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Analysis of the Spatial-temporal Evolution of Land Use and Driving Force based on the Production-Living-Ecological Space: A Case Study of Shenzhen

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Abstract— *Exploring the evolution of land use and its driving force in Shenzhen's Production-Living-Ecological Space* **(PLES)** *may serve as a reference for optimizing regional land spatial patterns and urban spatial structures, as well as providing a scientific foundation for supporting regional sustainable development. The research period was 2010 to 2020, and the spatial-temporal evolution was analyzed using GIS and a land use transfer matrix, followed by an examination of the driving factors of its change using geographic detectors. The results indicate that: (1) Shenzhen's production space increases initially before decreasing, while the living space increases little and then grows significantly, while the ecological space continues to shrink significantly. (2) From 2010 to 2015, the degree of conversion was quite low, but from 2015 to 2020, it climbed dramatically. (3) The majority of the factors have strong explanatory power for the land use intensity of* ***PLES*** *but the annual average temperature, NDVI, and the added value of tertiary industry are always important driving factors influencing the land use intensity (4) In the interactive detection, the average annual temperature, NDVI, PM2.5, population density, and the added value of tertiary industry were interacted with other factors, and the results significantly increased the explanatory power of the land use intensity of* ***PLES.***

Keywords— Production-Living-Ecological Space (PLES); Land use; Geodetector; Driving force analysis; Shenzhen City

I. INTRODUCTION

Changes in land use are one of the important indicators of how human activities affect the natural environment, reflected in the transformation of regional land cover [1]. With the advancement of science and technology, humanity's degree of land development and utilization has substantially grown, and the frequency of conversion between different land types has accelerated [2]. Land use change is the result of the interaction of various factors, with the combined effects of natural factors and social environmental factors driving the process of land use.

As research progresses, many scholars have proposed the concept of production-living-ecological space **(PLES)** from the perspective of land use function classification. This term refers to land that encompasses production, living, and ecological functions and is a product of the coordinated coupling between natural systems and socio-economic systems [3]. Among them, the production space refers to the functional area that provides agricultural products and industrial products to meet the basic needs of human life, and is the basis of the **PLES** system. Living space is related to the capacity to support and ensure human habitation. It is an area primarily focused on providing functions for human residence, consumption, leisure, and entertainment, which is the goal of the **PLES** system [4].

Ecological space is related to the natural background and is an area with the leading function of providing ecological products and ecological services. In regulating, maintaining, and ensuring regional ecological security. It plays an important role and is the support of the **PLES** system [5]. Land use transformation is a dynamic process that involves the quantitative and spatial reallocation and reallocation of land resources in production, life, and ecology at different stages of regional economic and social transformation [6]. Therefore, the spatio-temporal characteristics of land use evolution and its driving force analysis based on **PLES** have become a hot issue in current geography research.

In view of this, this study is based on the perspective of **PLES** and explores the spatio-temporal evolution law of land use data in Shenzhen from 2010 to 2020. By analyzing the driving factors that affect the changes of **PLES** through geodetector, the evolution characteristics of the **PLES** pattern in Shenzhen are summarized, providing reference for promoting the effective utilization of land resources and optimizing urban structure.

II. MATERIALS AND METHODS

2.1. Study Areas

Shenzhen is located on the southeast coast of Guangdong Province, bordered by Daya Bay and Dapeng Bay in the east, the Pearl River Estuary and Lingding Ocean in the west, Dongguan and Huizhou in the north, and Hong Kong in the south, with a total area of 1997.47 km2. It is one of Dawan District's main engine cities in Guangdong, Hong Kong, and Macao. At the same time, Shenzhen has had one of China's highest urbanization rates in recent years. Currently, land development intensity can reach 50%, and land resources are in short supply [7]. It has entered the stage of profound urbanization, which is characterized by the usage of existing land.

2.2. Data Sources

The data sources for this study include land use data, temperature and precipitation data, Normalized Difference Vegetation Index （NDVI） data, PM2.5 data, and socioeconomic statistics, which were analyzed after preprocessing (Table 1).

2.3. Methodology

2.3.1 Classification System of PLES

This study is based on the current land use classification, categorizing different land types according to their dominant functions. Additionally, it references the research of Yang et al. [8] and Wang and Xiang [9]. Through Table 2, which outlines the PLES classification system, it summarizes and consolidates six categories of primary land. Firstly, production space includes agricultural production space and industrial and mining production space, reflecting cultivated land and other construction land in the classification of land level;

Secondly, living space includes urban or rural living space, namely urban land and rural residential areas; Finally, ecological space includes three parts: green ecological space refers to grassland and forest land; water ecological space includes natural land, water, and water conservancy facilities; and other ecological space includes sand, Gobi, and other unused land, but it also plays a great role in supporting the ecosystem, so it is classified as ecological space land.

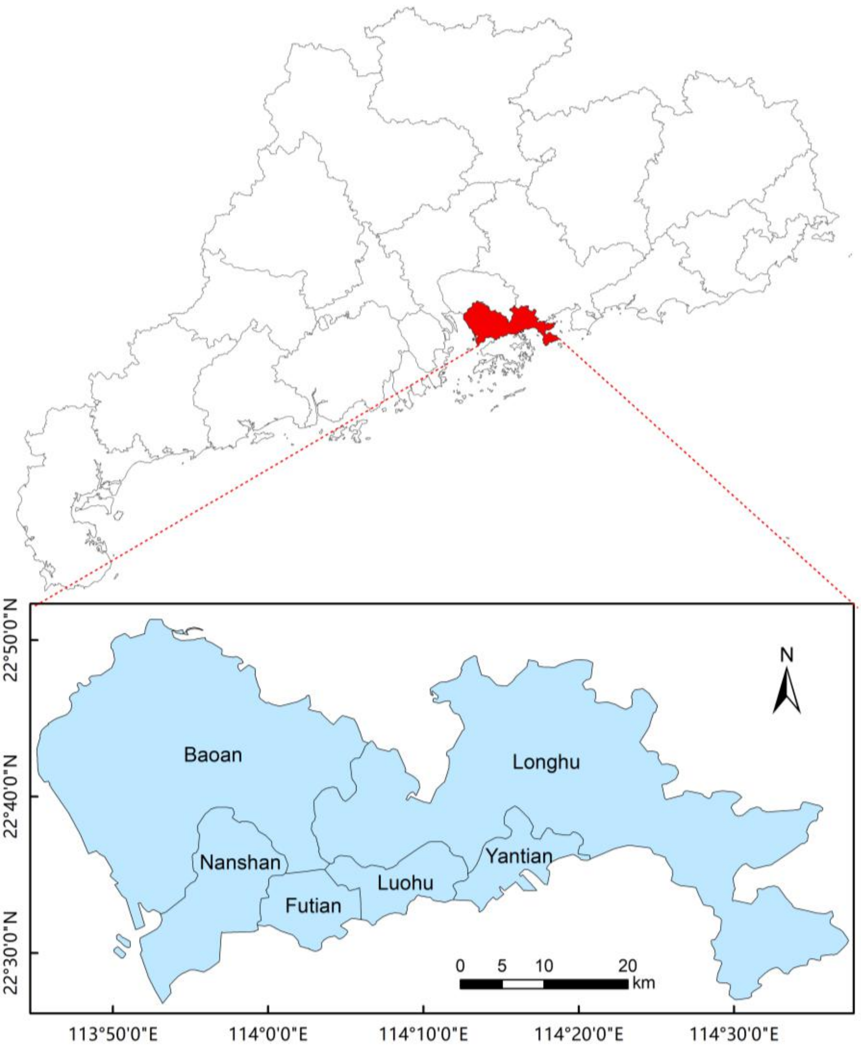


Fig.1 Administrative division map of the study area

Table 1 Data sources

Data Name	Data Sources	Pretreatment process
Land use data on 2010, 2015 and 2020 (30m resolution)	Resource and Environmental Science and Data Center, CAS(https://www.resdc.cn/)	Crop the study area
Temperature and precipitation data	The ERA5-Land dataset released by organizations such as the European Union and the European Centre for Medium-Range Weather Forecasts (https://cds.climate.copernicus.eu)	The original data consists of monthly average temperature raster data. Using the raster calculator, the average value of the average temperatures for the 12 months is calculated to obtain the annual

		average temperature raster data. Then, the average raster values for each district in Shenzhen are computed to derive the annual average temperature. The pretreatment of precipitation data is the same as above
NDVI data	MOD13A3 data under the MODIS dataset （https://search.earthdata.nasa.gov/search）	Based on the original NDVI data, calculate the average raster values for each district in Shenzhen to obtain the annual NDVI for each district.
PM2.5 data (Resolution of 0.01° × 0.01°)	Atmospheric Composition Analysis Group, Washington University, St. Louis （https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.02）	Convert original.nc format data to .tif format
Socio-economic statistical data	Shenzhen Statistical Yearbook 2010, 2015, 2020. （https://www.sz.gov.cn/）	Organize and merge data

Table 2 Classification system of PLES

Class I	Class II	Explain
Production Space (PS)	Agricultural production space (PS1)	Land on which crops are grown, including paddy fields and dry lands
	Industrial and mining Production space (PS2)	Refers to land for factories, large industrial zones, oil fields, salt fields, quarries, etc., that are independent of towns, as well as transportation roads, airports, and special land use.
Living Space (LS)	Urban living space（LS1）	Refers to urban land use, including land use in large, medium, and small cities as well as built-up areas in towns above the county level.
	Rural living space（LS2）	Rural residential areas
Ecological Space (ES)	Green ecological space（ES1）	Forest land refers to areas where trees, shrubs, bamboo, and coastal mangroves grow, while grassland refers to various types of land primarily covered by herbaceous plants with a coverage of over 5%.

	Water ecological space（ES2）	Refers to natural land water areas and land used for water conservancy facilities, including rivers, lakes, reservoirs, permanent glaciers and snowfields, tidal flats, and shoals.
	Other unused space（ES3）	Refers to unused land, including sandy land, Gobi desert, saline-alkali land, marshland, bare land, and bare rocky gravel land, among others.

2.3.2 Land Use Transition Matrix

The land use transfer matrix can reflect the sources, destinations, and conversion areas of various spatial types over a certain period. The matrix expression [10] is:

$$S = S_{ij} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & S_{1n} \\ S_{21} & S_{22} & S_{23} & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & S_{n3} & S_{nn} \end{bmatrix}$$

(1)

In the formula: S represents the total land use area of Shenzhen; n indicates the number of land use types in Shenzhen; i and j represent the land use types during the research period, respectively.

2.3.3 Geodetector

The geographic detector is a novel statistical tool for detecting geographical diversity and determining the driving forces behind it. This study investigates the impact of driving variables on land use changes as well as the interaction links between these driving factors using factor and interaction detection methods.

Factor detection: revealing the spatial differentiation characteristics of the dependent variable land use change Y, as well as the explanatory degree of factor X on the spatial differentiation of the dependent variable Y. The model expression [11] is:

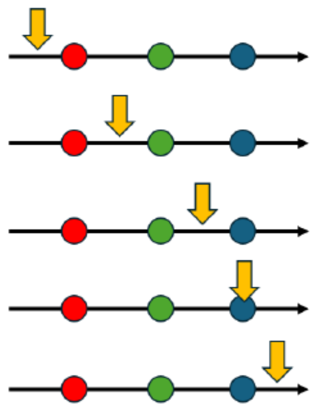
$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

$$\begin{cases} SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \\ SST = N\sigma^2 \end{cases} \qquad (2)$$

In the formula: q represents the degree to which factor X explains the spatial heterogeneity of land use change, with a range of values of [0,1]. The larger the q value, the greater the impact of the factor on land use change; h=1, 2,..., L is the number of partitions or classifications of factor X; Nh and N are the number of samples in the h-th class of factor X and the total number of samples in the region, respectively; σ h and σ are the variance of factor X's h-th class and the total variance of the region, respectively.

Interaction detection: The difference in explanatory power between the combined action of discriminative factors Xi and Xj and the action of a single factor. Firstly, calculate the explanatory power of factors Xi and Xj for Y separately (q (Xi), q (Xj)), then calculate the explanatory power of the interaction between the two factors (q (Xi ∩ Xj)), and compare q (Xi), q (Xj), and q (Xi ∩ Xj) to analyze the type of interaction between the two factors (Table 3).

Table 3 Types of interaction among independent variables [12]

Graphic	Discrimination criteria	Interaction type
	$q(X_i \cap X_j) < \min(q(X_i),q(X_j))$	Nonlinear weakening
	$\min(q(X_i),q(X_j)) < q(X_i \cap X_j) < \max(q(X_i),q(X_j))$	Single-factor Nonlinear weakening
	$q(X_i \cap X_j) > \max(q(X_i),q(X_j))$	Two-factor enhancement
	$q(X_i \cap X_j) = q(X_i)+q(X_j)$	Independent
	$q(X_i \cap X_j) > q(X_i)+q(X_j)$	Nonlinear enhancement
Tip: ● denote $\min(q(X_i),q(X_j))$; ● denote $\max(q(X_i),q(X_j))$; ● denote $\max(q(X_i),q(X_j))$; ⇩ denote $q(X_i \cap X_j)$		

III. RESULTS

3.1 Temporal and Spatial Evolution of PLES

3.1.1 Quantitative Analysis

Overall, from 2010 to 2020, the evolution of the **PLES** in Shenzhen shows a significant increase in living space, with the area growing from 814.96 km² to 851.29 km². The area of production space and ecological space has both decreased. Specifically, the area of production space saw a slight increase of 8.53 km² from 2010 to 2015, but then experienced a significant reduction of 21.45 km² from 2015 to 2020. Meanwhile, the ecological space continuously shrank from 2010 to 2020, decreasing in area from 853.73 km² to 828.31 km² (Figure 2).

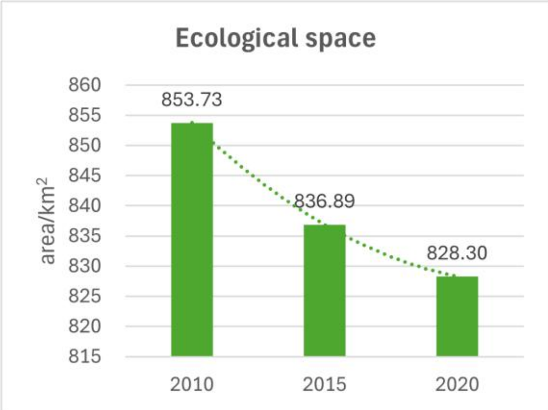


Fig.2 Change Map of PLES Area in Shenzhen from 2010 to 2020

From the ten-year span of 2010 to 2020, the total area of change in the **PLES** was 253.29 km², accounting for 13.15% of the total land area. In the conversion of areas among different spaces, only the area of living space has increased, while the areas of production space and ecological space have all decreased. Among them, the area transferred out of living space and the area transferred in are 69.53 km² and 106.41 km², respectively, with a difference of 36.88 km².

The area transferred out of production space and ecological space is 38.19 km² and 31.34 km², respectively, while the area transferred into production space and ecological space is 60.42 km² and 45.99 km².

The areas transferred out of production space and ecological space are 94.51 km² and 89.25 km², respectively, and the areas transferred in are 81.14 km² and 65.43 km² which decrease by 13.8% and 26.7% compared with 2010. Therefore, it can be seen that large areas of land in these two types of spaces are converted into living spaces (Table 4).

Table 4 Land use transfer matrix of PLES from 2010 to 2020 (Unit: km²)

Year		2020			
	PLES type	Production space	Living space	Ecological space	Transfer-out total
2010	Production space	——	60.42	34.09	94.51
	Living space	38.19	——	31.34	69.53
	Ecological space	43.26	45.99	——	89.25
	Transfer-in total	81.45	106.41	65.43	——

Further analysis of the land use types in Class II **PLES** reveals that the area of production space is small and primarily consists of agricultural production space. The area of living and ecological space is significant, with living space primarily consisting of urban living space, while ecological space mainly comprises green ecological space (Table 5).

Table 5 Proportion of various land use types in Shenzhen from 2010 to 2020

Year/ Land use types	Agricultural production space	Industrial and mining Production space	Urban living space	Rural living pace	Green ecological space	Water ecological space
2010	8.58%	4.9%	40.82%	1.44%	40.58%	3.68%
2015	8.13%	5.78%	41.25%	1.44%	39.96%	3.43%
2020	6.41%	6.4%	41.29%	2.9%	39.78%	3.22%

From 2010 to 2020, the land type that experienced the most transfer among the six Class II land categories was green ecological space, totaling 80.59 km², of which 35.21 km² was converted into urban living space. Secondly, the urban living space has been converted the most, with a large portion of the land being transformed into industrial and mining production space as well as green ecological space. The urban living space is the land type that accepts the largest area of land conversion, totaling 87.37 km², primarily transformed from agricultural production space and green ecological space.

Following this, the land areas that have been converted the most are industrial and mining production space, as well as green ecological space. These indicate that the mutual conversion among green ecological space, urban production space, and industrial and mining production space in Shenzhen is quite frequent, reflecting the intensive utilization and development of these three types of land. The agricultural production space and water ecological space are less transferred than transferred out, and the overall reduction is 57.72% less than that transferred out, most of which are transferred out to living space, and large areas of water ecological space are transferred out to industrial and mining production space and transferred into green ecological space (Table 6 and Figure 3).

Table 6 Land Use Transfer of PLES in Shenzhen from 2010 to 2020 (Unit: km²)

Year	2020						
	Production space		Living space		Ecological space		Transfer-out
2010	PS1	PS2	LS1	LS2	ES1	ES2	
PS1	——	8.42	36.74	15.61	8.48	3.01	72.26
PS2	7.97	——	7.64	0.43	19.98	2.61	38.63
LS1	10.43	25.07	——	17.66	24.10	1.39	78.65
LS2	1.53	1.17	2.82	——	5.40	0.45	11.37
ES1	8.68	18.70	35.21	5.72	——	12.28	80.59
ES2	1.94	13.94	4.96	0.10	7.10	——	28.04
Transfer-in	30.55	67.30	87.37	39.52	65.06	19.74	——

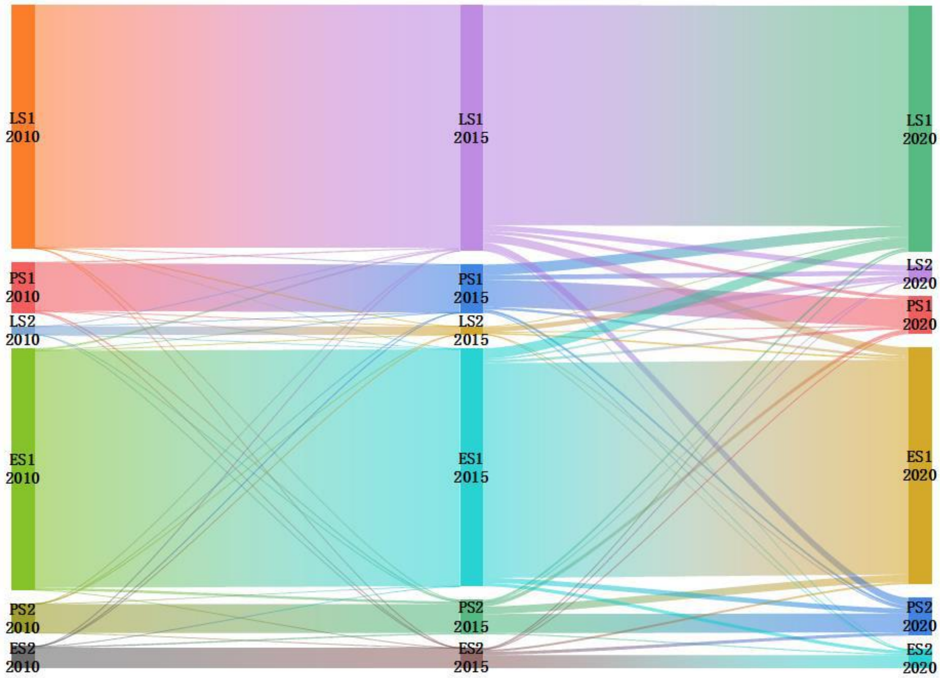
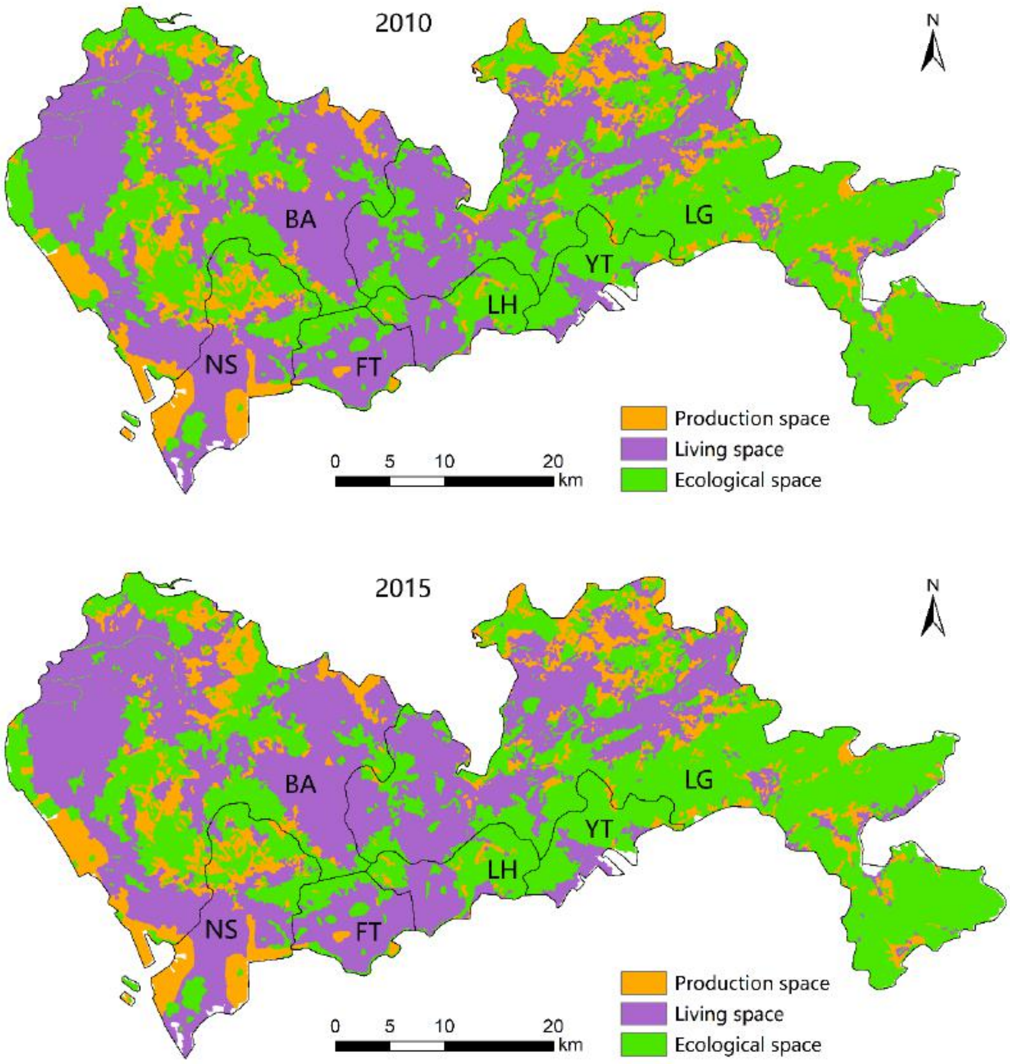


Fig.3 PLES of Land Use Transfer

3.1.2 Spatiotemporal Analysis

According to the analysis of different time periods, from 2010 to 2015, the land use change range of PLES in each district of Shenzhen is relatively small, mainly that part of ecological space in the west of Baoan is converted into production space, and a small part of ecological space in the west and north of Longgang is converted into living space and production space. From 2015 to 2020, the area of PLES in various districts has shown a significant increase, with a large area of production and ecological space within living space being converted into living space.

The ecological space in the western part of Baoan has further shrunk, being converted into production space, while some in the northern part has been transformed into ecological space. A similar land transformation has occurred in Longgang as well. Secondly, the large living spaces in the central and southern parts of Yantian are being converted into production spaces (Figure 4).



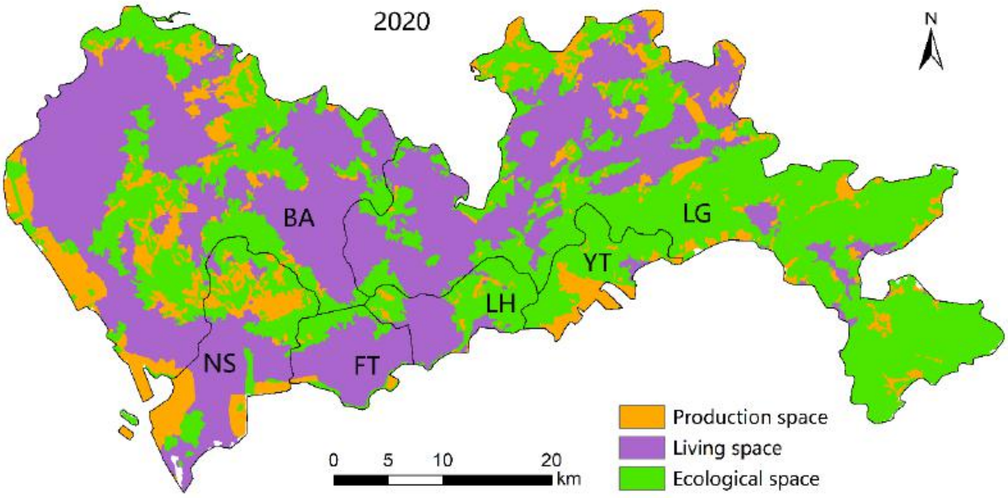
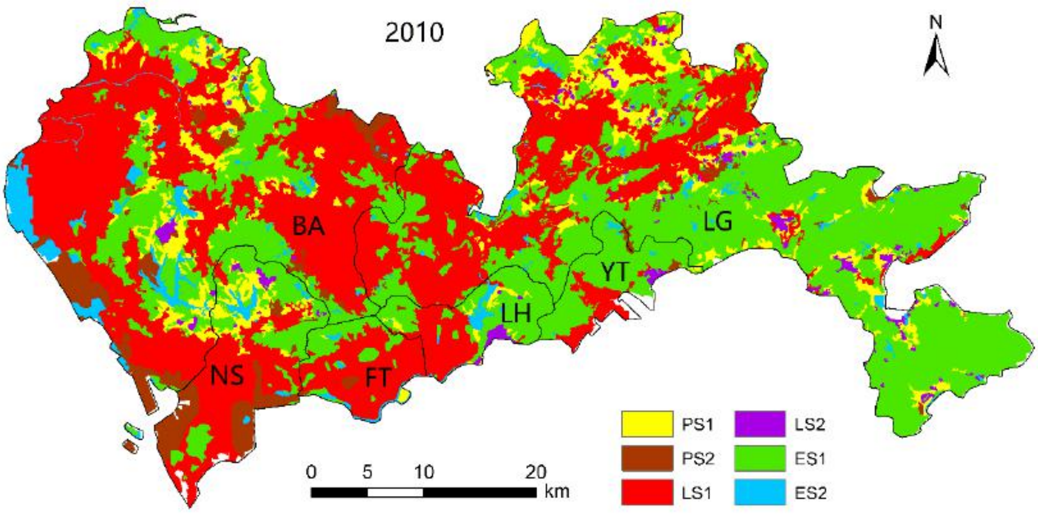


Fig.4 Distribution of PLES in Shenzhen from 2010 to 2020

Combined with the land use types of Class II PLES, the obvious change from 2010 to 2015 is that the ecological space of water ecological space in the west of Baoan continues to shrink and transform into industrial and mining production space; part of agricultural production space in the north of Longgang is transformed into urban living space, and urban living space is transformed into rural living space.

From 2015 to 2020, industrial and mining production space in the northwest of Baoan was transformed into green ecological space. The urban living space in Yantian has been extensively transformed into industrial and mining production space. A part of urban living space in the northern part of Nanshan has been converted into industrial and mining production spaces (Figure 5).



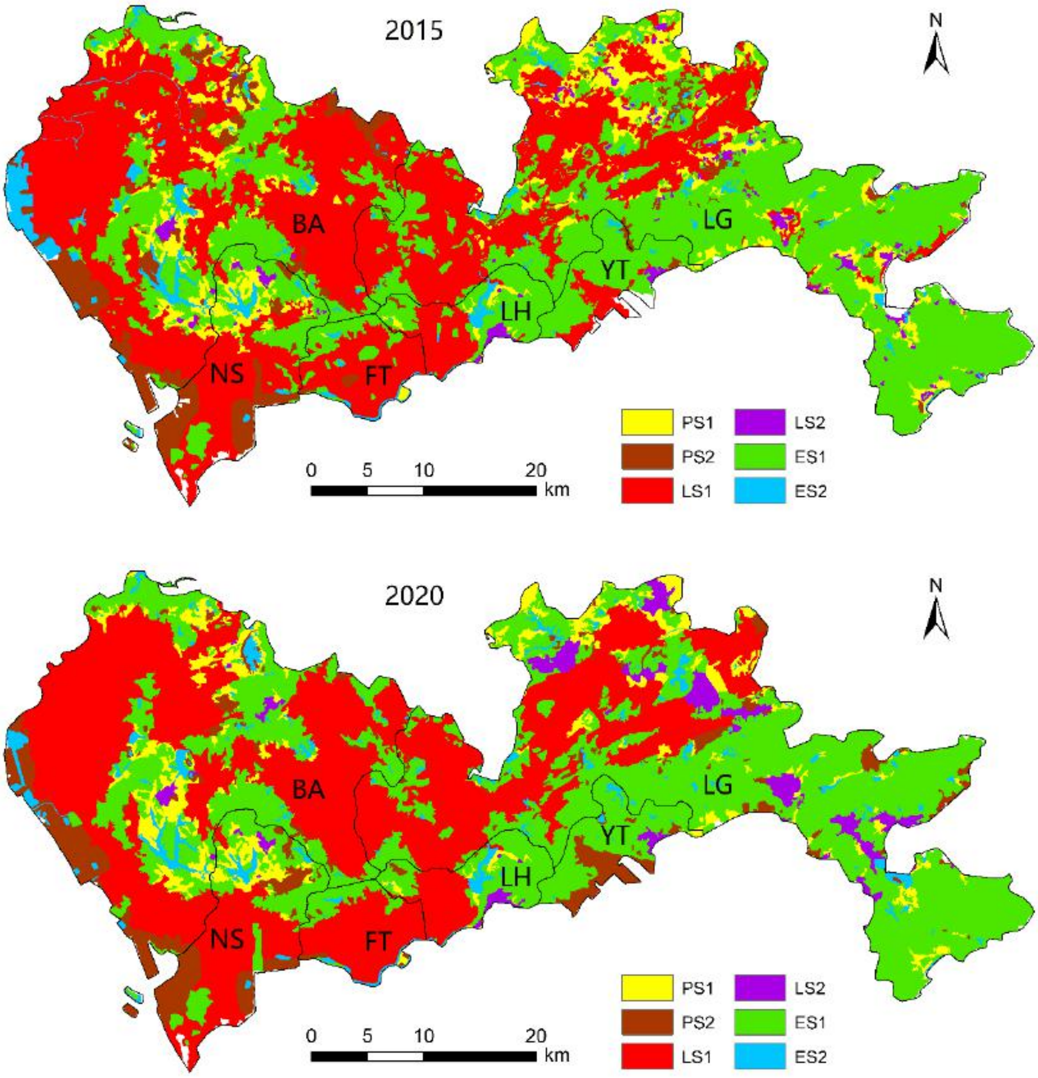


Fig.5 Distribution of Secondary Land Use Types in Shenzhen from 2010 to 2020

From the perspective of a single PLES, from 2010 to 2020, production space was fragmented and distributed in various districts. Among them, Baoan and the northern part of Longgang, as well as the central part of Nanshan, showed a significant decrease in small-scale production space. The large-scale increase in production space was mainly concentrated in the western part of Baoan and the central southern part of Yantian, while other districts also had small-scale increases, but the distribution was relatively scattered. The living space is generally distributed in a concentrated and contiguous manner, with a main decrease in block like contiguous areas.

The most obvious areas are in the central and southern parts of Yantian and the northwest part of Longgang. In areas with unchanged living space area, there are also many small areas with newly added area. The ecological space is concentrated in the eastern and central western regions of Shenzhen, with Longgang having the widest distribution, followed by Baoan, Yantian, Luohu, Nanshan, and Futian. The ecological space area of each district shows scattered and scattered decreases and increases (Figure 6).

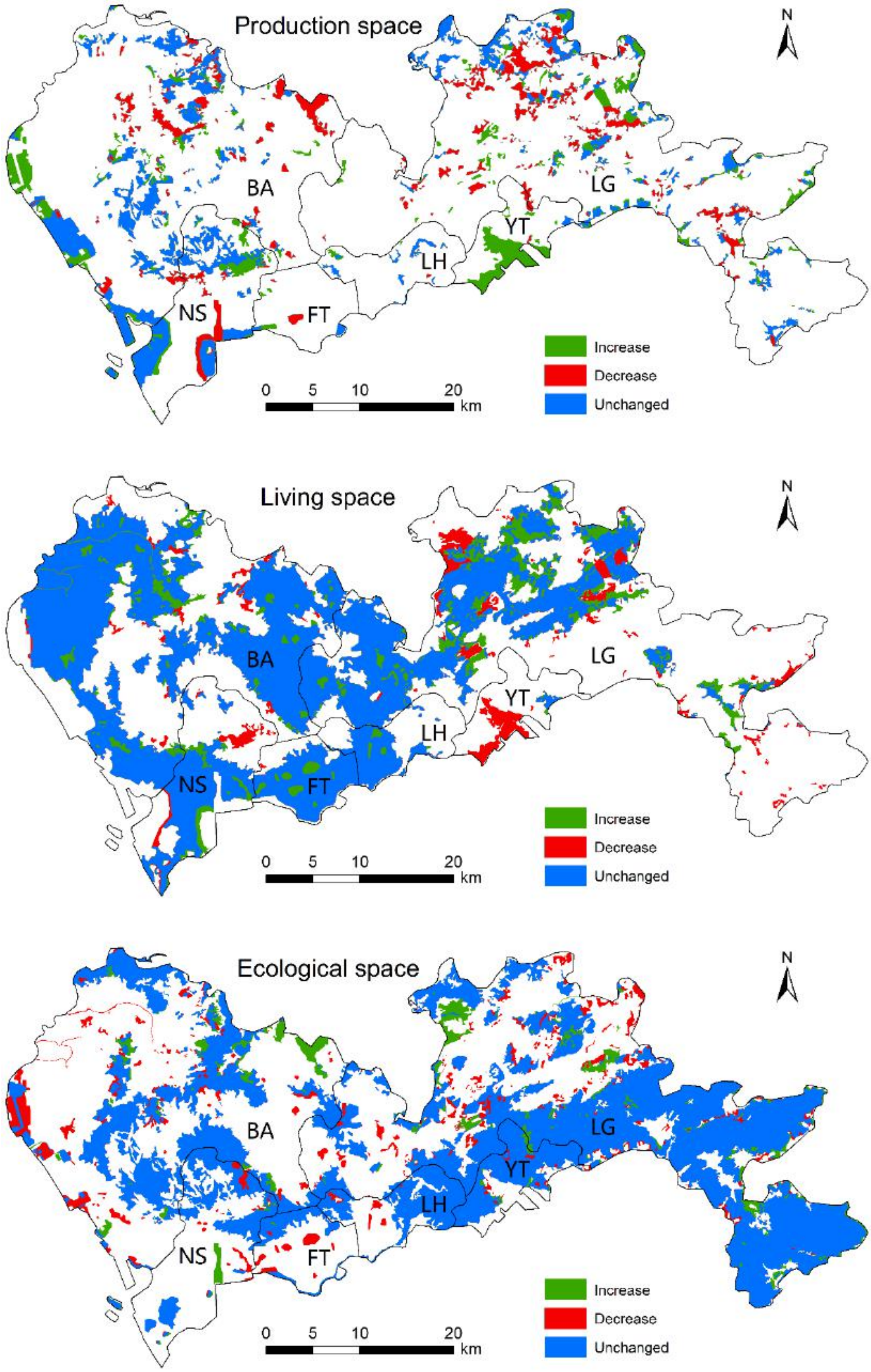


Fig.6 Spatial distribution of the change in Shenzhen from 2010 to 2020

3.2 Driving Factors Analysis

From 2010 to 2020, there have been varying degrees of changes in the land use types of the PLES in Shenzhen. Based on the actual situation of the research area and the availability of data, considering the representativeness and research significance of the selected factors, 11 driving factors were selected from the natural, social, and economic aspects to explore the driving mechanism of the spatio-temporal evolution of land use in the PLES in Shenzhen. The selection of each factor is shown in Table 7. This study discretized the treatment of numerical independent variables using the K-means classification algorithm. After repeated experiments, the results were more scientific when the number of clusters was 4.

Table 7 Classification of Influencing Factors

Factor Type	Factor	Unit
Natural Factors	X1: Average Annual Temperature	°C
	X2: Average Annual Precipitation	mm
	X3: NDVI	
	X4: PM2.5	
Social Factors	X5: Population Density	people/km²
Economic Factors	X6: Regional Gross Domestic Product	10,000 yuan
	X7: Per Capita Regional Gross Domestic Product	
	X8: Value Added of the Primary Industry	
	X9: Value Added of the Secondary Industry	
	X10: Value Added of the Tertiary Industry	
	X11: Fixed Asset Investment Amount	

3.2.1 Factor Detection Results

Using a geodetector, factor detection was conducted on the spatial distribution changes of land use types in the PLES in the three periods of 2010, 2015, and 2020 to explore the explanatory power of each factor on the land use intensity (Y value) of the PLES in Shenzhen.

The results of factor detection are shown in Table 8. It can be seen from the table that in 2010, the explanatory power of each factor to the land use change of Shenzhen's PLES from big to small is: annual average temperature>NDVI>population density>added value of the primary industry>added value of the secondary industry> fixed asset investment amount >added value of the tertiary industry>annual average precipitation>Regional Gross Domestic Product>PM2.5>Per Capita Regional Gross Domestic Product. Among them, X1 (annual average temperature), X3 (NDVI), and X5 (population density) have strong explanatory power. Annual average temperature has a direct impact on the growth of crops and vegetation, NDVI reflects regional vegetation coverage, and these two factors directly affect the process of land use change in the PLES. Population density reflects the degree of regional population aggregation and has an important impact on land use change in the PLES. Except for X7, the explanatory power of all other factors exceeds 0.5, indicating that the land use change of PLES in Shenzhen in 2010 was influenced by multiple factors, including natural, social, and economic factors.

Compared with 2010, the explanatory power of X6 (regional gross domestic product), X7 (per capita regional gross domestic product), X2 (annual average precipitation), and X8 (added value of the primary industry) has significantly increased in 2015. Among them, X1 (annual average temperature) has stronger explanatory power than in 2010, but the explanatory power of X5 (population density), X4 (PM2.5), and X3 (NDVI) has significantly decreased. During this period, it can be seen that land use change in the PLES has shifted to a situation dominated by economic development, while the intensity of the impact of climate factors is increasing. Compared with 2015, factors with significantly increased explanatory power in

2020 include X4 (PM2.5), X3 (NDVI), X5 (population density), and X10 (added value of the tertiary industry). In addition, factors with explanatory power greater than 0.5 include X1 (average annual temperature), X6 (regional GDP), X2 (average annual precipitation), and X8 (added value of the primary industry). From the above, it can be further inferred that the land use change of the PLES in Shenzhen is mainly influenced by economic and natural factors.

From the perspective of the entire research period, the driving factors that affect the land use change of the PLES in Shenzhen in different years have varying strengths. However, factors such as X1 (average annual temperature), X3 (NDVI), and X10 (added value of the tertiary industry) have strong explanatory power during the research period. Due to the development of strategic emerging industries in Shenzhen, which have high requirements for environmental quality, economic and natural factors directly determine the pattern of land use change in the PLES to a large extent.

Table 8 Q value of driving factors

Year\ Factors	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
2010	0.94	0.72	0.94	0.63	0.94	0.68	0.21	0.75	0.75	0.73	0.75
2015	0.94	0.94	0.50	0.20	0.41	0.99	0.50	0.94	0.49	0.69	0.49
2020	0.95	0.64	1.00	0.97	0.77	0.65	0.17	0.64	0.30	0.97	0.30

3.2.2 Interaction Detection Results

Interactive detection can reflect the combined effects of factors on land use change in the PLES and the differences between single factor effects. The results of interactive detection are shown in Figure 7. There was no independent or weakened interaction between the driving factors in each year, indicating that compared to single factor interaction, the explanatory power of the interaction between the two factors for land use change in the PLES was enhanced to varying degrees. This further demonstrates that land use change in the PLES is the result of the interaction and influence between different factors.

From the interaction detection result graph, it can be clearly seen that in 2010, X1 (average annual temperature), X3 (NDVI), X5 (population density), X10 (added value of the tertiary industry), and the interaction results with 10 other factors except for themselves all showed a dual factor enhancement, indicating that during this period, average annual temperature, NDVI, population density, and added value of the tertiary industry were the dominant driving factors jointly promoting the changes in land use in the PLES; In 2015, X1 (average annual temperature), X2 (average annual precipitation), X6 (regional gross domestic product), X8 (added value of the primary industry), and X10 (added value of the tertiary industry) were the dominant driving factors. Among them, the interaction between X3 (NDVI) ∩ X4 (PM2.5) and X4 (PM2.5) ∩ X7 (per capita regional gross domestic product) showed a non-linear enhancement, indicating that the impact of natural factors on the land use of the PLES in Shenzhen has become increasingly significant over time; In 2020, with X1 (average annual temperature), X2 (average annual precipitation), X3 (NDVI), X4 (PM2.5), X5 (population density), and X10 (added value of the tertiary industry) as the main driving factors, it can be seen that nature, society, and economy, especially the tertiary industry, have become important sources of jointly promoting land use change in the PLES.

The interaction mechanism of factors leading to land use change in the PLES varies significantly in different years, but X1 (annual average temperature), X3 (NDVI), X4 (PM2.5), X5 (population density), and X10 (added value of the tertiary industry) all show strong explanatory power for the interaction of other factors, indicating that these factors have a relatively active effect on land use change in the PLES in different periods.

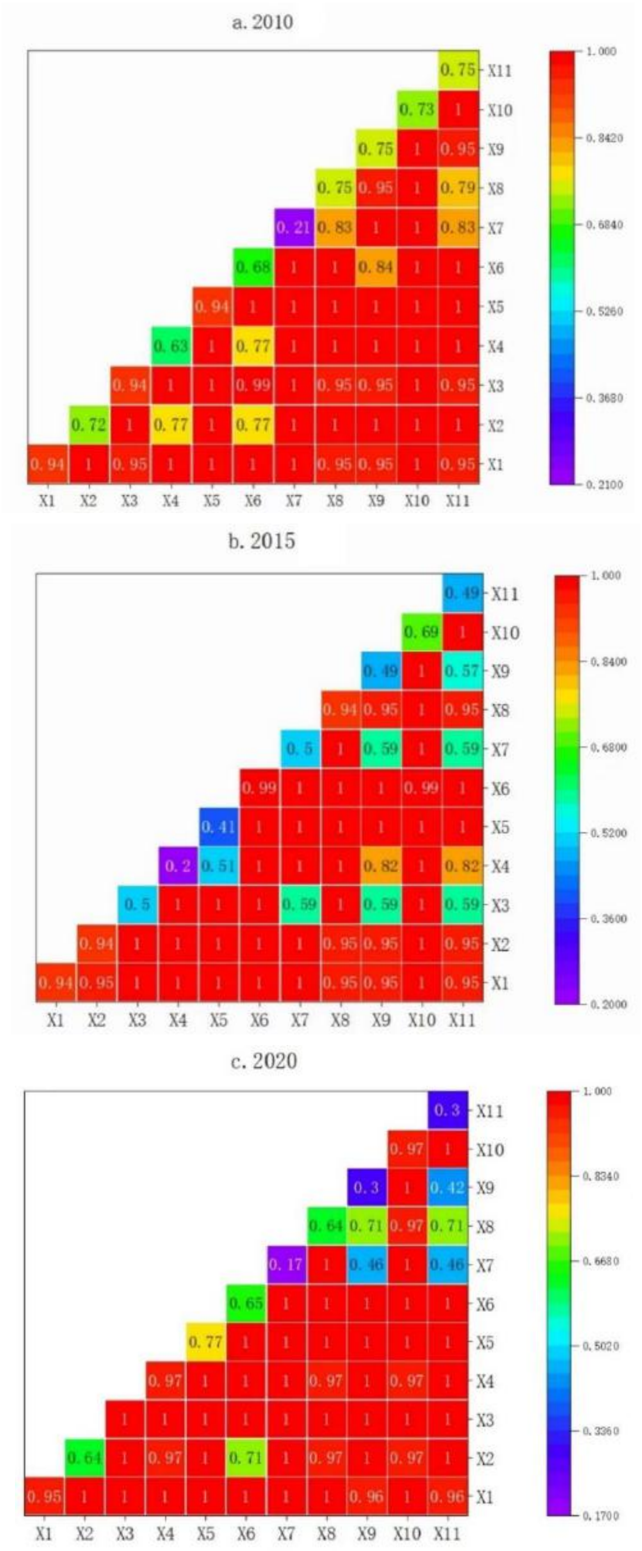


Fig.7 Interaction detection results

IV. DISCUSSION

This article first systematically analyzes the spatio-temporal evolution of land use in Shenzhen's PLES from the perspective of land use transfer matrix. During the research period, in terms of quantity, the production space first showed growth and then decreased, the living space continued to increase, and the ecological space continued to decrease. The area of each class II land use type in the space increased and decreased, showing varying degrees of fluctuation. In terms of temporal and spatial evolution, the evolution of land use in the PLES from 2010 to 2015 was relatively small, and the transformation of various class II land use types was also relatively small. From 2015 to 2020, the change in the PLES increased, and complex transformations occurred in the class II land use types of each district. Then, a geographic detector was used to analyze the driving factors affecting the land use evolution of Shenzhen's PLES.

The results showed that annual average temperature, NDVI, and added value of the tertiary industry were always important factors affecting the land use change of Shenzhen's PLES. At the same time, the interaction between factors in each year showed dual factor enhancement or nonlinear enhancement, indicating that the interaction between factors was relatively enhanced compared to single factors, further promoting the transformation of land use in the PLES.

Compared to previous studies [13-15], this study incorporates NDVI factors that more accurately reflect vegetation coverage, PM2.5 factors that focus on air quality, and increases the explanatory power of land use intensity in the PLES. Secondly, this study further explores the mechanism of land use change in the PLES from two aspects: single factor detection and interaction detection. At the same time, geodetectors were used in the research process. Due to their suitability for continuous dependent variables, numerical dependent variables need to be discretized. The choice of discretization methods for each factor is a limitation of geographic detectors and is prone to errors during the processing. There is also a certain subjectivity in the selection of factors, which has a certain impact on the analysis of land use evolution in the PLES.

The above issues need further in-depth research, and the next step should be to consider selecting more scientific and meaningful methods for driving force analysis. Moreover, the selection of factors should be more comprehensive and tailored to the characteristics of the research area.

V. CONCLUSIONS

This study used a land use transfer matrix to analyze the spatio-temporal evolution of land use in the PLES in Shenzhen from 2010 to 2020. Geodetectors were used to detect factors and interactions among selected factors, and the following conclusions were drawn:

(1) During the research period, the production space in Shenzhen showed an initial increase followed by a decrease, the living space showed a slight increase to a significant increase, and the ecological space showed a sustained and significant decrease trend; The frequent conversion of industrial and mining production space, urban living space, and green ecological space is the main type of secondary land.

(2) The conversion of land use types in the PLES of various districts in Shenzhen was relatively small from 2010 to 2015, but significantly increased from 2015 to 2020. Among the class II PLES land use types, the transformation of the ecological space in the western water ecological space of Baoan into an industrial and mining production space and the transformation of the large-scale urban living space in the central and southern parts of Yantian into an industrial and mining production space are more significant.

(3) The driving forces behind the evolution of land use in the PLES at different stages follow the following pattern: Most factors in factor detection have strong explanatory power for the intensity of land use in the PLES, but annual average temperature, NDVI, and added value of the tertiary industry are always important driving factors affecting the intensity of land use in the PLES.

(4) Interaction detection shows that the explanatory power of interaction factors on the land use intensity of the PLES is stronger than that of single factors. Among them, the interaction effects of annual average temperature, NDVI, PM2.5, population density, and added value of the tertiary industry on factors other than themselves significantly increase the explanatory power of the land use intensity of the PLES.

Overall, exploring the evolution of land use and its driving force in Shenzhen's PLES may serve as a reference for optimizing regional land spatial patterns and urban spatial structures, as well as providing a scientific foundation for supporting regional sustainable development.

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