are not significant. In contrast, GDP and population density exhibit significantly positive effects on WY and AP in local units. In terms of spatial variability in the determinants of multiple ESs (Fig. S1), the spatial patterns of the weighted regression coefficients of socioeconomic variables (as an example) show strong spatial heterogeneity at the county scale.

4. Discussion

4.1. Spatial associations between ESs and determinants and their causes

This study demonstrated that environmental and socioeconomic variables and landscape metrics were significantly correlated with multiple ESs (Tables 1 & 2 and Fig. 7), which could be applied as important indicators to monitor ecosystem states and reflect ecosystem functions, thus further directing landscape planning and optimization. These findings are essentially consistent with existing studies that also identified the close spatial associations between landscape structure and ESs (e.g., Mitchell et al., 2015; Chen et al., 2019b, 2020b; Jiang et al., 2020, 2021). Normally, material and energy transport within ecosystem sub-units are closely connected to landscape composition and structure (Mitchell et al., 2015). For example, the afforestation efforts in ERPs and SWCPs profoundly alter landscape patterns such as patch shape and composition, which further mitigate runoff generation and soil loss formation and transportation (Jiang et al., 2020; Li et al., 2020). Landscape elements such as corridors, nodes, and patches directly influence ecological processes and functions, such as species migration and biodiversity maintenance, and further alter the ecosystem state (Mitchell et al., 2015). As one of the environmental variables, NDVI positively correlates with SR and HQ (Table 2); this is because vegetative cover plays an important role in SR services via the root systems of vegetation (Jiang et al., 2020; Li et al., 2020) and facilitates the formation of suitable habitats for animal species (Zhu et al., 2020). In contrast, high vegetation cover, as reflected by NDVI (i.e., woodland landscape) exhibits negative effects on WY (Table 1); this is because canopy evaporation and soil transpiration processes consume water resources, which leads to WY decline, particularly in arid areas confronted with water scarcity (Jiang et al., 2018, 2021). Similarly, rainfall and

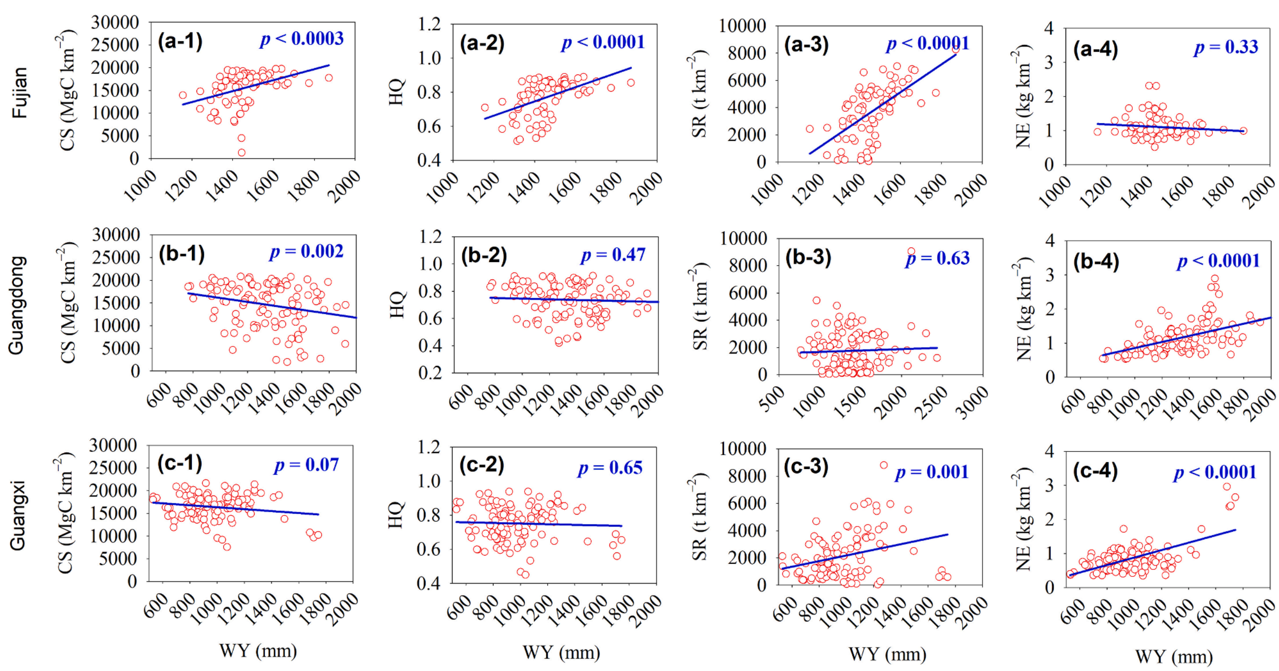

Fig. 6. Correlations between multiple ESs for three districts: (a) Fujian, (b) Guangdong, and (c) Guangxi.

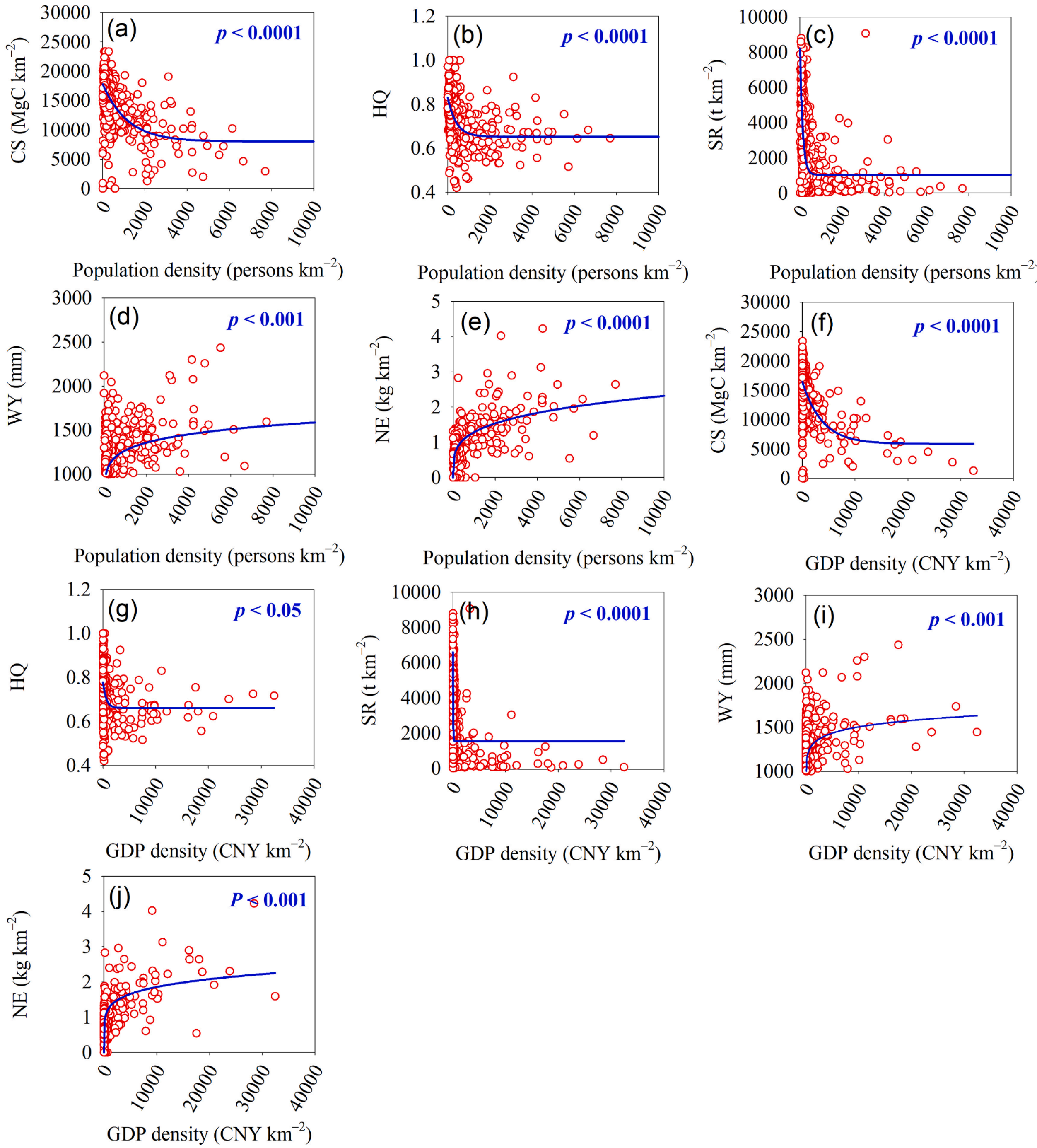

Fig. 7. Correlations between multiple ESs and GDP and population density for three studied districts.

temperature present positive and negative associations, respectively, for both WY and AP (Table 1). This is because rainfall is an important water source, which increases runoff yield, while temperature induces the opposite effect on runoff yield by promoting evapotranspiration in the water cycle (Jiang et al., 2018).

The socioeconomic variables (i.e., GDP and population density) negatively correlate with CS, SR, and HQ, while showing positive associations with WY and AP (Tables 1 & 2 and Fig. 7) due to built-up areas and rural settlements and their ecological and hydrological impacts (Hansen et al., 2018; Leibowitz et al., 2018). Natural ecosystems such as wetlands, woodlands, and grasslands exhibit strong hydrological regulation capacity, including water quantity and quality, which reduces the risk of flooding and water pollution (Leibowitz et al., 2018; Chen et al., 2019c). However, an increase in the impervious layer in the urbanization process directly leads to an increase in WY and subsequent urban waterlogging (i.e., urban flood disasters) under extreme climate conditions (Leibowitz et al., 2018; Zhang et al., 2021). The increasing usage of chemical substances also exacerbates pollutant discharge through domestic and industrial sewage (Lassaletta et al., 2010; Wang et al., 2021). Urbanization and associated socioeconomic development lead to rapid losses of mangroves and coastal wetlands, aggravation of landscape fragmentation, and further weakening of ESs (i.e., SR, CS, and HQ), which result in serious ecological consequences, including ES degradation by carbon loss, water pollution, soil loss, and natural habitat degradation (as shown in Figs. 4–5). For instance, pesticides, chemical additives, and antibiotics for aquaculture are discharged into rivers,

Table 1
Spatial associations between ESs (i.e., CS, WY, and AP) and related environmental, socioeconomic, and landscape variables using SPMs (i.e., SLM, SEM, and SDM).

Independent variables	CS			WY			AP		
	SLM	SEM	SDM	SLM	SEM	SDM	SLM	SEM	SDM
NP	0.393**	0.414**	0.432**	0.009	0.005	0.005	−0.00005	−0.00004	−0.0001
SHAPE	3359***	3887.4***	3424.5***	−104.47**	−175.1***	−179.04***	−0.437***	−0.415**	−0.472**
ENN	−2.157**	−1.131	−1.959**	−0.005	0.009	0.043	−0.0007***	−0.0008***	−0.0005**
PLADJ	105.8**	85.698	119.81**	−3.754	−3.374	−4.182	−0.011	−0.002	−0.010
IJI	42.033***	39.913***	37.141***	1.055**	0.05	0.392	0.002	0.0002	0.0003
COHESION	−508.57**	−529.79*	−685.52**	−6.629	4.411	−1.041	0.051	0.0538	0.092
DIVISION	−1075.9	−295.47	−181.01	−17.559	−28.351	−34.507	0.453**	0.368**	0.323*
SPLIT	−44.12	−26.929	−47.809	2.031	1.792	2.615	0.003	0.003	0.007
SHDI	−3099.4***	−4436.3***	−3807.8***	−80.682*	19.294	−15.29	−0.299*	−0.012	−0.041
GDP	−0.235***	−0.303***	−0.267***	0.001	0.005**	0.005***	0.00002**	0.00003***	0.00003***
POPD	−0.228***	−0.320***	−0.288***	0.006***	0.006***	0.006**	0.00005***	0.00006***	0.0001***
TEM	−20.75***	−35.293***	−66.232***	−0.126	−1.075	−1.273*	0.003***	0.005***	0.006**
RF	0.107***	0.061	−0.214	0.027***	0.055***	0.031***	0.00003***	0.00005***	0.00004
NDVI	10736***	10882***	11280***	−15.338	−131.47*	−83.767	−0.338	−0.450	−0.468
w*NP			−0.111			0.017			−0.00002
w*SHAPE			−1679			48.449			−0.190
w*ENN			−2.545			0.024			0.001**
w*PLADJ			74.25			−3.492			−0.059***
w*IJI			−6.334			1.219			0.008**
w*COHESION			748.39			−24.704			−0.099
w*DIVISION			−1991.2			−54.349			−0.006
w*SPLIT			−31.163			3.442			0.009
w*SHDI			5265.2***			−161.520*			−1.244***
w*GDP			0.233***			−0.009**			−0.00004***
w*POPD			0.198**			0.005			−0.00001
w*TEM			62.925***			1.165			−0.005*
w*RF			0.296**			−0.008			−0.00002
w*NDVI			731.94			86.045			−0.793
w*CS/WY/AP	0.356***		0.579***	0.784***		0.822***	0.482***		0.545***
w*μ		0.692***			0.941***			0.603***	
R^2	0.898	0.913	0.921	0.95	0.956	0.956	0.735	0.746	0.764
Adjusted R^2	0.893	0.909	0.917	0.948	0.954	0.953	0.723	0.734	0.753
σ^2	1,783,600	1,546,200	1,385,000	4960.3	4719.2	4420.9	0.075	0.073	0.067
Log − likelihood	−2666.742	−2660.458	−2636.298	−1781.269	−1796.923	−1767.587	−46.870	−47.936	−31.837

Notes: ***$p \le 0.01$, **$p \le 0.05$, *$p \le 0.1$. NP: number of patches, SHAPE: mean shape index, ENN: mean Euclidian nearest-neighbor distance, PLADJ: proportion of like adjacency, IJI: Interspersion and Juxtaposition index, COHESION: patch cohesion index, DIVISION: landscape division index, SPLIT: splitting index, SHDI: Shannon's diversity index, GDP: gross domestic productivity, POPD: population density, TEM: temperature, RF: rainfall, NDVI: normalized difference vegetation index.

resulting in water quality deterioration (UN-Water, 2018). It is estimated that the total amounts of nitrogen and phosphorus discharged annually from mariculture ponds into the ocean reach 47,700 tons and 3750 tons, respectively (Yang et al., 2017). Similarly, excessive nitrogen and phosphorus additions and the unrestricted use of antibiotics and chemicals lead to coastal seawater pollution in various developing countries (Ottinger et al., 2016). In addition to the negative consequences examined in this study, the loss and degradation of natural habitats further aggravates biodiversity degradation, and wetland loss weakens the natural ecosystem's capacity to regulate the urban heat island effect and haze (Wang et al., 2021; Zhang et al., 2021).

The spatial spillover effects between ESs and their determinants (Table 3) occur because landscape compositions and biophysical processes are interconnected (Chi and Ho, 2018; Meng et al., 2021). ES changes in an individual unit are determined by both local (internal) variables and external factors from neighboring units (Chi and Ho, 2018). Therefore, ES decline caused by landscape fragmentation and other factors within an individual unit is likely to result in the deterioration of neighboring units (Chen et al., 2019b, 2020b; Jiang et al., 2021). Therefore, spatial determinants and spillover effects should be well understood and considered in landscape planning and environmental conservation (Liu et al., 2021; Meng et al., 2021). Accordingly, prevention of ecosystem degradation and enhancement of ESs should not only be undertaken by local communities, organizations, or local agencies but also cross-sectoral collaborations from neighboring districts (units). Moreover, these collaborative efforts should be coordinated by local and regional governments from a holistic regional perspective.

4.2. Maintaining and enhancing ESs via coastal natural landscape conservation

Almost all coastal regions in China have experienced rapid coastal reclamation driven by socioeconomic development (Jia et al., 2018; Ren et al., 2019). The LUC transfer matrices in Tables S7 and S8and their spatial patterns (shown in Fig. S2) indicate that large areas of wetland, water bodies, woodlands, and croplands were converted into built-up areas in 1980–2000 and 2000–2017, particularly in Guangdong Province. The areas of conversion between cropland and urban area from 2000 to 2017 reached 1158.2, 2256.3, and 636.8 km2 in Fujian, Guangdong, and Guangxi, respectively. Moreover, the areas of conversion between woodland and urban areas from 2000 to 2017 reached 595.3, 1073.2, and 298.1 km2 in three districts, respectively. These results are consistent with those of previous studies, such as those by Mao et al. (2018) and Chen et al. (2019c). Mao et al. (2018) revealed the amount and pattern of wetland loss in eastern China due to urbanization and concluded that more than 2394 km2 of wetlands were converted into urban areas in the past two decades. The expansion of aquaculture ponds was expected to contribute most to land reclamation from wetlands and mangroves between 1990 and 2014 (Ma et al., 2015). Mangrove deforestation for aquaculture ponds is mainly driven by the development of the aquaculture industry in coastal provinces (Tian et al., 2016). In particular, Fujian Province adopted a strategy for developing mudflat aquaculture in the shallow sea in 1985, which contributed to the development of aquaculture into the region's pillar industry (Ren et al., 2019). The foundation of the aquaculture industry has become increasingly consolidated since 2000, which has further

Table 2
Spatial associations between ESs (i.e., SR and HQ) and related environmental, socioeconomic, and landscape variables using SPMs (i.e., SLM, SEM, and SDM).

Independent variables	SR			HQ		
	SLM	SEM	SDM	SLM	SEM	SDM
NP	0.132	0.118	0.133	0.00002***	0.00002***	0.00002***
SHAPE	1267.8***	1863.2***	1627.3***	0.103***	0.150***	0.144***
ENN	−1.112*	−0.377	−0.806	−0.00003	0.000008	−0.00004
PLADJ	80.974**	90.664***	104.33***	0.006***	0.006***	0.008***
IJI	14.785***	15.744***	15.368***	0.001***	0.001***	0.001***
COHESION	−225.58	−76.847	−157.11	−0.023***	−0.032***	−0.038***
DIVISION	−12.803	181.31	209.99	−0.105***	−0.061**	−0.071**
SPLIT	−33.237*	−19.131	−23.317	−0.0002	−0.0005	−0.001
SHDI	−1783.3***	−1925.1***	−1728.6***	−0.064**	−0.127***	−0.103***
GDP	−0.041*	−0.028	−0.012	−0.000002	−0.000002	−0.000003**
POPD	−0.022	−0.049**	−0.044*	−0.0000009	−0.0000005	−0.00000003
TEM	−33.398***	−64.052***	−81.902***	−0.001***	−0.002***	−0.002***
RF	0.119***	0.177***	0.09	0.000004***	0.000003	−0.000007
NDVI	3864.2***	3962.3***	3931.1***	0.328***	0.361***	0.381***
w*NP			−0.048			−0.00001
w*SHAPE			−1545.6*			−0.071
w*ENN			−2.218**			−0.0002***
w*PLADJ			−4.799			0.005
w*IJI			−10.8			−0.0008
w*COHESION			−35.074			0.035**
w*DIVISION			−525.51			−0.081
w*SPLIT			2.633			0.0003
w*SHDI			1420.9			0.218***
w*GDP			−0.024			−0.000002
w*POPD			0.08			0.000003
w*TEM			72.221***			0.002***
w*RF			−0.023			0.00001**
w*NDVI			−963.26			−0.097
w*SR/HQ	0.45***		0.677***	0.586***		0.668***
w*μ		0.761***			0.799***	
R^2	0.843	0.875	0.884	0.812	0.836	0.844
Adjusted R^2	0.835	0.869	0.878	0.803	0.828	0.837
σ^2	650,720	519,810	483,470	0.002	0.002	0.002
Log − likelihood	−2513.898	−2497.744	−2479.692	506.496	505.191	530.382

Notes: ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.1$.

increased the aquaculture pond area (Jia et al., 2018).

In contrast to aquaculture development, urbanization directly converts wetlands and agricultural ponds into urban areas; this process is considered irreversible and has attracted the attention of governments, researchers, and international organizations (Mao et al., 2018, 2019). To mitigate wetland shrinkage and degradation, more than 577 natural reserves and 468 wetland parks have been constructed to conserve wetlands (Zheng et al., 2012; Mao et al., 2018). In addition, numerous ecosystem conservation projects, such as the National Wetland Conservation Project, have been initiated since 2003 to promote wetland conservation and restoration (Mao et al., 2018). Since 2012, the central and regional governments have gradually regulated coastal land reclamation, and the development priority has shifted from the aquaculture industry to urban development, coastal economy, and manufacturing. Thus, the expansion speed of aquaculture ponds has slowed down (Ren et al., 2019). However, rapid population growth, increasing demand for seafood, and economic profits have jointly encouraged the slow expansion of the mariculture area (Jia et al., 2018). The coastal aquaculture industry has converted wetlands to ponds; thus, more than a third of mangroves have been deforested globally in the past few decades, and this trend has been especially notable for the decline of mangroves in the mudflats of southern China (Ma et al., 2015; Tian et al., 2016). The shrinkage and degradation of mangroves in southern China reflect nearly identical trends to those reported in South and Southeast Asian countries such as India, Vietnam, Thailand, Malaysia, and Indonesia (UN-Water (United Nations World Water Assessment Programme), 2018).

Considering the negative effects of wetland and mangrove loss caused by aquaculture ponds, the government has initiated a series of laws and regulations to protect and restore mangrove ecosystems, which are reflected by the establishment of nature reserves, national parks, and mangrove reforestation/afforestation (Jia et al., 2018). By 2002, more than 298, 783, and 369 ha of mangrove forests have been replanted in the Guangdong, Guangxi, and Fujian provinces, respectively, which mainly contributed to the increase in mangrove forests along the coastal regions of southeastern China (Jia et al., 2015). In contrast, the various mangrove restoration projects in South and Southeast Asian countries did not achieve significant progress, even though the expansion of aquaculture and paddy and oil palm plantations are still threatening mangrove ecosystems, which reduced mangrove area during 2000–2012 (Upadhyay et al., 2015; Giri et al., 2015).

4.3. Limitations, uncertainties, and future strategies

Allowing for the negative consequences of excessive coastal exploitations, including urbanization, land reclamation, aquaculture pond construction, and mangrove deforestation, governments and stakeholders have realized the importance of ecosystem conservation and restoration in landscape planning and ES management. Great progress has been achieved in wetland and woodland restoration in coastal areas, in particular for mangrove conservation, by optimizing land use allocation, ERPs, and SWCPs (Ouyang et al., 2016; Mao et al., 2018, 2019; Ren et al., 2019). However, there are still some limitations and deficiencies in current intervention measures in terms of mangrove restoration efforts. Existing mangrove restoration projects simply select mangrove species from a few native mangrove species, such as Rhizophora stylosa, Kandelia obovata, and Sonneratia caseolaris (Jia et al., 2015), which may deteriorate regional species biodiversity and weaken ES supply capacity (Upadhyay et al., 2015). Moreover, the selection of a fast-growing exotic mangrove species such as Sonneratia apetala might

Table 3
Direct and indirect effects (i.e., local and spillover effects) of independent variables on ESs estimated by SDM.

Independent variables	CS		WY		AP		SR		HQ	
	Direct effects	Indirect effects	Direct effects	Indirect effects	Direct effects	Indirect effects	Direct effects	Indirect effects	Direct effects	Indirect effects
NP	0.455**	0.306	0.013	0.112	−0.00007*	−0.0001	0.142	0.119	0.00003***	0.00002
SHAPE	3476.685***	669.138	−216.480***	−515.683	−0.542**	−0.914	1525.176**	−1272.535	0.149***	0.07
ENN	−2.590**	−8.105*	0.065	0.31	−0.0004*	0.001*	−1.441**	−7.911**	−0.0001**	−0.0007***
PLADJ	144.464***	316.444	−6.810*	−36.209	−0.020	−0.132***	119.444***	188.302	0.010***	0.028***
LJI	39.745***	33.424	0.977	8.055*	0.002	0.017**	15.275***	−1.151	0.001***	0.0005
COHESION	−625.169**	774.508	−10.739	−133.596	0.084	−0.100	−189.588	−404.636	−0.036***	0.027
DIVISION	−540.876	−4618.386	−65.887	−432.269	0.349*	0.347	121.894	−1097.483	−0.099***	−0.357**
SPLIT	−57.912*	−129.656	4.736*	29.222	0.009	0.027	−26.336	−37.618	−0.001	−0.001
SHDI	−3282.317***	6743.872*	−81.343	−909.908*	−0.237	−2.587***	−1670.802***	719.429	−0.070**	0.417**
GDP	−0.254***	−0.173	0.004	0.022	0.00002***	0.00006*	−0.020	−0.093	−0.000003**	−0.000001
POPD	−0.283***	−0.069	0.009***	0.048**	0.00006***	0.00005	−0.032	−0.143	−0.0000007	−0.00001
TEM	−62.012***	54.159***	−1.228*	−0.622	−0.006**	−0.004	−78.041***	−48.106***	−0.002***	0.002**
RF	−0.185	0.378**	0.038***	0.095***	0.00005*	0.00001	0.099	0.108	−0.000005	0.00002***
NDVI	12527.279***	16003.250**	−77.234	−90.001	−0.631**	−2.142*	4320.907***	4855.727	0.416***	0.44

Notes: ***$p \le 0.01$, **$p \le 0.05$, *$p \le 0.1$.

damage landscape integrity and threaten ecosystem biodiversity (Giri et al., 2015). Therefore, appropriate species with a stronger resistance capacity for natural disasters and severe conditions, such as extreme low temperature, biological invasion, and insect outbreaks, must be identified (Jia et al., 2018). Sufficient freshwater supply plays an important role in mangrove forest survival and in combating subsequent coastal erosion (Upadhyay et al., 2015). However, seawall construction destroys mangrove forests by obstructing the matter and energy exchanges between terrestrial and marine ecosystems, particularly for the freshwater cycle, which regulates and balances water–salinity relationship and sustains mangrove swamps (Ren et al., 2019). Therefore, seawalls and associated engineering measures should be removed or further optimized to facilitate mass and energy exchange and guarantee biological information transmission and biodiversity.

Although the importance of ecosystem conservation has been realized and prioritized in formulations of regional development strategies, the delicate balance between socioeconomic development and ecosystem conservation still must be carefully maintained through timely policy interventions. Model-based simulations revealed ES degradations in CS, SR, and HQ and resultant WY and NE increases in urban agglomeration and surrounding areas (Figs. 4 and 5). Population density and GDP were negatively correlated with ESs (Fig. 7), but it is not appropriate to simply constrain population growth, economic development, and urban expansion because economic profits are important for residents' livelihoods (Cai et al., 2021; Jiang et al., 2021). In the scenario of constraining economic development for ecosystem conservation, residents' economic profits cannot be safeguarded, which tends to fall into the "conservation trap" (Cao et al., 2017, 2021). In contrast, inappropriate urban expansion, population growth, and resource consumption lead to ecosystem degradation and degradation traps and further aggravate regional poverty (Cao et al., 2017, 2021). Therefore, to achieve win–win outcomes and reconcile the contradictions between ecosystem conservation and socioeconomic development in coastal regions, landscape and industrial structuring should be adjusted according to various environmental conditions, economic costs, and constraining factors (Ren et al., 2019). Specifically, the economic contribution of the coastal fishery industry and aquaculture should be controlled at a relatively low level because aquaculture is likely to cause environmental pollution and subsequent negative impacts on mangrove forests (Ottinger et al., 2016; Hansen et al., 2018).

The practices that deforested mangroves for aquaculture ponds and land reclamation should be strictly monitored and controlled by local authorities to avoid damaging mangroves and associated ESs (Jia et al., 2015). Regarding agricultural ponds, according to the experience of water caltrop planting and Phragmites growing (Liu et al., 2009), special attention should be paid to aquatic vegetation as it provides a habitat for amphibians and benthic invertebrates and is easily consumed by farmed fishes (UN-Water (United Nations World Water Assessment Programme), 2018; Chen et al., 2019c). Additionally, low-impact development, including the construction of rain gardens and forested buffers in riparian areas, is recommended. Agricultural ponds can act as naturalistic "sponges" that reduce nutrient loads downstream (Hansen et al., 2018). In addition, regional environmental conservation planning and landscape design should effectively ensure ES supplies and economic benefits by appropriately allocating green infrastructure and other landscape elements, avoiding landscape fragmentation and reducing the dependence of economic growth on natural resources by adjusting industrial structure (Ren et al., 2019; Cai et al., 2021). As for the important ecological functions and agricultural production functions of wetland and agricultural pond landscapes, appropriate proportions of wetlands and agricultural ponds should be maintained during aggressive urbanization to guarantee ecological and food security, while their specific spatial allocation is determined according to landscape integrity, connectivity, and multi-functionality supported by model simulations and scenario analyses (Peng et al., 2020; Jiang et al., 2021; Zhang et al., 2021).

Although the model simulations conducted in this study are still constrained by the accuracy and local suitability of input parameters, spatial scale effects, and other uncertainties arising from data processing and analyses, this study revealed the spatiotemporal evolution of LUC and ESs as well as their spatial determinants, which provide important references for the formulation of environmental conservation and restoration strategies and landscape optimization approaches. In the future, more accurate input data and adjusted parameters will be integrated into biophysical models to improve the accuracy of spatial simulations, and scenario analysis tools will be applied to forecast ES responses to environmental, socioeconomic, and landscape drivers. Accordingly, adaptive management strategies have been proposed to support landscape optimization and enhance ESs.

5. Conclusions

This study explored the evolution of dominant ESs in coastal areas of southeastern China and their responses to coastal activities such as urbanization, ecosystem conservation and restoration, and aquaculture industry development. In addition, the spatial associations between ESs and multi-aspect variables were investigated via spatial econometrics and GWR approaches, and their policy and practical implications are discussed.

In the past four decades, particularly during 2000–2017, intensive coastal exploitation, such as urbanization and aquaculture industry development, accelerated LUC conversion from natural LUC to urban areas and aquaculture ponds, which profoundly altered landscape structure. In rapidly urbanizing areas, LUC conversion weakened CS, SR, and HQ and increased WY and NE, thus threatening ecosystem sustainability. All ESs are closely associated with environmental, socioeconomic, and landscape variables, and the determinants present significant spatial heterogeneity and spillover effects, which could be applied in ecosystem assessment, modeling, and forecasting for land use management and ecosystem conservation efforts. The identified spatial determinants and their spillover effects demonstrate that regional landscape planning and ecosystem conservation must take environmental, socioeconomic, and landscape aspects into consideration and call for cross-sectoral collaboration from both local and adjacent units, which coordinate trade-offs between ecological and economic goals and conflicts of interests between neighboring units from a regionally integrated perspective, eventually facilitating the achievement of win–win outcomes and improving the efficacy of ERPs. The research findings provide important references for landscape optimization and policy revision for ES management, which are potentially applicable to global coastal regions in combination with targeted policies, localized practices, and delicate scenario simulations.

CRediT authorship contribution statement

Jicheng Guo: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Chong Jiang:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Yixin Wang:** Investigation, Methodology, Data curation. **Ji Yang:** Funding acquisition, Resources, Supervision, Project administration. **Wumeng Huang:** Funding acquisition, Resources, Supervision, Project administration. **Qinghua Gong:** Funding acquisition, Resources, Supervision, Project administration. **Ying Zhao:** Funding acquisition, Resources, Supervision, Project administration. **Zhiyuan Yang:** Investigation, Methodology, Data curation. **Weilian Chen:** Funding acquisition, Resources, Supervision, Project administration. **Hai Ren:** Funding acquisition, Resources, Supervision, Project administration.

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.

Acknowledgements

National Natural Science Foundation of China (42006170; 41901258; 42101084; 51861125101), the Guangdong Academy of Sciences (GDAS) Project of Science and Technology Development (2020GDASYL-20200103010; 2020GDASYL-20200301003), Guangdong Science and Technology Program (2021A0505060006), the Marine Economy Development Foundation of Guangdong Province (No. GDNRC[2020]051), and National Park Construction Project (2021GJGY029).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.108860.

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