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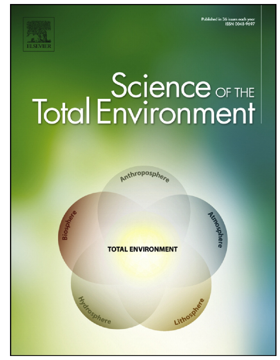

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Spatial-temporal patterns and influencing factors of ecological land degradation-restoration in Guangdong-Hong Kong-Macao Greater Bay Area

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Abstract: Despite the fact that urban agglomerations have undergone extensive ecological land coverage modifications, exploration of the patterns and driving mechanisms associated with ecological land degradation (ELD) and ecological land restoration (ELR) in urban agglomerations is still limited. This study combined remote sensing technology, as well as landscape index and geographical detector to characterize the spatiotemporal patterns of ELD (isolating, adjacent, and enclosing degradation) and ELR (outlying, edge-expansion, and infilling restoration) in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) from 1990-2019. Subsequently, the contributions, interactions, and driver changes were quantified. The results showed an ecological land shift from over-exploitation to balanced co-existence, which was facilitated by a spatiotemporal pattern transition from adjacent degradation-led (1990-2010) to edge-expansion restoration-led (2010-2019). Land urbanization rate and population density showed a stronger promoting effect on ELD than natural factors, while tertiary industry, topography, and soil conditions were more significant in ELR. The factors' nonlinear interaction enhanced the degradation-restoration pattern evolution and continued to increase over time—particularly the interaction between construction land expansion and other drivers. Additionally, from 2010-2019, 80% of the ELR socio-economic factors turned from negative to positive and gradually became to play a significant role. This study is expected to help ecological protection and restoration planners/managers recognize the factors' interactions and variations, and ultimately improve the ecological network structure that is designed to integrate the city with the ecosystem.

Keywords: Ecological land degradation; Ecological land restoration; Spatial-temporal patterns; Influencing mechanism; Guangdong-Hong Kong-Macao Greater Bay Area

1 Introduction

Ecological land supports ecological circulation and biodiversity, balances regional and global ecosystems (Colding, 2007), and aids in achieving sustainable development (Marrero-Rodríguez et al., 2020). Thus, it is particularly concerning that ecological land degradation (ELD) has become one of the most serious environmental problems worldwide (Puskás et al., 2021). Global vegetation cover has declined by ~ 20% in the last 15 years (UNCCD, 2017), which poses a threat to food and energy security (Dobbs et al., 2017), as well as to ecological habitats (Reed et al., 2015). In response, the United Nations has implemented a series of initiatives and programs, including the Convention on Biological Diversity (Land Degradation Neutral; LDN) and the 2030 Agenda for Sustainable Development (Tóth et al., 2018). As a world-class urban agglomeration, the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) plays a significant role in supporting the global economic supply chain and promoting sustainable and coordinated development (Feng et al., 2021). However, because it has also experienced a sharp reduction in ecological land, the land ecological networks need to be reconstructed (Bi et al., 2020). Spatiotemporal modeling and driving force analysis of the GBA's ecological land degradation-restoration patterns can provide insights into the holistic and systematic layout of ecological restoration in urban agglomerations, and contribute to global sustainable development (Lü et al., 2015).

ELD is defined as the loss of important ecosystem functions on ecological lands, such as soil and water conservation, productivity, biodiversity, or other ecosystem services (Lambin et al., 2003; Mao et al., 2018). It is also considered to be a combination of natural and anthropogenic processes that negatively impacts ecosystem services (Adamo and Crews-Meyer, 2006). Ecological land restoration (ELR) refers to the process of restoring ecosystems that have been destroyed and degraded (Lewis, 2005) and is usually achieved by incrementally changing the ecosystem functionality (Kust et al., 2017). Previous studies on ecological land degradation-restoration mainly include the investigation of land cover changes, driving factors, and regulation mechanisms (Batunacun et al., 2019; Jiang et al., 2020; Lawler et al., 2014). Deforestation, desertification, grassland degradation, and wetland loss are typical ELD features (Dlamini, 2016; López-Barrera et al., 2014). In addition, the expansion of construction land continually results in ELD (Mao et al., 2018); while climate change and anthropogenic activities jointly dominate ELD in arid and semiarid zones (Batunacun et al., 2019; Ren et al., 2020). Early research and practical application in ELR mainly focused on biotechnologies, engineering technologies (Alexander et al., 2016; Aronson and Alexander, 2013), and exploration of biophysical and chemical mechanisms (Lü et al., 2015; Reed et al., 2015). However, regional scale research on ELR structure, function, and evolutionary patterns gradually became a focus of the scientific community (Bakshi et al., 2015). These studies demonstrated that ELR is geospatially coupled with vegetation regeneration and anthropogenic activities in arid and semi-arid regions (Sun et al., 2019; Xu and

Wang, 2019). Furthermore, the results showed that restoration activities are also consistent with anthropogenic ecological needs and that restoration efforts are concentrated near population centers in coastal areas (Stanford et al., 2018). Due to the development of concepts like ecological civilization, as well as holistic and systematic restoration trends, the restoration approaches in China that pertain to a single, defined territory are no longer practical (Fu, 2021). Therefore, numerous scholars and land-use planners advocate for a comprehensive study of ecological degradation-restoration patterns (Reed et al., 2015; Zhang et al., 2021).

With respect to influencing factors, natural conditions (e.g., precipitation, temperature, and sunshine duration) play a fundamental role in ecological land degradation-restoration (Jiang et al., 2020), as increasing rainfall, prevailing winds, and changes in hydrothermal conditions all contribute to vegetation growth (Fensholt and Rasmussen, 2011; Xu and Wang, 2019). In addition, anthropogenic factors, such as population and economic growth, agricultural activities, urban land expansion, and ecological engineering are also important drivers for ecological land evolution (Lü et al., 2015; Nassauer and Raskin, 2014). In fact, anthropogenic activities are the main influence on ecological space in urban areas (Sun et al., 2019) and exhibit a dual and conflicting impact. From one perspective, urbanization and industrialization are usually accompanied by construction land expansion and increased environmental pollution, which seriously threaten ecological land security (Puskás et al., 2021; Sutton et al., 2016). Contrarily, the implementation of ecological policies and projects significantly promotes ecological restoration and protection (Ren et al., 2020).

Methodologically, regression models (Ren et al., 2020; Xu and Wang, 2019), residual trend methods (Mao et al., 2018), biophysical model-based methods (e.g., terrestrial ecosystem model) (Xu et al., 2020), and land use models (Dlamini, 2016) have been used to identify the ecological land evolution mechanisms on the global (Xu et al., 2020), national (Dlamini, 2016; Lü et al., 2015), urban (Jiang et al., 2017), and natural geographic regional scales (e.g., topographic and climatic zones) (Mao et al., 2018; Ren et al., 2020). These statistical methods are effective for quantifying the relationships between representative indicators (Jiang et al., 2020; Jiang et al., 2017), such as Fractional Vegetation Cover (FVC), Net Primary Productivity (NPP), Normalized Difference Vegetation Index (NDVI), and Leaf Area Index (LAI). Early warning systems based on earth observation serve as a tool for urban ecological monitoring (Wellmann et al., 2020) and provide important information on the direction and intensity of ecological land change from multiple dimensions over an extended period of time (Fensholt and Rasmussen, 2011; Mao et al., 2018; Ren et al., 2020).

However, previous studies were hindered by two primary limitations. First, ELD and ELR are generally concurrent geographical processes (Bennett and Smith, 2017), and studying them simultaneously offers a more comprehensive view of the land ecosystem processes. Although some studies have focused on quantitative changes in ELD (Batunacun et al., 2019; Dlamini, 2016; Jiang et al., 2020; López-Barrera et al., 2014; Xia et al., 2020), few have jointly identified spatial-temporal patterns in ELD and ELR (Lü et al., 2015; Mao et al., 2018; Reed et al., 2015). Second, urban agglomerations are among the regions with the most intense land cover changes (Liu et al., 2021), and multiple factors, as well as their interactions, all influence ecological land degradation-restoration (Sun et al., 2019). However, existing studies seldom quantitatively characterize the interactions among various drivers (Batunacun et al., 2019; Fu et al., 2018; Jiang et al., 2020; Turner and Carpenter, 2017; Xie et al., 2017) and the variability of their effects over time, which has restricted the overall understanding of ecological land evolution mechanisms (Hu et al., 2020).

Herein, these gaps were addressed by conducting an urban agglomeration case study in the GBA from 1990-2019, in which the spatiotemporal patterns and driving mechanisms of ecological land degradation-restoration were explored. It was assumed that ELD and ELR in urban agglomerations are affected by natural and anthropogenic factors, and their influence changes over time. Therefore, a geographical detector method was used to quantify the impact of forces, interactions, and temporal changes in driving factors on ecological land degradation-restoration. The results obtained from this study will enhance our understanding of how the natural environment and anthropogenic activities jointly influence the dynamic changes in ecosystem evolution patterns and help decision makers harmonize human-nature relationships in urban agglomerations.

2 Materials and methods

2.1 Study area

The GBA refers to a cluster of world-class cities spread throughout nine administrative divisions consisting of Guangzhou (GZ), Shenzhen (SZ), Dongguan (DG), Foshan (FS), Zhongshan (ZS), Huizhou (HZ), Zhaoqing (ZQ), Zhuhai, and Jiangmen (JM); as well as the Hong Kong and Macao special administrative regions (Fig. 1). In 2019, it was characterized by a population of 72.65 million, GDP of 11.62 trillion RMB, and an urbanization rate of 86.1%. As one of the four greater bay areas, the GBA has surpassed Tokyo as the largest metropolitan area with respect to size and population, and it is expected to build a new open economic system for further integration into the world economy (Bi et al., 2020). However, due to rapid population growth and high-intensity integrated development, the GBA territorial space is facing serious regional ecological degradation and pollution problems (Feng et al., 2021). The dramatic impact of anthropogenic activities on the GBA's surface environment makes the driving mechanisms and spatiotemporal characteristics of ecological land degradation-restoration evolution more complex. Therefore, identifying patterns and influencing mechanisms of ecological land degradation-restoration evolution is critically important for providing protection, systematic restoration, and comprehensive management of the ecological environment.

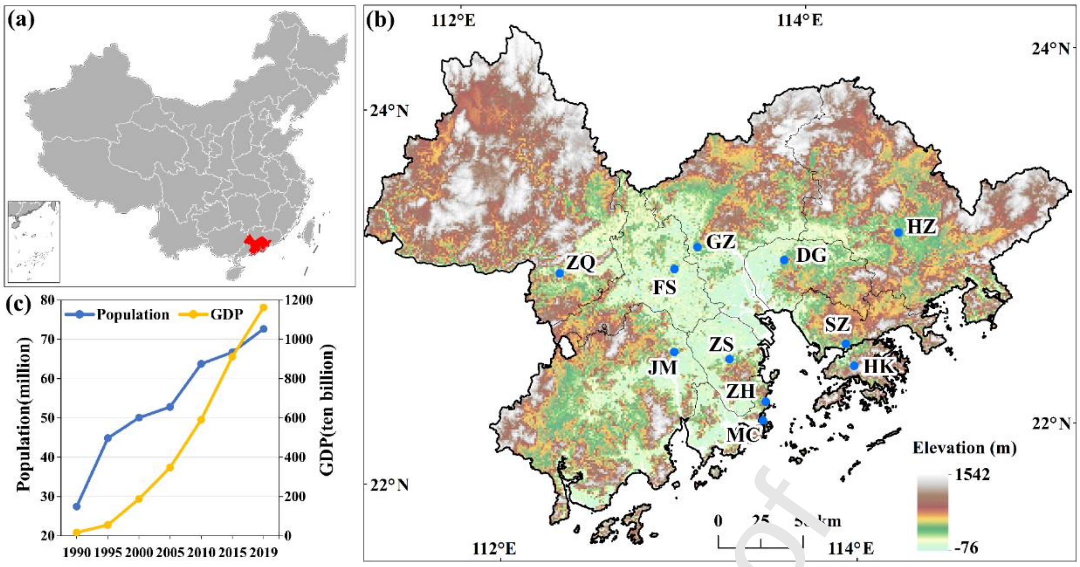

Fig. 1 (a) GBA's location in China, (b) GBA administrative and topographic map, and (c) population and GDP changes from 1990 to 2019. ZQ: Zhaoqing; GZ: Guangzhou; FS: Foshan; JM: Jiangmen; ZS: Zhongshan; ZH: Zhuhai; MC: Macao; DG: Dongguan; HZ: Huizhou; SZ: Shenzhen; and HK: Hong Kong.

2.2 Data sources and processing

According to the definition of ecological land in the *Opinions on the Delineation and Strict Observance of the Red Line of Ecological Protection* (http://www.gov.cn/zhengce/2017-02/07/content_5166291.htm), ELD and ELR are defined based on land use conversion. ELD refers to the spatial contraction and quantitative loss resulting from ecological land transformation (e.g., forest land, grassland, and water body) to other land types; while ELR is the spatial expansion and quantitative increase caused by transformation of other land types into ecological land. The GBA land use data employed herein spanned from 1990 to 2019 (Fig. S1) and were obtained from 30-m-resolution land use/cover datasets with a classification accuracy of 0.92 ± 0.02 and 0.94 ± 0.06 for ecological land and construction land respectively (Feng et al., 2021). The ELD and ELR in the study area were divided into three analysis periods (1990-2000, 2000-2010, and 2010-2019) based on the results of an ecological land evolution study in the GBA conducted by Feng et al. (2021). In addition, elevation (DEM), slope (Sp), average annual temperature (Tem), average annual rainfall (Pre), soil erosion intensity (SEI), population density (POP), GDP per capita (GDPPC), land urbanization rate (LUR), nearest road distance (NRD), and proportion of tertiary industry (PTI) were selected as the influencing factors (Table 1). DEM and Sp remained unchanged throughout the study period, while TEM, PRE, POP, GDPPC, LUR, and PTI changed throughout, and SEI and NRD were the state quantities of the initial year. GDPPC and PTI were obtained based on county-level administrative districts, while other influencing factors were 1 km resolution. All the land use data and influencing factors data were divided into 1 km × 1 km grids for spatial analysis.

Table 1 Selected data in this study.

	Data	Data Sources	Abbreviation	Time series	Resolution
Ecological land	Land use/cover data	Feng et al. (2021)	-	1990-2019	30 m
Natural factors	Elevation	http://www.resdc.cn	DEM	-	1 km
	Slope	Calculated according to elevation	Sp	-	1 km
	Changes in average annual precipitation	https://data.nodc.noaa.gov/cgi-bin/	Tem	1990-2019	1 km
	Changes in average annual temperature	http://www.climatologylab.org/terraclimate.html	Pre	1990-2019	1 km
	Soil erosion intensity	http://www.resdc.cn	SEI	1990/2000/2010	1 km
Anthropogenic factors	Changes in population density	https://www.worldpop.org/ http://www.resdc.cn	POP	1990-2019	1 km
	Changes in GDP per capita	http://www.stats.gov.cn/tjsj/	GDPPC	1990-2019	County-level administrative districts
	Changes in land urbanization rate	Calculated according to the land cover data	LUR	1990-2019	30 m

Distance to the nearest road	Calculated according to Euclidean Distance	NRD	1990/2000/2010	1 km
Changes in tertiary industry percentage	http://www.stats.gov.cn/tjsj/	PTI	1990-2019	County-level administrative districts

2.3 Methods

(1) Ecological land degradation-restoration patterns

The emerging/reconstructed ecological patch restoration patterns and the extinct/damaged ecological patch degradation patterns were classified and identified according to the spatial evolution characteristics of ecological land patches (Fig. 2). Specifically, restoration patterns are defined as outlying, edge-expansion, or infilling types (Hoffhine Wilson et al., 2003; Liu et al., 2010). Outlying is the enclave growth of new ecological patches that are isolated from existing patches, and thus indicates an increase in the amount and coverage of ecological land within the regional ecosystem. Edge-expansion is defined as a newly grown ecological patch spreading unidirectionally in roughly parallel strips from an existing edge and represents an increase in the area and size of ecological land. Infilling refers to filling in gaps or holes between or within initial ecological patches with new patches, implying both an increase in the internal coverage and improved integrity of ecological lands. In contrast, degradation patterns include enclosing, adjacent, and isolating types (Xia et al., 2020). An enclosing patch is an extinct ecological patch that becomes a gap or a hole between or within existing patches, and thereby signifies damage to the ecological patch integrity. An extinct patch that is located on the patch perimeter is classified as an adjacent type and represents erosion of the ecological patches' edges. An isolating patch is defined as an extinct patch that is isolated from old patches and results in the reduction of regionally dispersed ecological land.

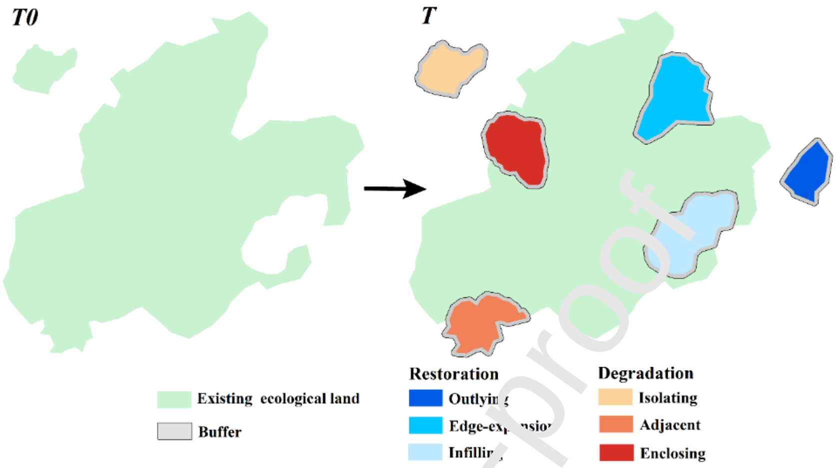

Fig. 2 Ecological land degradation-restoration landscape patterns.

Using the landscape expansion index (LEI) as a base (Liu et al., 2010), Xia et al. (2020) proposed a shape-weighted landscape evolution index (SWLEI) for simultaneously analyzing the types of patch expansion and shrinkage patterns within the landscape over two or more periods. Compared with existing landscape metrics, the SWLEI has better robustness and can characterize the relationship between new and old patches in terms of detailed geospatial identification (Xia et al., 2020). Therefore, the spatial patterns of ELD and ELR can be defined by the following equations:

$$SWLEI = (-1)^{\lambda} \times \frac{N_i^*}{N_i} \times 100 \quad (1)$$

$$N_i = D_i \times P_i + 4 \times D_i! \quad (2)$$

$$D_i = \left\lceil \frac{S_i}{P_i} \right\rceil \quad (3)$$

where λ is a binary variable representing the ecological patch status (i.e., degraded or restored) during the study period (T_0, T). If there is a restored patch at T, then λ=0; However, if the patch exists at T_0 but disappears at T, then it is defined as a degraded patch and λ=1. N_i is the number of pixels in the ecological patch's neighborhood at T, and N_i^* is the number of pixels in the area where the ecological patch's neighborhood intersects with existing patches. D_i is the neighborhood radius, S_i is the number of pixels in the ecological patch, and P_i is the ratio of the ecological patch's perimeter to the spatial resolution.

SWLEI values vary between -100 and 100. Based on parameter settings from previous studies (Liu et al., 2010; Xia et al., 2020), if the SWLEI value is within (-1, 1), then a new patch is classified as an outlying type, and an extinct patch is defined as an isolating type. A SWLEI value within [50, 100] indicates an infilling patch; while a range of [1, 50) denotes a patch undergoing edge-expansion. An extinct patch is defined as adjacent once its ELDOR value is within (-50, -1] or enclosing if the value is within [-100, -50].

(2) Geographical detector

The geographical detector is a method for exploring the spatial heterogeneity of a geographic phenomenon and the potential influencing factors (Wang et al., 2016; Wang et al., 2010). The technique operates on the assumption that if the driving factors have a significant effect on ecological land degradation-restoration, then the spatial distribution of the independent and dependent variables should be similar.

Compared with the traditional linear model, the geographical detector has the advantage of being able to detect the relationship between the driving factors and geographical phenomena, without any assumption of linearity; and thus, can test the impact of interactions between variables. Furthermore, the geographical detector has four modules, two of which were employed in this study—the factor detector and interaction detector. The factor detector uses a q value to quantify the factors' influence, which is mathematically expressed as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}, \; SSW = \sum_{h=1}^{L} N_h \sigma_h^2, \; SST = N\sigma^2 \quad (4)$$

where q is the determinant power; N and N_h are the number of sample units in the entire region and sub-region, respectively; h=1, 2… L is the number of secondary regions; σ^2 is the global variance of Y over the entire study region; and σ_h is the samples' variance in sub-region h. SSW and SST are the sum of squares and the total sum of squares, respectively. The value range of q is [0,1], meaning that the driving factor explains q × 100% of the explained variable. Moreover, the larger the q value, the stronger the factor's influence.

The interaction detector was used to examine the interaction of two factors and whether the factors' interaction weakens, enhances, or is altogether independent of any impacts. The interactive relationship can be divided into five categories by comparing the two factors' interactive q value and the q value of each factor independently (Table 2). The Spearman correlation coefficient (ρ) was used to determine the direction of the influencing factors on ecological land degradation-restoration. Based on previous studies (Feng et al., 2021; Wang et al., 2016), p value < 0.01 was considered as statistically significant for the factors' q

values and Spearman correlation coefficient (ρ).

Table 2 The interactive categories of two factors

Description	Interaction
$q(X1 \cap X2) < Min(q(X1), q(X2))$	Nonlinear−weaken
$Min(q(X1), q(X2)) < q(X1 \cap X2) < Max(q(X1), q(X2))$	Uni−weaken
$q(X1 \cap X2) > Max(q(X1), q(X2))$	Bivariate-enhance
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear−enhance

3 Results

3.1 Spatial-temporal patterns of ecological land degradation-restoration

From 1990 to 2019, the GBA's ecological landscape transformed from severe degradation (1990-2010) to restoration (2010-2019) (Fig. 3). Furthermore, 2,520.04 km^2 of degraded ecological land was offset by 1,156.17 km^2 of restoration, accounting for 9.43% and 4.33% of the total ecological land area, respectively. Moreover, the adjacent and isolating degradation clearly decreased with respect to area and quantity proportions (Table 3). In contrast, the enclosing degradation was relatively stable, while the edge-expansion and outlying restoration increased significantly. These results show that the integrity of some ecological environments has improved over the last 29 years. In addition, outlying restoration was particularly prolific, and rapidly increased from 0.06% (1990-2000) to 13.33% (2010-2019). This increase expanded the area of restored "ecological enclaves" by 145.75 km^2. Degraded patches were mainly distributed in the GZ-FS–DG-SZ metropolitan belt (Fig. 3a). Adjacent degradation (31.99%) dominated, whereas enclosing (20.88%) and isolating (15.68%) degradation representing relatively smaller proportions. The restored patches were scattered in the peripheral cities such as ZQ, JM, and HZ (Fig. 3a). Edge-expansion (18.09%) and infilling (10.61%) were the most prevalent restoration types, with outlying (2.75%) contributing the least.

From 1990-2000, the ELD area (992.80 km^2) was 1.95 times larger than the ELR area (508.03 km^2). During this period, adjacent degradation was the primary degradation type in terms of area (38.11%) and quantity (42.13%) proportions. The adjacent degradation mainly occurred near the urban, built-up areas in FS, DG, and SZ, where urbanization and industrialization have encroached on the edges of the original ecological patches (Fig. 3b). Infilling restoration accounted for the largest proportion of ELR during this period, with area and quantity proportions of 31.32% and 16.73%, respectively. The infilling restoration occurred mainly in HK and peripheral GBA forest zones (e.g., HZ and ZQ) (Fig. 3b), indicating that urban greening and ecological protection measures in these areas improved the ecological land patches' integrity.

From 2000-2010, the scale of ELD (1891.91 km^2) was significantly larger than that of ELR (399.09 km^2). The ELD increased by 899.11 km^2 (90.56%) compared with the previous period. Furthermore, it was spatially concentrated in the built-up areas of SZ, GZ, and FS; as well as in the periphery of JM and HZ (Fig. 3c). Adjacent degradation was the predominant type in terms of area (31.78%) and quantity (27.48%) proportions, and rapid urbanization and industrialization encroached in the ecological space periphery. The enclave-type expansion, which is a characteristic of industrial park development, promoted isolating degradation, and accounted for 29.06%

and 33.48% of the area and quantity proportions, respectively. Clearly, the ecological patch fragmentation trend was evident. However, the area undergoing ELR declined by 108.94 km^2 (21.44%) during this period and was mostly found in HK and ZQ (Fig. 3c). The pattern was still dominated by the infilling type, but the area (9.37%) and quantity (7.65%) proportions decreased significantly.

From 2010-2019, ELR (581.12 km^2) was more prevalent than ELD (519.07 km^2), and the degree of ecological landscape dominance increased. Compared with the preceding period, the area associated with ELD decreased by 457.61 km^2 (72.56%). During this time, enclosing was the most common type of degradation, with area and quantity proportions of 38.11% and 42.13%, respectively. Spatially, the enclosing degradation was mainly located in the urban periphery of FS and DG (Fig. 3d). Interestingly, the area and quantity proportions of isolating degradation decreased significantly to 6.18% and 11.97%, respectively, and the implementation of ecological policies and projects mitigated ecological land loss. ELR increased by 182.03 km^2 (45.61%) during the last period and was concentrated within two core cities (GZ and SZ) and two peripheral cities (ZQ and HZ) (Fig. 3d). The pattern was dominated by edge-expansion, which accounted for 31.97% of the area proportion and 20.06% of the quantity proportion. In contrast, the infilling expansion decreased to an area proportion of 7.52% and a quantity proportion of 7.34%. The clear growth trend at the ecological patches' edges and remote areas could be ascribed to the implementation of numerous ecological restoration projects in peri-urban areas, marginal coastal zones, and remote abandoned mining areas in the GBA. However, there is relatively little infilling restoration due to the high cost in a densely developed region.

Further analysis showed that 883.74 km^2 of ecological land in the GBA has been repeatedly degraded in a “degradation-restoration-re-degradation” cycle that was observed over the entire study period (Fig. 3e). This cycle was mainly present in the city center and reflected the repeated tug-of-war between urban ELR and anthropogenic occupation. On one hand, the GBA’s extensive policy measures have promoted ELR within urban built-up areas. On the other hand, industrialization and urbanization have brought environmental stress to urban ecosystems. Moreover, ecological landscape configuration in urban planning was neither adequately systematic nor sufficiently proactive, which resulted in the restored ecological patches being repeatedly encroached upon.

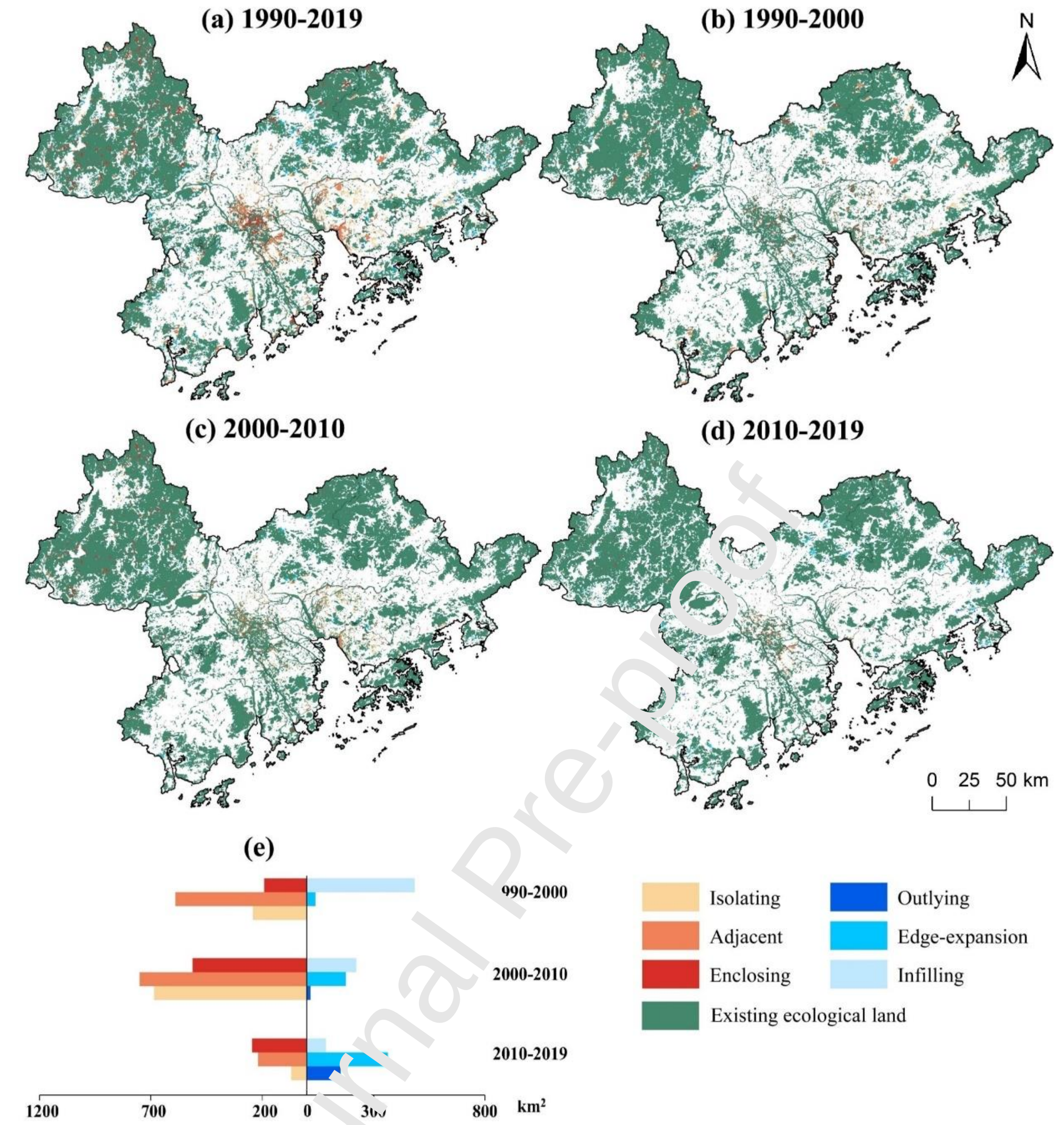

Fig. 3 Spatial-temporal patterns of ecological land degradation-restoration. (a) 1990-2019, (b) 1990-2000, (c) 2000-2010, (d) 2010-2019, (e) area variations.

Table 3 Area and quantity proportions of ecological land degradation-restoration.

Periods	Area proportion (%)						Quantity proportion (%)					
	Degradation types			Restoration types			Degradation types			Restoration types		
	Isolating	Adjacent	Enclosing	Outlying	Edge expansion	Infilling	Isolating	Adjacent	Enclosing	Outlying	Edge expansion	Infilling
1990-2000	15.65	38.11	12.39	0.06	2.47	31.32	16.56	42.13	21.38	0.24	2.96	16.73
2000-2010	29.06	31.78	21.74	0.66	7.39	9.37	33.48	27.48	23.87	1.22	6.30	7.65
2010-2019	6.18	19.32	21.68	13.33	31.97	7.52	11.97	22.39	25.83	12.41	20.06	7.34
1990-2019	15.68	31.99	20.88	2.75	10.61	18.09	17.41	21.71	28.80	5.98	13.09	13.01

3.2 Influencing factors' effect on ecological land degradation-restoration

The factor detector was used to calculate each factor's determinant power (q) on ecological land degradation-restoration from 1990-2019 (Table 4). For ELD, 76.67% of the factors' q values were statistically significant at the 1% level. LUR dominated the isolating, adjacent, and enclosing degradation types with q values of 0.69, 0.74, and 0.71, respectively. LUR was followed by POP, GDP, and PTI, which shows that anthropogenic activities are the primary driver of ELD in the GBA. In addition, DEM and Sp controlled 68% of adjacent degradation and 65% of enclosing degradation, implying the ecological land with flatter topography and lower elevation is more likely to be exploited around or within built-up areas. Furthermore, NRD (q=0.64) had a significant positive effect on isolating degradation. Road construction caused ecosystem fragmentation and made separated ecological patches more vulnerable to encroachment, especially in areas with high SEI (q=0.45). However, the mean effects of Pre (q=0.41) and Tem (q=0.36) were minor, which indicates that the contribution of climatic conditions to ELD is insignificant compared with other factors. In general, the impact of anthropogenic factors such as LUR, POP, and GDP are significantly greater than those of natural factors.

Table 4 Determinant power (q) and Spearman correlation coefficient (ρ) of factors about ecological land degradation-restoration. Factor abbreviations are listed in Table 1.

	Ecological land degradation						Ecological land restoration					
	Isolating		Adjacent		Enclosing		Outlying		Edge-expansion		Infilling	
	q	ρ	q	ρ	q	ρ	q	ρ	q	ρ	q	ρ
DEM	0.45^{***}	-0.38^{***}	0.68^{***}	-0.66^{***}	0.68^{***}	0.62^{***}	0.54^{***}	0.43^{***}	0.52^{***}	0.53^{***}	0.55^{***}	0.50^{***}
Sp	0.40^{**}	-0.34^{***}	0.65^{***}	-0.57^{***}	0.55^{***}	0.56^{***}	0.49^{***}	0.40^{***}	0.46^{***}	0.44^{***}	0.48^{***}	0.43^{***}

Pre	0.26	-0.25	0.33	-0.16	0.36*	-0.21	0.46**	-0.41	0.50	0.33	0.33*	0.37
Tem	0.30	-0.18	0.36	-0.13	0.43	-0.21	0.42**	0.37	0.46	0.39	0.35**	0.25
SEI	0.45***	0.56***	0.47***	0.60***	0.58***	0.60***	0.53***	-0.49***	0.50***	-0.43***	0.53***	-0.44***
POP	0.61***	0.53***	0.68***	0.63***	0.65***	0.64***	0.47***	-0.43***	0.51***	-0.55***	0.54***	-0.56***
GDPPC	0.66***	0.59***	0.65***	0.57***	0.54***	0.57***	0.51***	-0.44***	0.55***	-0.53***	0.62***	-0.58***
LUR	0.69***	0.62***	0.74***	0.69***	0.71***	0.69***	0.54***	-0.51***	0.63***	-0.61***	0.62***	-0.64***
NRD	0.64***	-0.59***	0.46***	-0.42***	0.37	-0.24	0.67***	0.61***	0.60***	-0.57***	0.46	-0.41
PTI	0.44**	0.39***	0.51***	0.46***	0.40	0.17	0.39	-0.25	0.49*	-0.45	0.44	-0.31

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

For ELR, 83.33% of the influencing factors were statistically significant at the 1% level (Table 4). LUR showed a significant negative effect on edge-expansion (q=0.63) and infilling (q=0.62) restoration, indicating the rapid urban expansion severely limits ELR. In addition, the demand for green space in city centers, low elevation areas, and locales with sufficient precipitation favored edge-expansion and were heavily influenced by POP (q=0.51), GDP (q=0.55), DEM (q=0.52), and Pre (q=0.50). However, PTI negatively affected 45% of edge-expansion and 44% of infilling during the study period but had a relatively weak effect on outlying (q=0.39). Moreover, NRD (q=0.67) and SEI (q=0.53) significantly limited outlying restoration. The mean effect of Tem (q=0.41) was the smallest, ELR has a relatively low response to temperature. Overall, the construction of cities and roads, as well as economic development, have a greater impact on ELR than topography, soil conditions, and climatic factors.

Ten factors and 45 pairs of interactions between them were evaluated using the interaction detector. Results showed that the interactive q value for each pair of factors exceeded the q value of each contributing factor but was smaller than the sum of the two factors' q values (Fig. 4). In addition, 65.19% of the q values were statistically significant at the 1% level (Fig. S2). Thus, the interactive relationship between each pair of factors was bivariate, and they enhance each other in influencing ecological land evolution. Specifically, for ELD, q(LUR∩SEI), q(POP∩SEI), and q(GDPPC∩NRD) had the largest effect (all = 0.88) (Fig. 4a) on isolating degradation type. Furthermore, the interaction of LUR and POP was the dominant factor influencing adjacent degradation (Fig. 4b), and q(DEM∩LUR) explained 87% of the enclosing degradation (Fig. 4c). For ELR, q(Sp ∩ NRD) dominated outlying restoration (q=0.91) (Fig. 4d), and the interaction of LUR and SEI explained 95% of edge-expansion restoration (Fig. 4e). Finally, q(Sp∩LUR) was the most important factor influencing infilling restoration (q=0.85) (Fig. 4f), showing that in the context of rapid urban sprawl, infilling restoration is mainly concentrated in suburban areas with low slopes (Fig. 3).

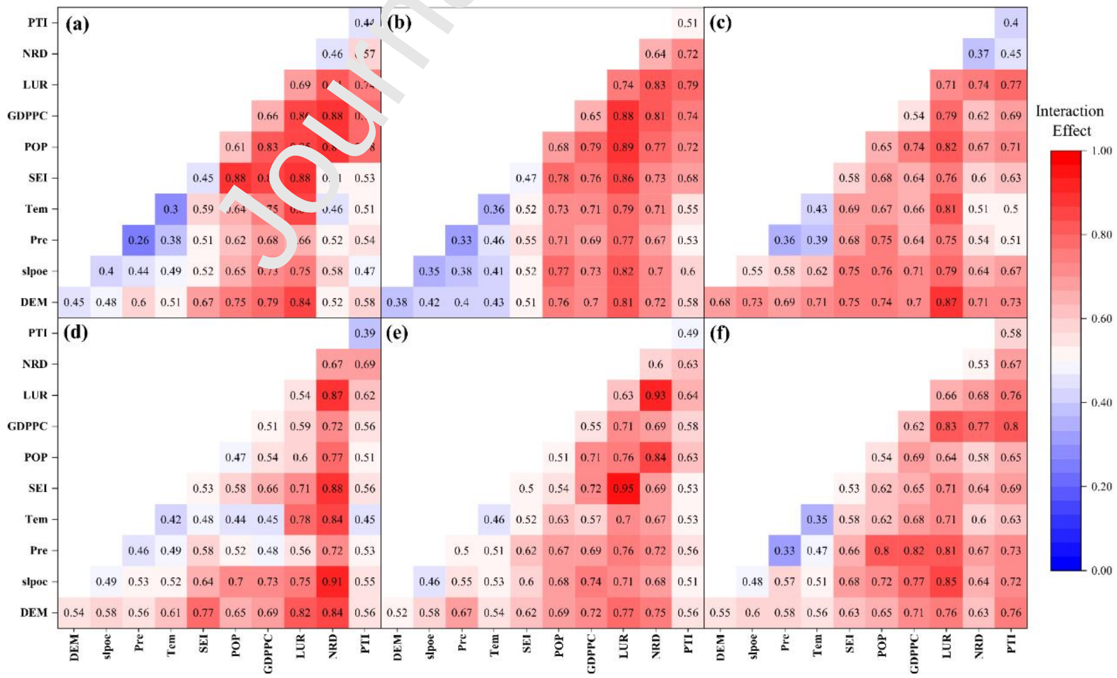

Fig. 4 Interaction effect (q) between influencing factors on ecological land degradation (e.g., (a) Isolating, (b) Adjacent and (c) Enclosing) and ecological land restoration (e.g., (d) Outlying, (e)

Edge-expansion and (f) Infilling) in 1990-2019. Factor abbreviations are listed in Table 1.

3.3 Dynamic changes of factors' impact on ecological land degradation-restoration

The *q* values (i.e., factors' impact) and correlation coefficient at all three stages were calculated using the geographical detector and Spearman correlation coefficient (Fig. 5). Herein, 85% of the factors' *q* values and 83.3% of their correlation coefficients showed a *p* value less than 0.01. In addition, natural factors depicted a constant influence direction on ELR, while 80% of anthropogenic factors changed from a negative to positive influence.

For ELD, the SEI and NRD impact was significantly decreased for all three degradation patterns, which indicates a diminished role of soil conditions and road construction (Figs. 5a, b, and c). In contrast, PTI facilitated a continuous increase, with isolating, adjacent, and enclosing degradation rising by 43.75%, 28.13%, and 45.45%, respectively. As the industrial structure transformed, the GBA's tertiary industry replaced numerous secondary industries (Fig. S3), which limited the impact of industrialization on the ELD and strengthened the role of PTI. In addition, DEM, Sp, Tem, Pre, POP, GDPPC, and LUR depicted an increasing impact on isolating degradation, while simultaneously exhibiting a decreasing impact on adjacent and enclosing degradation.

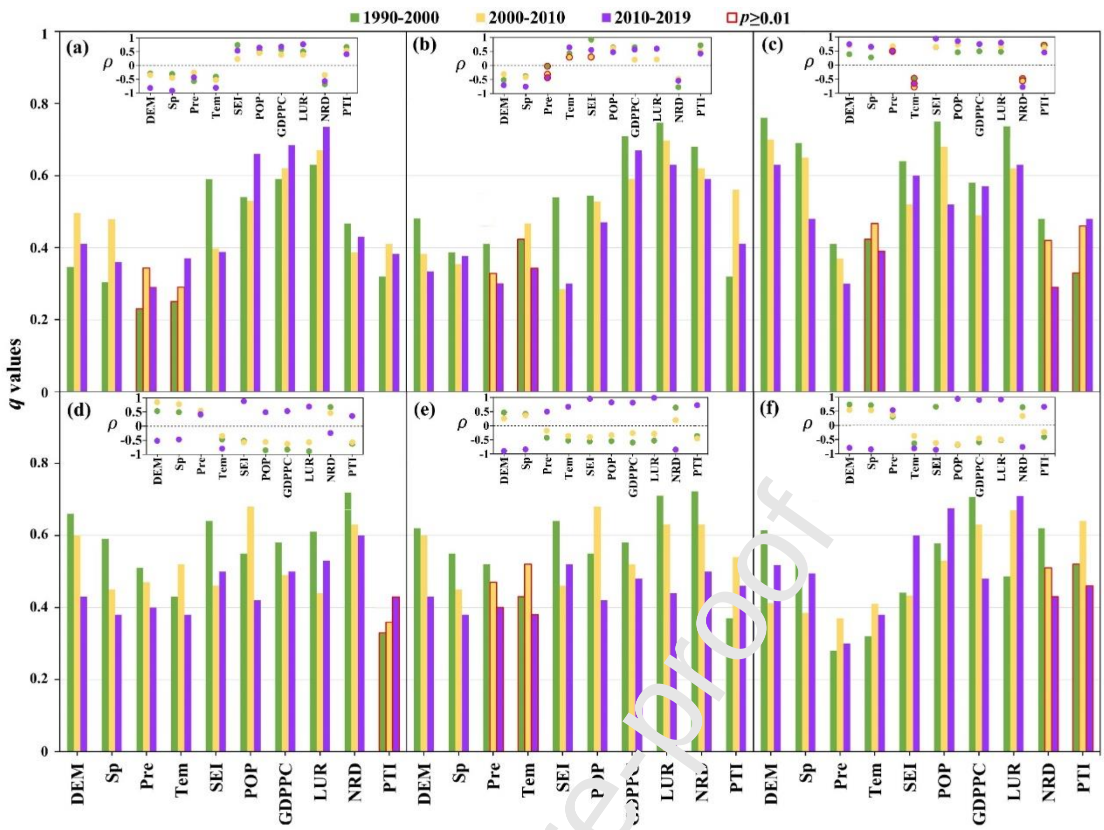

Fig. 5 The trend of determinant power (q) and Spearman's correlation coefficient (ρ) for influencing factors on ecological land degradation (i.e., (a) Isolating, (b) Adjacent and (c) Enclosing) and restoration (i.e., (d) Outlying, (e) Edge-expansion and (f) Infilling) over 1990-2019. Factor abbreviations are listed in Table 1.

For ELR, the impact of DEM, Sp, Pre, GDPPC, and NRD has continuously declined for all three patterns (Figs. 5d, e, and f). In outlying and edge-expansion restoration, the effects of Tem, SEI, POP, and LUR significantly reduced, however, the role of these factors in infilling restoration dramatically intensified, especially that of LUR, which increased by 45.87%. For example, HK effectively facilitated the infill growth of ecological patches in high build-up density areas by improving green space landscape planning (e.g., green space connectivity design). The impact of PTI on outlying and edge-expansion restoration increased by 30.30% and 24.32%, respectively, and that on infilling restoration decreased by 11.54%, with the role of the tertiary industry in outlying and edge-expansion restoration gradually improving.

All the interactive impact results for the three periods are shown in Tables S1-6. Although the marginal effect of a single factor had an obvious downward trend, the interaction between the factors was gradually enhanced. For ELD, 88.89%, 97.78%, and 95.56% of the factor interactions for isolating, adjacent, and enclosing types, respectively, were elevated during the study period. In particular, q(POP∩SEI) and q(GDPPC∩NRD) exhibited a continuously increasing influence on isolating degradation (Table S1), which was amplified by urbanization, economic development, and road construction. The interaction of LUR with POP and DEM dominated the adjacent and enclosing degradation; the q values increased from 0.78 to 0.93 and 0.72 to 0.95, respectively (Table S2 and S3). For ELR, 84.44%, 82.22%, and 100.00% of the factor interactions exhibited an increasing influence on outlying, edge-expansion, and infilling restoration, respectively. The interaction of Sp with NRD and LUR gradually predominated edge-expansion and infilling restoration, with q values increasing from 0.70 to 0.93 and 0.79 to 0.88, respectively (Table S4 and S5). In this case, the superimposed factors of slope, road, and urbanization exhibited stronger influence. In addition, the q(LUR∩SEI) on edge-expansion increased from 0.77 to 0.97 (Table S6).

4 Discussion

The GBA's ecological space gradually shifted from over-exploitation to a more balanced co-existence by transitioning from adjacent degradation-led (1990-2010) to edge-expansion restoration-led (2010-2019). The massive population migrations, rapid GDP growth, and increasing industrialization have accelerated construction land expansion and ELD in the GBA (Peng et al., 2017) and occupied a substantial amount of ecological land, especially around or within built-up areas with flatter topography and lower elevation (Bonan, 2008; López-Barrera et al., 2014). The new isolating degraded patches are small and separated from the ecological patches from which they originated, resulting in the formation of “ecological islands” that would be increasingly influenced by topography, population, economy, and urbanization. For adjacent and enclosing degradation types, the new patches remain connected with the original patches, are generally large, and are gradually weakened by the effect of natural conditions and anthropogenic activities that are constrained by ecological shelter protection and key eco-function zone protection policies. With respect to the three ELR types, infilling has continuously declined, while outlying and edge-expansion have significantly increased. Due to the high cost of restoration within built-up areas, the government primarily opted to refocus restoration efforts on outlying and edge-expansion in suburban or distant areas (Feng et al., 2021). In addition, due to rapid development of the tertiary industry is reducing the contiguous expansion of industrial land (Bi et al., 2020; Yang et al., 2019), thus PTI has become increasingly more influential on outlying and edge-expansion restoration. Throughout urban expansion in the GBA, the rural residential areas and agricultural land in the suburbs have been preserved and turned into “urban villages” (Liang et al., 2018) that are mainly concentrated in GZ, FS, DG, and SZ. During the rapid urbanization since 1990, the rural residential land type, dense population, and extensive housing hindered ELR (Huang et al., 2015). Beginning around 2010, special policies for urban village renewal promoted ELR (e.g., outlying restoration) (Gao et al., 2020; Wu et al., 2018) in the metropolitan interlocking region of GZ-FS and SZ-DG. However, it is worth noting that the substantial increase in outlying restoration will lead to a scattered distribution of ecological patches (Lü et al., 2015), which will negate the effect of enhancing the ecosystem's integrity (Ren et al., 2020).

Analysis of the spatial-temporal pattern of ecological land degradation-restoration in the GBA enabled the relationship between urban space (i.e., industrial and living space) and ecological space to be divided into three stages (Fig. 6). The first stage, which corresponds to 1990-2010, is characterized by overexploitation and conflict. During this stage, the scale of ELD was much larger than that of ELR. Rapid industrialization and urbanization led to a reduction in ecological land and a large ecosystem service loss in the GBA (Yang et al., 2019). In response, the government and policy makers attempted to reverse the disorganized territorial space development by formulating a series of plans to delineate industrial, living, and ecological area boundaries. Examples include the *Ecological Environment Construction Planning in Guangdong Province* and the *Outline of the Plan for the Reform and Development of the Pearl River Delta (2008-2020)* (Table S7). The second stage, which mostly corresponds to the period from 2010-2019, exemplifies coordination and governance. During this stage, urbanization in the GBA slowed down and ELD declined significantly. Furthermore, large-scale ELR projects, such as the *A New Round of Greening Guangdong* (Table S7), were implemented, which restored woodlands in forested areas at the edge of the GBA. Based on the above development trend, the GBA's ecosystem pattern will gradually move towards the third stage (harmony and coexistence) (Liu et al., 2021). With the goal of improving ecological livability, the GBA will promote positive evolution and coordinated development of a human-earth system, in which human societies beneficially interact with natural ecology (Bi et al., 2020). In essence, they will strive to organically integrate production and living space into ecological space, and coordinate the systematic management of "mountain, water, forest, farmland, lake, grassland, and sea" (Fu, 2021).

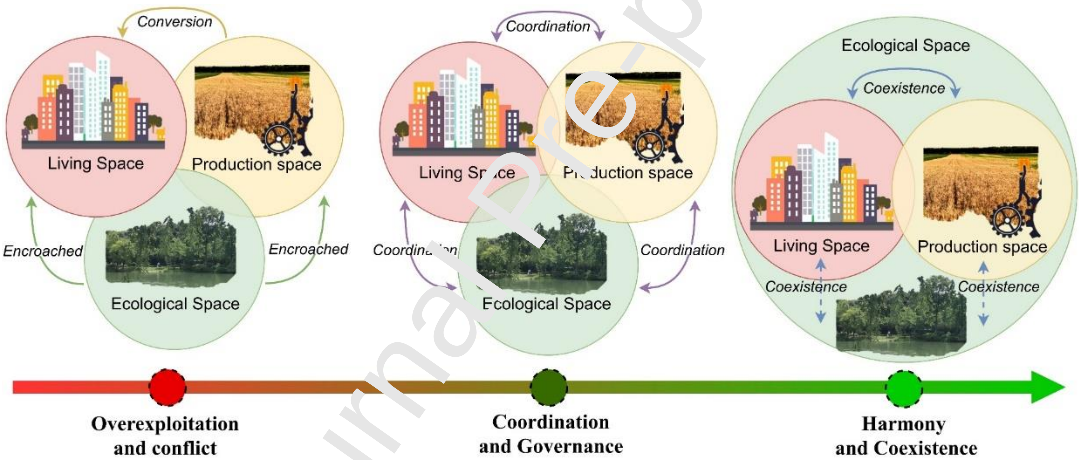

Fig. 6 Evolutionary relationship between ecological space, production space and living space.

A confluence of natural and anthropogenic factors dominated the GBA's ecological land degradation-restoration (Fig. 7). Anthropogenic activities played a more active role than natural factors, which is consistent with reports from previous studies (Feng et al., 2021; Jiang et al., 2017; Lü et al., 2015). Urban construction and population migration have a stronger influence on adjacent and isolating degradation (Jiang et al., 2020; Long et al., 2014; Xia et al., 2020), while natural factors, such as elevation and soil erosion, are more significant in enclosing degradation (Mao et al., 2018). Regions with high land urbanization rates subsequently develop massive populations. When also characterized by a gently sloping geographical environment, these areas contribute to adjacent and enclosing degradation of ecological lands within and at the edges of built-up areas (Puskás et al., 2021; Sutton et al., 2016). Simultaneously, urban construction and tertiary industry development dominate edge-expansion and infilling restoration (Batunacun et al., 2019), while natural factors, such as topography and climate, have a stronger impact on outlying restoration (Stanford et al., 2018). In contrast to previous studies (Dobbs et al., 2017; Puskás et al., 2021; Shi et al., 2011; Sutton et al., 2016), we found that the influence of anthropogenic factors on ELR—such as population, GDP, and tertiary industry—gradually shifted from negative to positive, indicating that social demand for habitat quality will be the essential factor going forward (Xun et al., 2014). However, the role of single factors gradually decreased, which is related to the urban agglomerations' development and environmental protection policies and plans (Dou and Kuang, 2020). For example, ecological land evolution from 1990 to 2000 was dominated by urban land encroachment and ecological restoration of peripheral forest zones (e.g., ZQ and HZ). During this time, the influence of single factors was relatively prominent. In contrast, with the implementation of ecological security and sustainable development strategies in 2010-2019, major ecological restoration policies and projects (Table S7) put more emphasis on multiple elements coupling with the social-ecological systems (Lü et al., 2015; Ren et al., 2020), and factor interaction effects became dominant. Therefore, within the GBA's complex, natural-socio-economic system, the spatial interactions of urbanization, transportation infrastructure, population, topography, and soil conditions are the main factors influencing ecological land degradation-restoration.

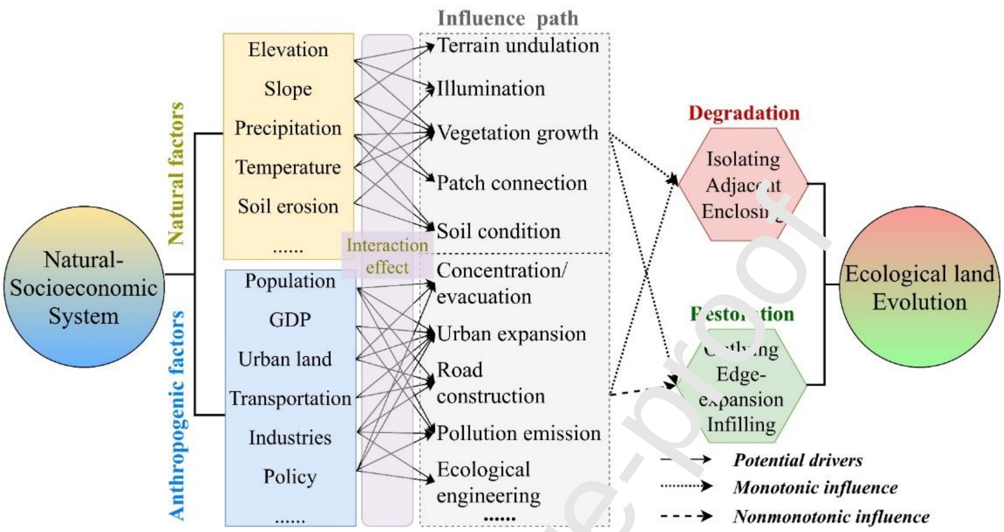

Fig. 7 Ecological land degradation-restoration mechanism.

While this study yielded a plethora of valuable results, there are some limitations. To begin with, this study has mapped six ecological land degradation-restoration patterns mainly based on the ecological land area data. However, it is also well known that the quality/effectiveness of ecological land degradation-restoration is of wide interest to governments and scientists (Batunacun et al., 2019; Dobbs et al., 2017; Zhang et al., 2021). Thus, the pattern of ecosystem service changes influenced by ecological degradation-restoration needs to be further evaluated, but it may involve more data on ecosystem characteristics. In addition, the different time intervals may introduce uncertainty to the pattern identification and geographic detector analysis results (Wang et al., 2016). Like other studies with a time span about 30 years (Dou and Kuang, 2020; Ren et al., 2020; Yang et al., 2019), land cover data with a 10-year interval was selected for spatial analysis in our study. Although the findings are well typical and reasonable at the 10-year scale, future studies can try to use different time intervals (e.g., 5 years) to explore possible new findings. Moreover, this research mainly uses quantitative methods, and most quantitative factors have been considered, while additional qualitative factors need to be further investigated to deepen the understanding of the ecological land degradation-restoration mechanisms.

In addition to these limitations and uncertainties, the findings have practical implications. To begin, decision makers should consider the interaction between anthropogenic and natural factors and understand how that relationship impacts urban planning. For example, the results show that LUR significantly interacted with other factors to jointly dominate ELD. As such, population evacuation, industrial transfer, and economic polycentric development should be carried out in areas with high land urbanization rates to alleviate the pressure of adjacent and enclosing degradation and promote edge-expansion and infilling restoration. However, the topography, soil conditions, and temperature significantly affected ELR, especially when interacting with LUR. Therefore, the macro impact of natural factors should not be ignored in ecological protection planning. Thus, the first step is to scientifically assess the suitability of ecological restoration based on topography, climate, and urbanization factors within the context of the natural geography. Subsequently, the governing bodies should coordinate systematic management of ecological restoration and natural ecosystem succession to improve quality of life.

Furthermore, in response to the ELD's spatial distribution and evolutionary trend, policy makers should formulate effective countermeasures that will prevent ecological degradation in key areas and promote a healthy cycle between ecological protection and high-quality economic development. Ecological land degradation-restoration in the urban agglomeration occurs at a regional scale. As such, the participation of individual cities in ecological integration planning and protection should be increased to prevent a disorganized and decentralized distribution of ecological restoration projects. In addition, the GBA should also perform cross-regional holistic restoration of key ecological function areas, delineate traffic routes and rivers as ecological corridors, promote ecological network construction, and organically connect ecological patches— such as green spaces, wetlands, and forests—to maximize the role of ecological restoration projects in enhancing ecosystem services. Ultimately, ecology should be integrated into the city, as opposed to being used to embellish the city.

5 Conclusions

This study combined remote sensing, landscape evolution index, and geographic detector methodologies to quantitatively characterize the contributions, interactions, and dynamics of multiple natural-anthropogenic factors on six ecological land degradation-restoration patterns in the GBA. The results showed that from 1990-2019, ecological land gradually shifted from conflict-fragmentation (e.g., adjacent degradation) to coordination-restoration. In addition, the influence of anthropogenic factors—such as LUR, POP, and GDP—was significantly greater than that of natural factors—such as Pre and Tem. As the overall marginal effect of a single factor decreased, the non-linear influence between factors increased. The results reflect both the surface land use changes and the growing and shrinking relationship between urban space and ecological space; and thus, contribute to our understanding of the spatial-temporal coupling of urbanization and ecosystem changes in urban agglomerations.

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Credit Author Statement

Rundong Feng: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing- Original draft preparation.

Fuyuan Wang: Formal analysis, Project administration, Supervision, Editing, Supervision

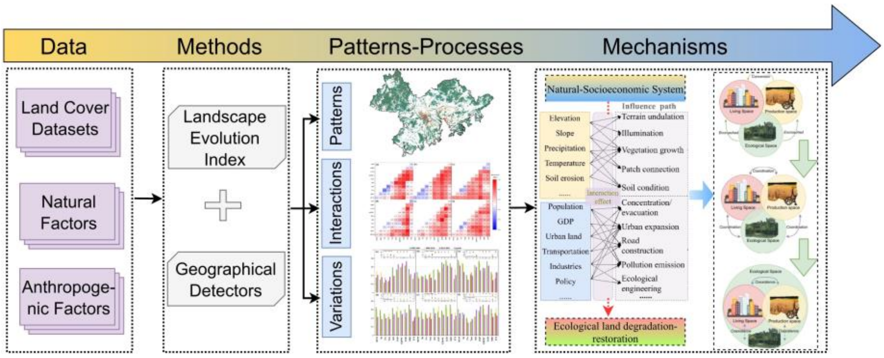
Kaiyong Wang: Writing- Reviewing, Supervision

Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Graphical abstract



Highlights

- Six patterns of ecological land degradation-restoration were identified
- Ecological land shifted from adjacent degradation to edge-expansion restoration
- Land urbanization rate dominated 71.33% of ecological land degradation
- 80% of anthropogenic factors shifted to positive in the ecological restoration
- Marginal effect of single factors decreased and interactions nonlinearly enhanced