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# Analysis of Spatiotemporal Changes and Driving Forces of Vegetation Coverage in Foshan City, Guangdong Province

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***Abstract*— *Quantitative analysis of the spatiotemporal distribution characteristics and driving forces of regional fractional vegetation coverage (FVC) is of great significance for promoting urban ecological protection and high-quality development. This study utilized the GEE platform and Landsat series remote sensing data to invert the FVC of Foshan City from 2001 to 2020 based on a pixel binary model. The spatial pattern and spatiotemporal variation characteristics were analyzed, and combined with meteorological, topographic, and land use data of the same period in the region, Sen +Mann Kendall trend analysis and parameter optimal geographic detector model were used to analyze its driving factors. The results showed that: 1. From 2001 to 2020, the overall vegetation coverage showed a slight downward trend (with a reduction rate of 2.87%), and the average vegetation coverage over the years was 51.53%, indicating that the vegetation coverage in the study area was generally at a moderate level. In terms of spatial distribution, the overall vegetation coverage shows a pattern of "high in the northwest and low in the southeast," with significant regional differences, and the types are mainly moderate and low vegetation coverage. 2. The proportion of vegetation improvement areas in the research area is 49.53%, which is larger than the area of degraded areas. 3. In the detection of driving factors, land use type is the main driving factor with an average explanatory power of 61.25%, while vegetation, topography, precipitation, and altitude are secondary driving factors; The explanatory power (Q value) of the interaction between each factor is higher than that of a single factor, showing a synergistic and nonlinear enhancement relationship between two factors.*

***Keywords*— *Fractional vegetation coverage (FVC), Trend analysis, Spatiotemporal differentiation, Optimal Parameters-based Geographic Detector (OPGD) model, Driving factors.***

## I. INTRODUCTION

Land cover change is one of the core contents of global change research, and vegetation is the most important part of land cover. Its changes have significant impacts on global energy cycling and material biochemical cycling 0[2]. Fractional vegetation cover (FVC) is not only an important control factor for soil erosion but also an effective indicator for evaluating land degradation, salinization, and desertification. It is also an indispensable parameter in models such as evapotranspiration and climate change and is of great significance for measuring the surface coverage and ecosystem status of plant communities [3]. Mastering the spatiotemporal changes in vegetation coverage, analyzing and predicting its development trends, and exploring the driving effects of factors such as terrain and climate has important theoretical and practical significance for evaluating ecosystem environmental quality and regulating ecological processes[3].

With the development of remote sensing technology, many scholars at home and abroad have used satellite remote sensing images to extract and analyze vegetation coverage. In terms of data, domestic and foreign scholars have achieved fruitful results in the extraction and spatiotemporal changes of vegetation coverage based on MODIS, SPOT, GIMMS, and Landsat series satellite image data [6]. The research on the driving factors of vegetation coverage has also made significant progress [7]. Although different resolutions of data have been applied to vegetation monitoring in different regions, research that simultaneously considers higher spatial resolution and longer time series is still one of the development trends on larger spatial scales. Previous studies have lacked accurate quantitative evaluation of the driving factors behind long-term changes in vegetation coverage. The Optimal Parameters-based Geographic Detector (OPGD) model can improve the overall ability of spatial heterogeneity analysis [8]. Therefore, it is of great significance to combine the Google Earth Engine (GEE) platform and OPGD model to analyze the long-term spatiotemporal changes and influencing factors of vegetation coverage.

Foshan is located in the central part of Guangdong Province and the hinterland of the Pearl River Delta. Quantitative analysis of temporal and spatial variation characteristics and driving factors of vegetation coverage in Foshan City is of great significance for understanding the changes in regional ecological environment quality and promoting the construction of ecological protection and high-quality development pilot areas in the Pearl River Basin.

This study uses the Landsat series of satellite remote sensing data from 2001 to 2020, combined with meteorological, topographic, vegetation, and geomorphic data of the same period in the region and comprehensively uses the pixel dichotomy model, Sen+Mann Kendall trend analysis, and OPGD model to conduct qualitative and quantitative analysis of regional vegetation coverage changes and driving factors. By mastering the distribution and evolution characteristics of vegetation in the region, we deepen our understanding of the driving mechanism of vegetation change in Foshan City, with a view to providing data support and a scientific basis for the sustainable development of Foshan City and the implementation of the Pearl River Basin protection strategy [2].

## II. STUDY AREA

Foshan is located in the central and southern part of Guangdong Province, in the hinterland of the Pearl River Delta (PRD), east of Guangzhou, and adjacent to Hong Kong and Macao. Located at 113° 06 'E and 23° 02' N, with an administrative area of 3797.72 square kilometers. The terrain of Foshan City is generally high in the north and low in the south, high in the west and low in the east. Most areas are relatively flat, with little topographic relief. It is dominated by plains. The climate is mild, the rainfall is abundant, and the four seasons are like spring. It is a subtropical monsoon humid climate, with an annual average temperature of 23.2°C. The Xijiang River, Beijiang River, and their tributaries in the Pearl River water system run through Foshan City, which is a typical delta river network area. The main rivers are the Pearl River, Xijiang River, and Beijiang River, which provide Foshan with rich water resources. The rainfall is 1490.6 millimeters, and the annual sunshine hours are around 1800 hours. The soil is mainly red soil and yellow soil, and the surface vegetation types are mainly subtropical evergreen broad-leaved forests and shrub grasslands.

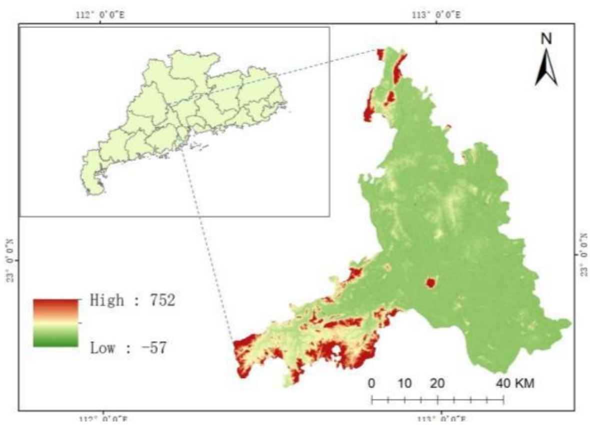



*Fig.1 Geographical Location of the Study Region*

## III. MATERIALS AND METHODS

### 3.1 Data Sources

#### 3.1.1 Remote Sensing Data

The remote sensing image data used in this study was sourced from the United States Geological Survey (https://www.usgs.gov/). The data production provider is the Land Use and Global Change Remote Sensing Team of the Institute of Geographic Sciences and Resources, Chinese Academy of Sciences. Through the GEE cloud platform, we selected the Level-2 surface reflectance product of Landsat 5 (2001-2012) and Landsat 8 (2013-2020) satellites, with a spatial resolution of 30 m, which has been atmospheric corrected [9].

The maximum Normalized Difference Vegetation Index (NDVI) dataset in China from 2000 to 2022 is based on the GEE cloud computing platform. Using all Landsat 5/7/8/9 remote sensing data throughout the year, all Landsat effective observation data are obtained by removing clouds and shadows. Then, the NDVI index of each Landsat effective observation is calculated, and combined with linear interpolation and S-G smoothing methods; the maximum NDVI value of each pixel location in a year is finally obtained. The spatial resolution of this dataset is 30 m, and the temporal resolution is annual. [10]

#### 3.1.2 Factor Data

The terrain data adopts geospatial data cloud (http://www.gscloud.cn/). The downloaded ASTER Global Digital Elevation Model (GDEM) digital elevation data product [11] has a spatial resolution of 30 m. Using ArcGIS to extract slope and aspect data from DEM data, obtain data for the study area.

The temperature, precipitation, and humidity data are sourced from the National Science and Technology Infrastructure Platform—National Earth System Science Data Center (http://www.geodata.cn/). The temperature data and precipitation data are respectively sourced from the monthly average temperature dataset at 1 km resolution in China from 1901 to 2021 and the annual precipitation data at 1 km resolution in China from 2001 to 2020. The data on sunshine hours is sourced from the National Bureau of Statistics (http://www.stats.gov.cn/).

The land use data is sourced from the annual land cover data of 30 m in China from 1990 to 2021 (http://irsip.whu.edu.cn/resources/CLCD.php). This product includes 9 types of land use, namely: farmland, forest, shrub, grassland, water area, ice and snow, unused land, construction land, and wetland [12].

The vegetation type data and landform types are sourced from the resource and environmental science data of the Chinese Academy of Sciences (http://www.resdc.cn). The spatial resolution is 1 km. Based on the 1:1 million Chinese Vegetation Atlas and the 1:1 million Topographic Atlas of the People's Republic of China, combined with the actual situation of the research area, the vegetation types are divided into 8 types: coniferous forest, broad-leaved forest, shrub, desert, grassland, cultivated vegetation, and others. The landform types are divided into 5 categories: plain, plateau, hill, small undulating mountain, and medium undulating mountain.

All factor data were extracted using ArcGIS software according to the vector boundaries of the study area and resampled to match the resolution of NDVI data. Using ArcGIS to create a fishing net tool randomly generate a 1 km × 1 km grid within the study area with a total of 4151 center points as sampling points and input them into the geographic detector for processing.

### 3.2 Research Methods

#### 3.2.1 Vegetation Coverage Estimation

Using the pixel binary model for vegetation coverage inversion [13], the FVC calculation formula is shown in (1).

$$\mathrm{FVC} = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \#(1)$$

In the formula, FVC is the vegetation coverage of a certain pixel; NDVI is the value of the pixel; $NDV_{Soil}$ is the NDVI value of pure soil pixels in the image; $NDVI_{Veg}$ is the value of pure vegetation pixels in the image. Considering the issues of image outliers and noise, combined with the actual situation of vegetation coverage in the study area and relevant research experience [14], this paper adopts the NDVI value when the cumulative histogram of NDVI results reaches 5% as the $NDV_{Soil}$ value and the NDVI value when the cumulative histogram of NDVI results reaches 95% as the $NDVI_{Veg}$ value.

Referring to relevant research and expert experience [15], combined with the actual situation of the study area, the vegetation coverage in the study area is divided into 5 levels (Table 1).

*Table 1 Classification of FVC Level*

| FVC Level | FVC value |
|---|---|
| Extremely low | 0～0.2 |
| Low | 0.2～0.4 |
| Medium | 0.4～0.6 |
| High | 0.6～0.8 |
| Extremely high | 0.8～1 |

### 3.2.2 FVC Trend Analysis

The Sen+Mann Kendall method was used to analyze the long-term trend of vegetation coverage changes [16]. Sen's slope is a non-parametric statistical method for calculating stable trends, which can be used to represent the degree and trend of FVC changes [17-18]. The calculation formula is as follows:

$$S_{FVC} = \text{median}\left(\frac{FVC_j - FVC_i}{j-1}\right), \forall j > i \quad \#(2)$$

In the formula, $FVC_i$ and $FVC_j$ represent the vegetation coverage in the i-th and j-th year, respectively; $S_{FVC}$ is the slope, $S_{FVC}>0$ indicates an upward trend in regional vegetation coverage, while $S_{FVC}<0$ indicates a downward trend in regional vegetation coverage.

Mann-Kendall trend analysis does not require data to follow a certain distribution and is not easily affected by outliers. It has a solid statistical theoretical basis for testing significance levels [19-20] and is suitable for non-normally distributed data. It is currently a widely used nonparametric testing method. The calculation formula is as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} s\,gn(x_j - x_i)$$

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0, \\ 0, & x_j - x_i = 0, \\ -1, & x_j - x_i < 0. \end{cases}$$

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1) - (2t_i-5)}{18} \quad \#(3)$$

$$U = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & S > 0, \\ 0, & S = 0, \\ \frac{S+1}{\sqrt{Var(S)}}, & S < 0. \end{cases}$$

In the formula, S is a normal distribution; the mean is 0: Var (5) is the variance, "is the number of time series, and when it is greater than 10, U tends to follow a normal distribution; m is the number of repeated data sets in the time series; t is the number of duplicate data in the i-th duplicate data group. S is x and x; the size relationship. The range of U values (- ∞, +∞), if | U |> $U_{1-\alpha/2}$, it is considered that there is a significant trend of change at the confidence level of a. U>0 indicates an increasing trend, and U<0 indicates a decreasing trend.

### 3.2.3 Geographic Detector Model Based on Optimal Parameters

The traditional geographic detector model suffers from subjective interference when discretizing continuous factors [21]. Therefore, this study chooses the OPGD model to analyze the driving factors of vegetation coverage changes in the research area. Meanwhile, we applied vegetation coverage as the dependent variable and tertiary indicators as explanatory factors for geographic detector analysis. Use the "gdm" function in the geographic detector R language package "GD" to select the optimal discretization method and quantity combination [22]. On this basis, differentiation and factor detection, interaction detection, and risk detection were selected to analyze the influencing factors of vegetation coverage in the study area. The types and indicators of detection factors are shown in Table 2.

*Table 2 Probe Factors*

| Type | Probe factors | Index | Unit |
|---|---|---|---|
| Terrain | $X_1$ | Aspect | ° |
| | $X_2$ | Slope | ° |
| | $X_3$ | Elevation | m |
| Climate | $X_4$ | Annual cumulative sunshine hours | h |
| | $X_5$ | Annual temperature | ℃ |
| | $X_6$ | Annual precipitation | mm |

| | | | |
|---|---|---|---|
| Landform | $X_7$ | Landform type | — |
| Vegetation | $X_8$ | Vegetation type | — |
| Human activity | $X_9$ | Land-use type | — |

Notes: "—" indicates no unit

(1) Factor detection is used to calculate the degree of impact Q of each factor on vegetation coverage. The calculation formula is as follows:

$$Q = 1 - \frac{\sum_{h=1}^{l} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$
$$\mathrm{SSW} = \sum_{h=1}^{l} N_h\, \sigma_h^2 \quad \#(4)$$
$$\mathrm{SST} = N\sigma^2$$

In the formula, Q is the spatial differentiation index; l is the stratification of FVC attributes or natural and human factors; Nh and N are the number of units in a specific layer and the entire region, respectively; The variances of FVC values in the h layer and the entire region are represented by $\sigma_h^2$ and $\sigma^2$, respectively; SSW and SST are the sum of intralayer variances and the total variance of the entire region, respectively. The range of Q values is [0, 1], and the larger the Q value, the greater the spatial difference of FVC. In extreme cases, a Q value of 1 indicates that factor X completely controls the spatial distribution of Y, while a Q value of 0 indicates that factor X is independent of Y.

(2) Interaction detection is mainly used to identify the combined effect of two evaluation indicators on vegetation coverage [23], that is, to evaluate the combined effect (enhancement or weakening) and the impact of individual effects on FVC. The steps are as follows: Firstly, calculate the Q values [Q (Xi)] and [(Xj)] of the two factors relative to FVC, and then calculate the Q value [Q (Xi ∩ Xj)] regarding the interaction between the factors, and compare it with Q (Xi) and Q (Xj).

## IV. ANALYSIS AND RESULTS

### 4.1 FVC Temporal Variation Characteristics

Analysis shows that the average vegetation coverage in the study area has decreased from 53.9% in 2001 to 52.4% in 2020 over a 20-year period, showing a slight decrease overall (P<0.01) at a rate of 2.87%. The average vegetation coverage over the years is 51.53%, and the overall vegetation coverage is at a moderate level (Figure 2). The vegetation coverage in the study area showed irregular fluctuations within the range of 47.89%–54.5%, with peaks in 2003, 2013, and 2016, and valleys in 2005, 2009, 2012, and 2014. Among them, the highest value was reached in 2003 at 53.9%, and the lowest value appeared in 2012 at 47.89% [24].

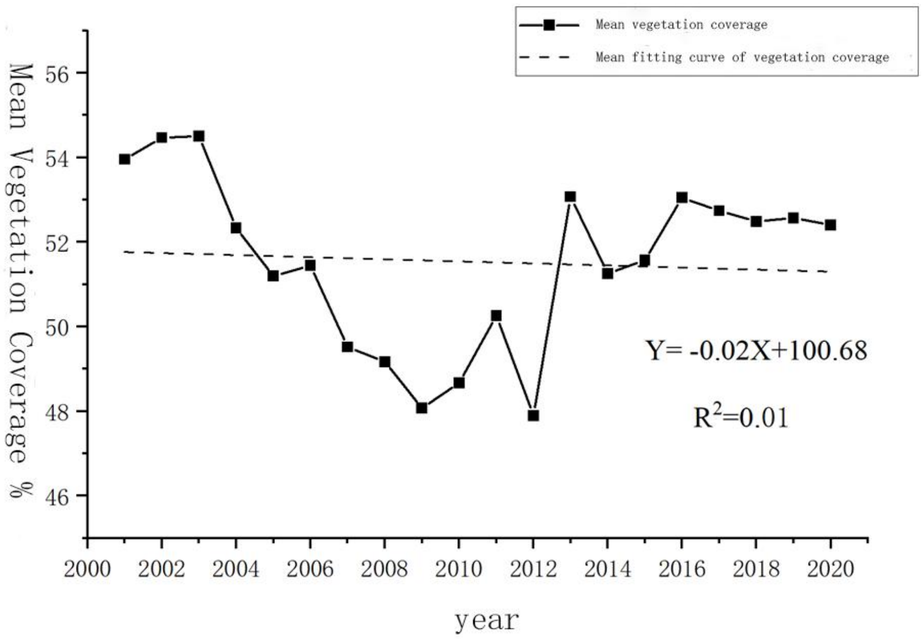



*Fig.2 Changes and Trends of FVC from 2001 to 2020*

**4.2 FVC Spatial Distribution Pattern**

Analysis shows that there are significant regional differences in vegetation coverage in the study area, with an overall trend of "high in the west and low in the east" and "high in the north and low in the south." The types are mainly moderate and low vegetation coverage (Figure 3, Figure 4). The area with moderate vegetation coverage accounts for the largest proportion, reaching 22.8%, mainly distributed in the central and western parts of the South China Sea and the southern part of the Sanshui District. The area with low vegetation coverage is distributed, accounting for 22.5% of the total area; the area with extremely low vegetation coverage accounts for the smallest proportion, at 15.8%, distributed in the northern part of Chancheng District and Shunde District; the high vegetation coverage and extremely high vegetation coverage account for 17.2% and 21.7% of the total area, respectively, distributed in Gaoming District and the northern part of Sanshui District. The above results are consistent with previous research findings [25].


*Fig.3 Annual Changes in the Distribution of Vegetation Coverage from 2000 to 2020*

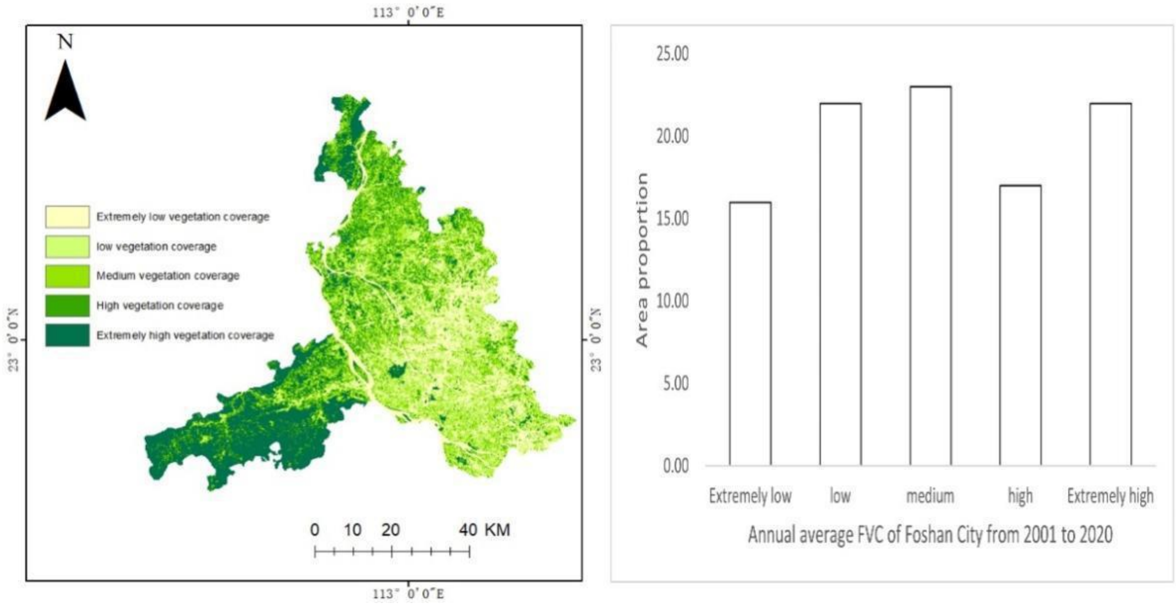



*Fig.4 Average FVC Spatial Distribution and Area Ratio of Each Class from 2001 to 2020*

### 4.3 FVC Spatial Variation Characteristics

Based on Sen+Mann Kendall trend analysis, the spatial distribution of vegetation change trends in the study area from 2001 to 2020 was obtained (Figure 5). According to the actual situation of SFVC and U values in the study area [26], the trend of vegetation coverage changes in the study area is divided into five categories: significant improvement, slight improvement, stable and unchanged, slight degradation, and significant degradation. From Table 3, it can be seen that from 2001 to 2020, the area with changes in vegetation coverage in the study area accounted for 87.3% of the total area, with improved areas accounting for 49.53% of the total vegetation coverage, degraded areas accounting for 37.77%, and stable areas without significant changes accounting for 12.70%. Overall, the area of vegetation coverage improvement in the study area is nearly half of the total area, showing an overall trend of improvement. From a spatial distribution perspective, the regional spatial characteristics of vegetation coverage improvement and degradation are not significant. Compared to Lingshan, the overall trend is improvement in the eastern, southeastern, and southwestern parts, while some areas in the southern, northern, and central parts show a degradation trend.

*Table 3: Statistical Trends of FVC Changes from 2001 to 2020*

| $S_{FVC}$ | \|U\| value | FVC trend | Area/km$^2$ | Ratio/% |
|---|---|---|---|---|
| ≥0.0005 | ≥1.96 | Significant improvement | 1121.24 | 27.21 |
| ≥0.0005 | \|U\|<1.96 | Slight improvement | 920.04 | 22.32 |
| -0.0005~0.0005 | \|U\|<1.96 | Stable and unchanging | 523.32 | 12.70 |
| <-0.0005 | \|U\|<1.96 | Slight degradation | 795.47 | 19.30 |
| <-0.0005 | ≥1.96 | Significant degradation | 761.13 | 18.47 |

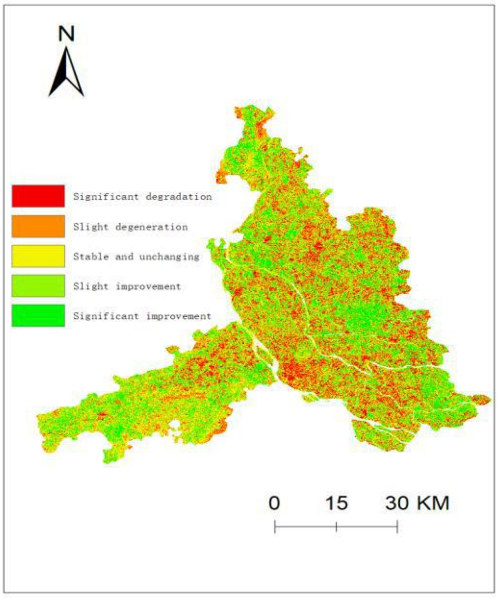



*Fig.5 Changes Trend of the FVC from 2001 to 2020*

### 4.4 FVC Driving Force Analysis

#### 4.4.1 Continuous Factor Discretization

Referring to relevant research and the actual situation of the research area [22], the initial interval of interruption is set as 4-8 categories, and the letters A~H are used to represent different categories. Through model calculations, select the scheme with the highest Q value for each continuous dependent variable under different classification methods and hierarchical levels for spatial discretization [27]. Taking 2001 as an example, the optimal spatial data discretization parameters were set as follows: natural spacing classification was used to classify sunshine into 10 categories, and quantile spacing classification was used to classify terrain, slope, altitude, precipitation, and temperature into 9, 10, 10, 10, and 10 categories, respectively.

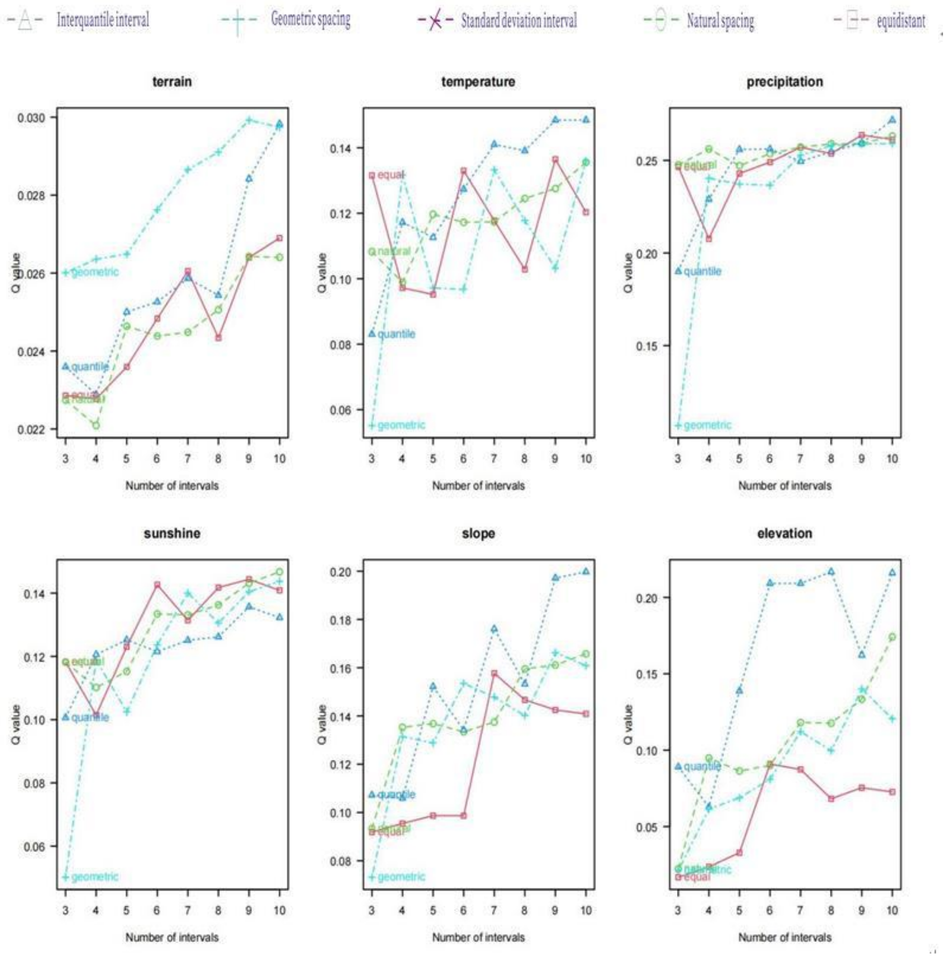



*Fig.6 Continuous Factor Discretization Processes*

#### 4.4.2 Factor Detection

The explanatory power of each factor in the research area from 2001 to 2020 is shown in Figure 7. The average explanatory power of each factor from 2001 to 2020 is ranked as follows: land use (0.6125)>vegetation type (0.3662)>landform (0.2893)>precipitation (0.2717)>altitude (0.2167)>humidity (0.1997)>temperature (0.1485)>sunshine (0.1467)>terrain (0.0299). The Q values of each factor have passed the significance test. Among them, the average explanatory power of land use types is 61.25%, which is much greater than the explanatory power of other factors and is the main driving factor affecting changes in vegetation coverage in the study area; Vegetation, topography, precipitation, and altitude all have explanatory power of over 20% and are secondary driving factors; The explanatory power of slope, temperature, and sunshine hours all exceed 10%; The explanatory power of terrain is less than 10%, and its impact on vegetation coverage changes in the study area is minimal [24].

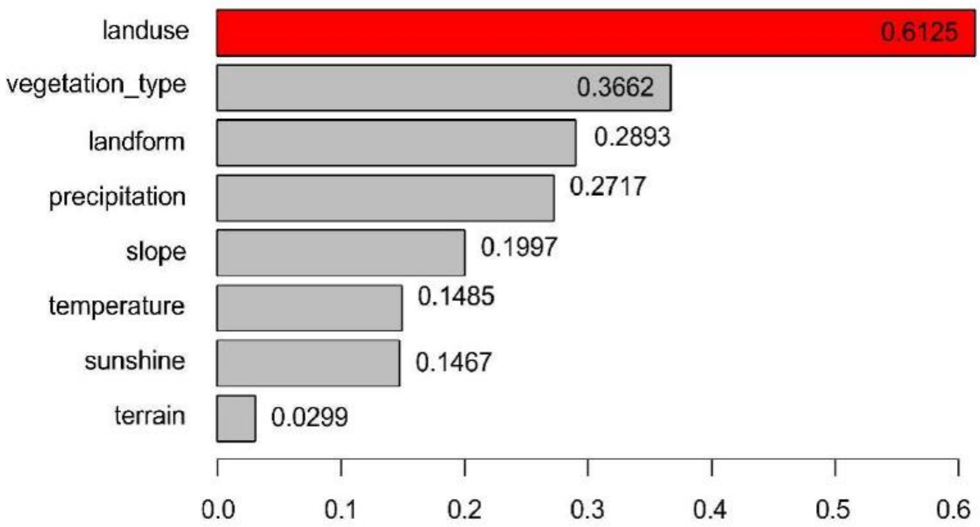


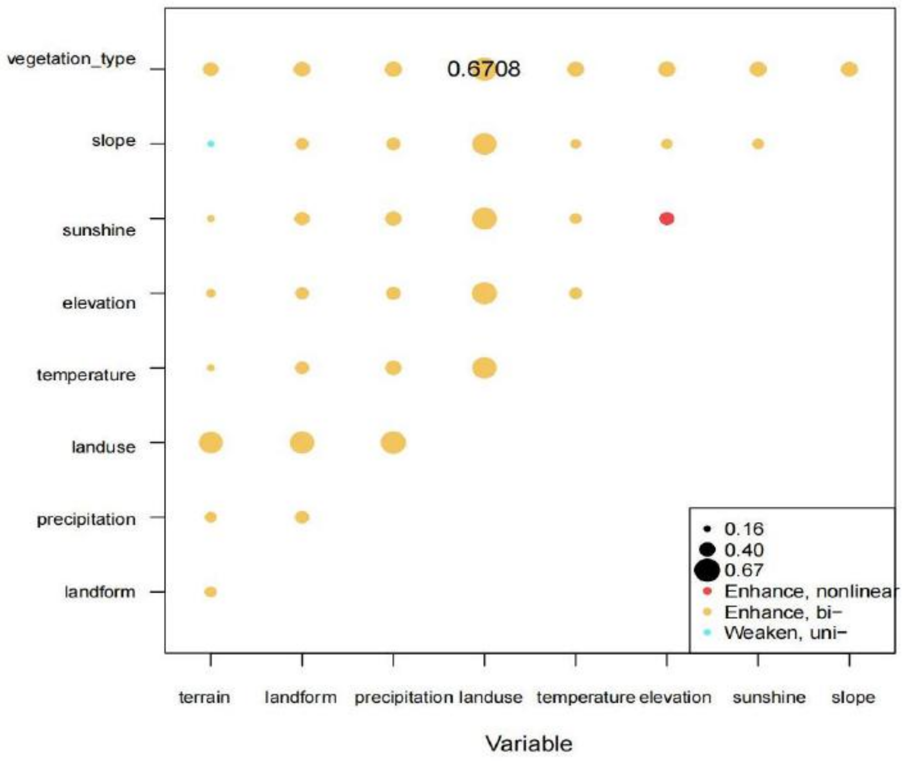

*Fig.7 Result of the FVC Factor Detector from 2001 to 2020*

#### 4.4.3 Interaction Detection

Analyze the interaction between various factors of vegetation coverage through interactive detection (Figure 8). From a temporal perspective, the Q values of the interactions between various factors showed an overall trend of increasing from 2001 to 2010 and decreasing from 2011 to 2020. From a factor perspective, the interaction between two factors shows an enhancing effect, and over 75% of factor combinations exhibit a dual factor enhancing effect, while the remaining factors show non-linear enhancement, meaning that the superposition of two factors greatly enhances the impact of a single factor on vegetation coverage.

Among them, the Q value of the interaction between land use and terrain, slope, altitude, precipitation, sunshine, temperature, and vegetation type is the highest (all>0.64), indicating that the influence of spatial superposition on vegetation coverage is dominant. This suggests that the interaction between land use and other natural factors significantly enhances the influence of natural factors on vegetation coverage, indicating a clear dual factor synergistic enhancement relationship, demonstrating the dominant role of land use.

The interaction between sunshine and terrain, slope, altitude, temperature, and annual precipitation, as well as the interaction between terrain, temperature, vegetation, and precipitation, shows a non-linear enhancement. The interaction between vegetation type and topography and other factors is significant, while the interaction between sunlight, topography and other factors is relatively weak. Overall, the interaction and influence of human factors and natural factors have shown an increasing trend, indicating that changes in vegetation coverage are influenced by both natural factors and human activities [28].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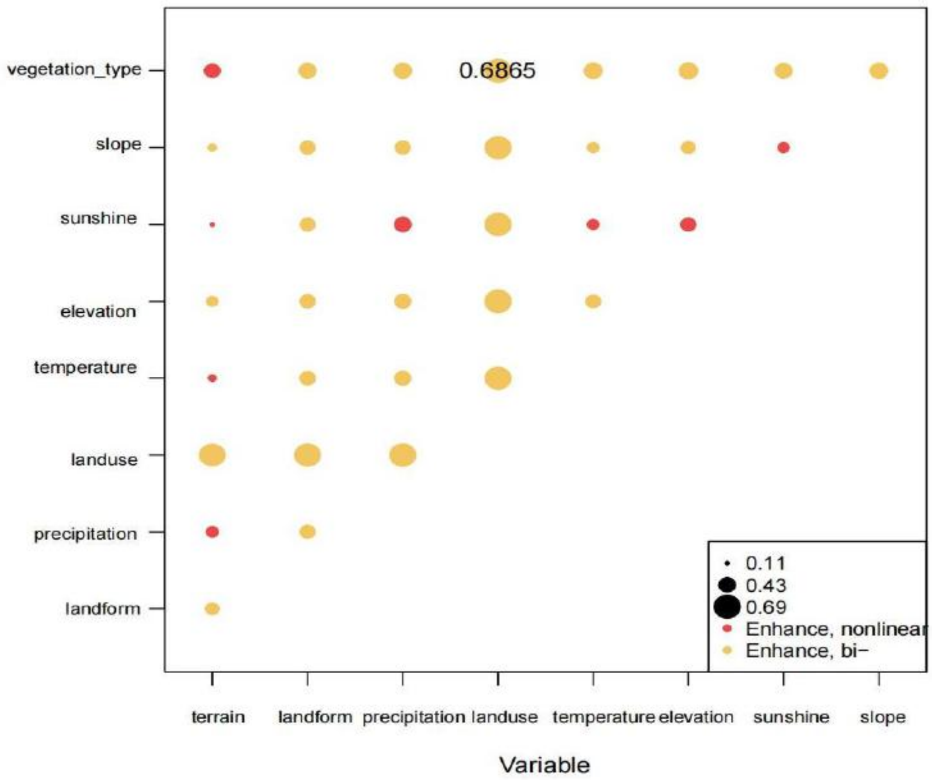
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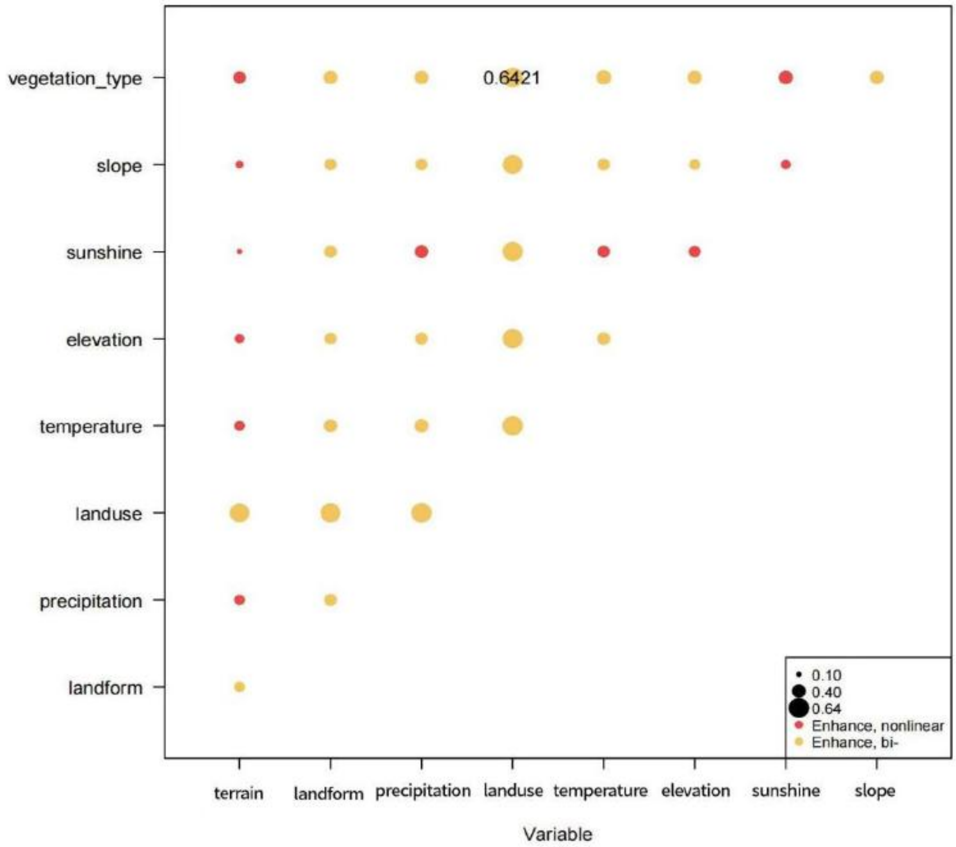


*Fig.8 The Q Value of FVC Interaction Detector in 2001, 2010, and 2020*

## V. DISCUSSION

### 5.1 Spatiotemporal Evolution Characteristics of FVC in Foshan City

Vegetation changes can directly reflect the changes in the local ecological environment [29]. From a temporal perspective, the vegetation coverage in the study area showed an overall downward trend from 2001 to 2020. Over the past 20 years, the vegetation coverage in the study area has shown irregular fluctuations within the range of 47.89%–54.5%. Analyzing the reasons: 1. Over the past 20 years, Foshan's economy has been continuously developing, and land use changes have led to the loss of vegetation. Many green spaces have been converted into buildings, transportation, industrial parks, commercial squares, etc. 2. From 2002 to 2012, the industrial land in Foshan City continued to increase, and reclamation of arable land. 3. The new round of returning farmland to forests project in 2015 has just been implemented, resulting in a decrease in arable land area and a lower coverage of newly planted vegetation. By 2016, FVC had increased. From 2013 to 2020, Foshan City relocated some factories, reclaimed and green some land, and restricted the development of some land.

From a spatial perspective, the vegetation coverage in the study area has obvious spatial differentiation, and the typical terrain in the region lays the foundation for its distribution pattern of "high in the west and low in the east" and "high in the north and low in the south" vegetation coverage. The high-value coverage areas are distributed in the Gaoming District in the west and the Sanshui District in the north, with continuous mountains, steep terrain, and large relative height differences. The Beijiang and Xijiang rivers provide abundant irrigation water for the areas they pass through. The low-value areas are distributed in the eastern region, which is located in non-river flowing areas and has a high urbanization rate. The overall vegetation coverage is relatively low.

In terms of spatial change trend, the area of vegetation coverage improvement is greater than the area of degradation. This may be due to Foshan City's emphasis on land reclamation and greening, which restricts the development of some land, resulting in a certain area of vegetation coverage improvement.

### 5.2 Driving Factors Affecting Vegetation Changes

Vegetation cover change is the result of the combined effects of natural and human factors. Quantifying the impact of natural and human factors on vegetation change and identifying dominant factors can provide valuable references for decision-makers. The research results indicate that both natural and human factors have a significant impact on vegetation changes. Overall, the changes in vegetation coverage in the study area are highly correlated with five driving factors (land use, vegetation, topography, precipitation, and altitude) (Q value > 0.2), with land use type having the greatest impact.

#### 5.2.1 The Impact of Human Factors on Vegetation Changes

Land use type, as the most direct reflection of human activities, plays an important role in vegetation change. Compared to climate factors, the overall impact of human factors on FVC is relatively high. As the only human factor, the explanatory power of land use types remains at a high level, indicating that human habitation and activities significantly affect the trend of vegetation cover change. The analyzed data shows that from 2004 to 2012, the continuous expansion of economic construction and the conversion from arable land to other land use types in Foshan City led to a significant decrease in vegetation coverage. After 2013, Foshan City took measures to improve the ecological environment, relocating some factories, reclaiming and greening some land, and restricting the development of some land, resulting in the gradual restoration of vegetation coverage.

#### 5.2.2 The Impact of Natural Factors on Vegetation Changes

Terrain mainly affects vegetation distribution by altering the water and heat conditions in the environment [31]. As an important terrain factor, altitude has a significant impact on the growth process of surface vegetation and is the main factor affecting the distribution of water and heat conditions in mountainous areas, with a certain degree of complexity. As the altitude increases, the temperature decreases, solar radiation and wind speed increase, and local precipitation and relative humidity first increase and then decrease. Soil types show significant differences, forming changes in environmental gradients, resulting in different plant types and growth characteristics at different altitudes. In this study, vegetation types can explain approximately 36.62% of vegetation changes in the study area, and the impact of vegetation types on vegetation coverage is greater than other natural factors. The vegetation type in the research area is mainly cultivated vegetation, mainly distributed in towns and their edges in plain areas, and the natural environmental conditions are suitable for vegetation growth.

Different types of landforms have distinct topographical features, soils, and land use patterns, which can significantly affect the distribution of vegetation. The landform type can explain 28.93% of the vegetation changes in the study area and has a significant impact on the vegetation changes in the study area. The landform types in the research area are mainly plains and hills, with high vegetation coverage mainly distributed in the western and northern hilly areas. The Beijiang and Xijiang rivers flow through, and the water and heat conditions are sufficient. The altitude is relatively suitable and is conducive to vegetation growth.

The explanatory power of precipitation on vegetation changes in the study area is 27.17%. From the perspective of urban green vegetation in Foshan City, most of the vegetation on both sides of parks, green belts, and streets in the city relies on precipitation to maintain growth. Adequate precipitation contributes to the healthy growth of various trees, shrubs, and herbaceous plants, improving the coverage of urban greenery. From the perspective of natural vegetation in suburban areas, forests, shrubs, and grasslands in the natural ecosystems of suburban areas are also directly affected by precipitation. Adequate precipitation is beneficial for the flourishing of forests and shrubs, increasing vegetation coverage in these areas and maintaining ecological balance. From the perspective of water vegetation, rivers and lakes and river system vegetation in Foshan City also rely on appropriate rainfall to maintain the stability of the wetland environment. Adequate precipitation contributes to the richness and diversity of aquatic vegetation, increasing the coverage and biodiversity of aquatic ecosystems.

Previous studies on the impact of natural factors on vegetation cover have shown that in most subtropical monsoon regions, temperature and precipitation are considered the most important climate factors affecting vegetation distribution and change [32]. In this study, compared with other factors, the Q values of temperature and precipitation were relatively low. The reason is that the long-term development and trend of vegetation cover are more directly affected by human activity factors [5], which leads to the insensitivity of vegetation in the region to changes in temperature and precipitation.

## 6. CONCLUSIONS

(1) In terms of time, the overall vegetation coverage showed a slight downward trend from 2001 to 2020 (with a reduction rate of 2.87%). Except for the period from 2004 to 2012, when Foshan City experienced a significant and drastic decline due to continuous economic development, the average vegetation coverage for the rest of the years was 51.53%, indicating that the vegetation coverage in the study area was generally at a moderate level. The overall distribution pattern of vegetation coverage in space shows a pattern of "high in the northwest and low in the southeast," with significant regional differences. The types are mainly moderate and low vegetation coverage.

(2) From 2001 to 2020, the proportion of vegetation improvement areas in the study area was 49.53%, which is larger than the area of degraded areas. (It is mainly manifested in the restoration of vegetation coverage after 2012, which is related to the improvement of policies and human activity factors).

(3) The detection results of driving factors indicate that the average explanatory power of land use types is 61.25%, which is the main driving factor affecting the changes in vegetation coverage in the study area, with vegetation, topography, precipitation, and altitude as secondary driving factors; the explanatory power (Q value) of the interaction between each factor is higher than that of a single factor, showing a synergistic and nonlinear enhancement relationship between two factors; and the impact of each driving factor on vegetation growth in the study area has its appropriate range.

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