# Spatio-temporal Evolution of Land Use in Guangdong-Hong Kong-Macao Greater Bay Economic Area, 1985-2022 and Analysis of Influencing Factors

Keding Sheng[#, *], Xingshuai Mei[#], Xitong Yang[#]

School of School of Politics and Public Administration, Qinghai Minzu University, Xining, China, 810007

* Corresponding Author Email: SKD140821@163.com

[#]These authors contributed equally

**Abstract.** This research employs GIS and remote sensing technology, along with time-series Land cover data, to examine the evolving patterns of various land use categories (such as forest land, cultivated land, and impervious surfaces) within the Guangdong-Hong Kong-Macao Greater Bay Area. The results indicate that the predominant spatial configuration of land use in this region follows a sequence of "forest land-cultivated land-impervious land." Notably, the key transformation observed involves the conversion of cultivated land to impervious surfaces, resulting in a cumulative expansion of impervious areas by 3,346,985 hectares between 1985 and 2022. Moreover, the level of spatial integration among land use types in the Greater Bay Area is progressively standardizing, with notable advancements in scientific, technological, economic, and transportation sectors leading to a high degree of synergy. The system as a whole demonstrates effective coordination and operational efficiency. The methodology section outlines the data sources and analytical techniques employed, encompassing the utilization of the land use transfer matrix, individual land use degree assessment, and spatial coupling function model. Through these methodologies, the study identifies urban economic development as the primary driver behind the proliferation of impervious surfaces, offering valuable insights to inform regional development strategies and environmental governance policies.

**Keywords:** Guangdong-Hong Kong-Macao Greater Bay Economic Area, Land Use Change, Spatially Coupled Feature Model, Land Use Dynamic Degree.

## 1. Introduction

Alterations in land use patterns represent a prominent outcome of human activities that impact the natural environment of the Earth. These changes not only modify the types, quantities, structures, and functions of land use but also lead to prominent issues such as the deterioration of ecological environment quality and human-land conflicts, becoming key factors affecting ecological environment quality [1-2]. After the Chinese government established the development strategy for the urban agglomeration of the Greater Bay Area [3]. The development of the Greater Bay Area (including nine cities in the Pearl River Delta and the two cities of Hong Kong and Macao) has entered an accelerated phase, ushering Guangdong, Hong Kong, and Macao into a new era of development [4]. The land use situation in the Guangdong-Hong Kong-Macao Greater Bay Area is closely related to the value of ecosystem services.

Research by Jie Zhang et al. [5] indicates a close spatial relationship between the ecological environment quality and land use changes in the Guangdong-Hong Kong-Macao Greater Bay Area, with a negative correlation between land use changes and ecological environment quality. The expansion of artificial surfaces aligns with regions of low ecological environment quality. The remote sensing ecological index is applicable in large-scale regional studies. Over the past few years, changes in the coastline and land use in the Greater Bay Area have been ongoing [6]. Research by Zhitao LIU et al. [7] shows that various influencing factors play significant roles in the land use evolution of the Greater Bay Area, including climate, topography, soil, vegetation types, and land use types and patterns [7]. Over the past 20 years, the urban quality and correlation of the city cluster in the

Guangdong-Hong Kong-Macao Greater Bay Area have improved, indicating an increasing degree of urban agglomeration in the region [8].

This study, through learning from the a forementioned research and recognizing the importance of the Greater Bay Areas development, integrates high-precision data from the team of Zhang [9] to study the land transformation in the Greater Bay Area. This research delves into the land use transformations within the Guangdong-Hong Kong-Macao Greater Bay Area by employing the land use transfer matrix and land use degree calculations. It utilizes coordination coefficients to examine the correlation between land alterations and economic progress, elucidating the factors influencing its spatial and temporal evolution. The investigation systematically scrutinizes the spatiotemporal changes in land use across the Greater Bay Area and extensively investigates the intricate interconnections among economic advancement, urbanization trends, and environmental consequences. The findings offer valuable academic and practical perspectives for informing future decision-making processes related to regional development.

## 2. Data and Methods

### 2.1. Overview of the Study Area

The Greater Bay Economic Zone generally refers to the Guangdong-Hong Kong-Macao Greater Bay Area (Figure 1), an important economic zone in southern China. The Greater Bay Area is located in southern China, roughly between 21°N-23°N latitude and 112°E-114°E longitude. This region includes the urban agglomeration in the southeast of Guangdong Province and the two special administrative regions of Hong Kong and Macao. Specifically, it involves nine cities in Guangdong Province (Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Zhongshan, Jiangmen, Zhaoqing, Huizhou), as well as the Hong Kong Special Administrative Region and the Macao Special Administrative Region.

The Guangdong-Hong Kong-Macao Greater Bay Area features diverse topography and abundant land resources. Each city has unique characteristics in land use: Hong Kong and Macao primarily rely on land reclamation due to limited land; Guangzhou, Shenzhen, and Foshan focus mainly on industrial, commercial, and residential uses; Zhuhai and Huizhou balance high-tech industries, tourism, and agriculture.

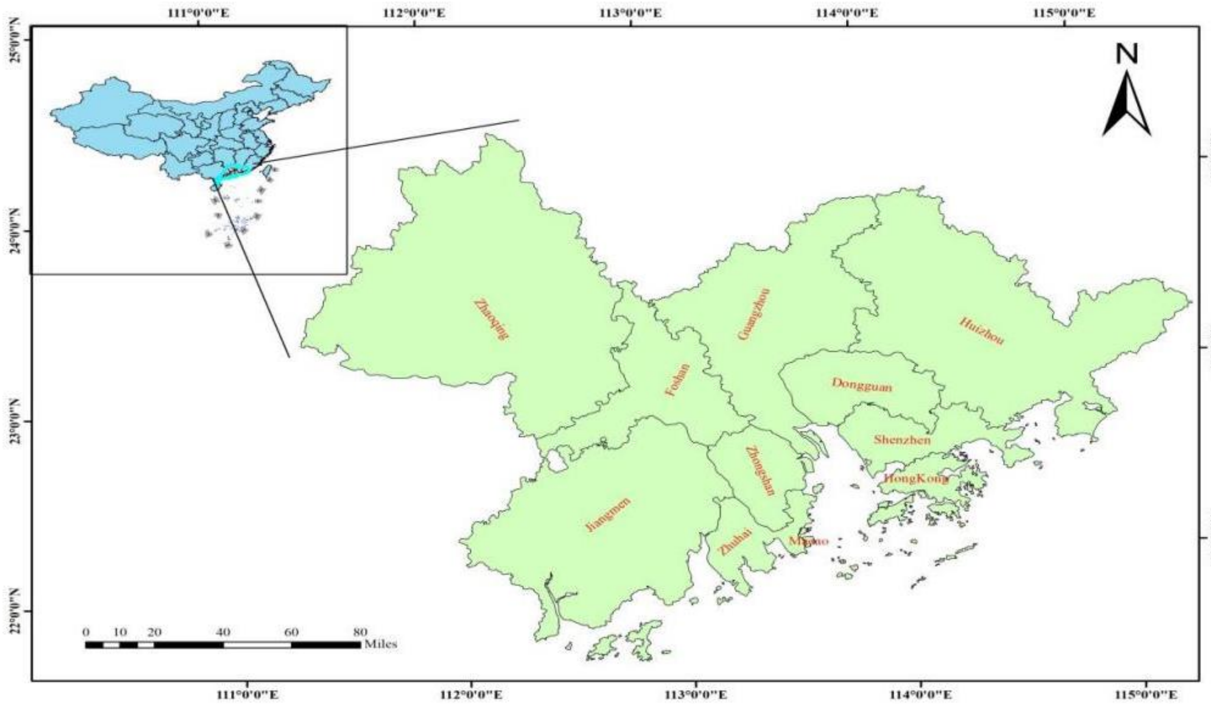


**Fig. 1** Research area

### 2.2. Data Sources

The data for this paper comes from Earth System Science Data (https://doi.org/10.5194/essd-13-2753-2021). This data was developed by integrating continuous change detection methods, locally adaptive updating models, and spatiotemporal optimization algorithms from dense time series Landsat images. It has been verified, achieving an overall accuracy of 80.88% (±0.27%) in the basic classification system (10 major land cover types) and 73.24% (±0.30%) in the LCCS level 1 verification system (17 LCCS land cover types) [9].

### 2.3. Research Methods

#### 2.3.1. Changes in Land Use Structure and Research Methods

(1) Land Use Transition Matrix

The land use transition matrix (formula 1) can statistically show the quantitative relationship between different land use types, directly reflecting the direction and structural characteristics of land use type distribution conversion under the background of social development within a certain time scale. It effectively separates different types of change characteristics to describe the transition of area, proportion, and quantity of each land use type during the study period. It is a further application of the Markov chain [10]. The formula is as follows:

$$\boldsymbol{S_{ij}} = \begin{bmatrix} \boldsymbol{S_{11}} & \boldsymbol{S_{12}} & \cdots & \boldsymbol{S_{1n}} \\ \boldsymbol{S_{21}} & \boldsymbol{S_{22}} & \cdots & \boldsymbol{S_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ \boldsymbol{S_{n1}} & \boldsymbol{S_{n2}} & \cdots & \boldsymbol{S_{nn}} \end{bmatrix} \tag{1}$$

In the formula, $S_{ij}$ represents the probability or proportion of transition from land use type i to type j within a given time period (n=1,2,3,…n).

(2) Single Land Use Degree

Single Land Use Degree (Formula 2) is an indicator that measures the uniqueness of land use in a specific area. It is determined mainly by analyzing the proportion of land area used for a single type within that area. A high value reflects that the land in a region is predominantly used for a single purpose, while a low value indicates diversity in land use types. The formula is as follows:

$$\mathrm{P} = \frac{(\mathrm{S}_b - \mathrm{S}_\mathrm{a})}{\mathrm{S}_a} \times \frac{1}{T} \times 100\% \tag{2}$$

In the formula, P represents the single land use rate of a certain land type, $\mathrm{S_b} - \mathrm{S_a}$represents the area difference of a certain land type between the end and the beginning of the study period, and T represents the time interval in years.

(3) Comprehensive Land Use Rate

The comprehensive land use dynamic degree (formula 3) is an indicator used to measure the land use change in a specific area over a specific period. It mainly reflects the extent and speed at which land types change from one use to another. By analyzing land use data at different time points, this indicator can calculate the proportion of land use changes and comprehensively consider the overall trends and speeds of these changes. The formula is as follows:

$$LUD = (\textstyle\sum_{i=1}^{n} \Delta \mathrm{L}_{\mathrm{t-o}} / 2 \sum_{i=1}^{n} \mathrm{L}_t) \times \frac{1}{T} \times 100\% \tag{3}$$

In the formula, LUD represents the comprehensive land use rate of the area, $\mathrm{L_t}$ represents the land use status at the end of the observation period,$\mathrm{L_o}$ represents the land use status at the beginning of the observation period, and T represents the observation time interval in years.

#### 2.3.2. Spatial Coupling Characteristic Model

The coordination coefficient is usually used to measure and evaluate the synchronicity and mutual influence between different systems or variables. In the spatial coupling characteristic model of economic development (measured by general GDP, income levels, and other economic indicators), population expansion (usually represented by total population, population growth rate, and other demographic data), and land expansion (usually measured by urbanization rate, land use change, and other indicators), the coordination coefficient is an important indicator used to characterize the degree of coordination and coupling relationship between these variables. According to the literature [12], this study proposes the hypothesis that land expansion in the Greater Bay Area promotes economic development in the region to some extent. Considering the significant differences in economic development in the Greater Bay Area during the period, regions with slower development might affect the analysis of spatial coupling characteristics. Therefore, the time scale of the study was extended, and three research stages were selected: 1985-1997, 1998-2010, and 2011-2022, to study the coupling coordination relationship between land expansion and economic development [11-13]. The formula is as follows:

$$T = \mathrm{nU}_1 + \mathrm{mU}_2, 1{,}2 = P, L, E \ \ (i \neq j) \tag{4}$$

$$\mathrm{M} = 2 \times \{\mathrm{U}_1 \times \mathrm{U}_2 / (\mathrm{U}_1 + \mathrm{U}_2)^2\}^{1/2}, 1{,}2 = \mathrm{P, L, E} \ \ (i \neq j) \tag{5}$$

$$Q = \sqrt{M \times T} \tag{6}$$

Where T is the coordinated development index, M is the coupling degree index and Q is the coupling coordination degree index, where the development of the city requires a balance of development.Let $\mathrm{n} = \mathrm{m} = 0.5$,$\mathrm{T} \in [0,1]$,Let $\mathrm{n} = \mathrm{m} = 0.5$,$\mathrm{T} \in [0,1]$,E is economic development, P is population growth and L is land expansion. $\mathrm{U}_1$ and $\mathrm{U}_2$ are the weights of the two systems, respectively. $\mathrm{M} \in [0,1]$,The larger its value indicates the greater influence on each other, and vice versa, the smaller, the coupling coordination degree M is divided into five parts[14], as shown in Table I:

**Table 1.** The Standard for Coupling Coordination Degree Classification

| Coupling Coordination Degree D Value Interval | Coordination Level | Coordination Extent |
|---|---|---|
| $0 \leq \mathrm{M} \leq 0.3$ | 2 | Highly Non |
| $0.3 \leq \mathrm{M} \leq 0.4$ | 4 | Moderately Non |
| $0.4 \leq \mathrm{M} \leq 0.6$ | 6 | Weakly Coupled |
| $0.6 \leq \mathrm{M} \leq 0.8$ | 8 | Moderately Coupled |
| $0.8 \leq \mathrm{M} \leq 1$ | 10 | Strongly Coupled |

## 3. Results and Analysis

### 3.1. Changes in Land Use Structure

#### 3.1.1. Temporal Characteristics of Land Use Types

Table 2 shows the land use types in the Guangdong-Hong Kong-Macao Greater Bay Area from 1985 to 2022. The land use in this region is primarily dominated by forest land and cultivated land. The area of forest land accounts for 45.44%～37.32% of the Greater Bay Area's total area, while cultivated land accounts for 38.51% t～ 28.24%. Over these 37 years, the land types in the Greater Bay Area have exhibited different trends. The areas of cultivated land and forest land have shown significant declines, with cultivated land decreasing by 10.26% and forest land decreasing by 8.12%. On the other hand, the areas of shrubland and impervious surfaces have significantly increased, with shrubland increasing by 5.30% and impervious surfaces by 12.22%. Additionally, the areas of water bodies, wetlands, and bare land have shown relatively minor changes. The area of water bodies has fluctuated the most, with an increase of 1.46%, while the overall area of bare land has remained relatively stable.

**Table 2.** Temporal Characteristics of Land Use Structure in the Greater Bay Area

| Land classification | 1985 Area/mu$^2$ | 1990 Area/hm$^2$ | 1995 Area/hm$^2$ | 2000 Area/hm$^2$ | 2005 Area/hm$^2$ | 2010 Area/hm$^2$ | 2015 Area/hm$^2$ | 2020 Area/hm$^2$ | 2022 Area/hm$^2$ |
|---|---|---|---|---|---|---|---|---|---|
| **Cropland** | 25913956 | 25395421 | 23928730 | 20401102 | 19707492 | 19586680 | 19007990 | 19385729 | 19626227 |
| **Forest** | 30580890 | 30277644 | 30045687 | 29165089 | 27796214 | 26314920 | 25739871 | 25114675 | 25241977 |
| **Shrubland** | 4938460 | 4907187 | 4843299 | 6167664 | 6409829 | 7326228 | 8056232 | 8409835 | 8285445 |
| **Grassland** | 13 | 11 | 1 | 42 | 47 | 25 | 4599 | 1787 | 2193 |
| **Wetland** | 1173295 | 950165 | 889119 | 1110257 | 1184837 | 1284243 | 1049087 | 1225125 | 1182591 |
| **Impervious surface** | 2044077 | 2665079 | 3961829 | 7138786 | 8991901 | 9856906 | 10270671 | 10186244 | 10087568 |
| **Bare areas** | 1002 | 902 | 502 | 449 | 285 | 270 | 224 | 124 | 112 |
| **Water body** | 2652040 | 3107224 | 3632066 | 3319744 | 3212175 | 2933412 | 3174060 | 2979215 | 2876621 |

### 3.1.2. Spatial Characteristics of Land Use Types

As shown in Figure 2, forest land is the dominant land use type in the region, primarily distributed in Zhaoqing, Huizhou, and the Hong Kong Special Administrative Region. Cultivated land is mainly concentrated in the central part of the Greater Bay Area, initially forming a "Ʊ" shape. However, with urbanization and economic development, a significant portion of the cultivated land has been replaced by impervious surfaces. This change was most notable between 1995 and 2000, during which the cultivated land area saw the most significant reduction.

Over the 37 years of the Greater Bay Area, Jiangmen City, Zhaoqing City, and Huizhou City have the three most widely distributed forest and cropland occupancies in the region. Impervious surface areas were mainly urban construction land, concentrated in Guangdong City, Zhongshan City, Shenzhen City, Dongguan City, and Foshan City. Between 1995 and 2000, the land area of impervious surface type increased the most, reaching 16.01%. From the dynamic process to see in the 37-year development process, urban construction mainly around the two cities of Shenzhen and Guangzhou as the center of the radial expansion of the development process outward, and eventually formed a large-scale, strong continuity of the urban landscape substrate [4].

Overall, the spatial distribution of land use types in the Guangdong-Hong Kong-Macao Greater Bay Area predominantly features forest land, impervious surfaces, and cultivated land as the main components, with other land types playing a supplementary role.

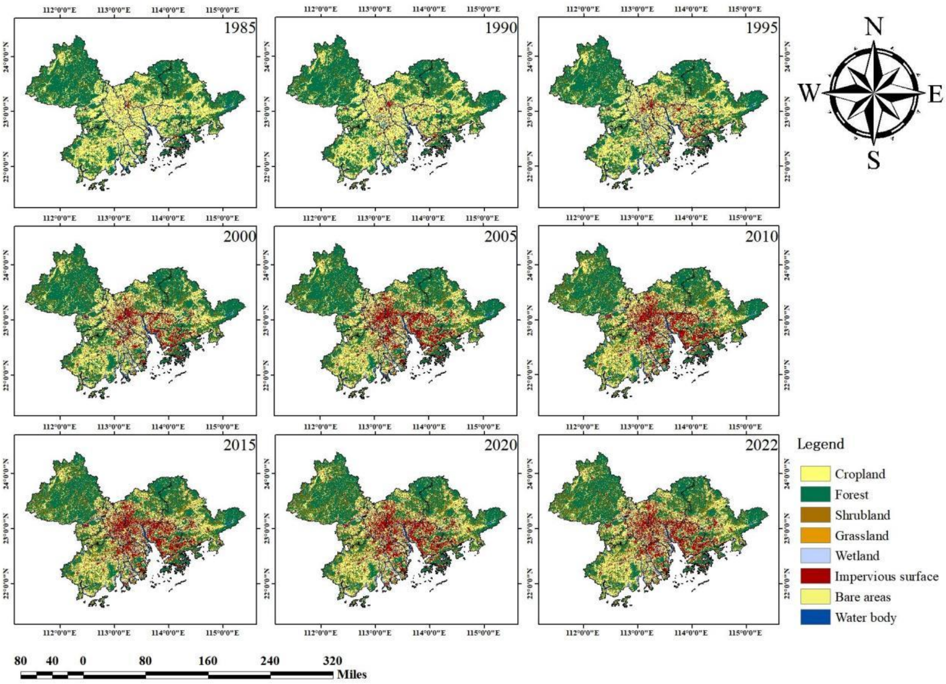


**Fig. 2** 1985-2022 changes in land use structure in the Greater Bay Area

#### 3.1.3. Land use and its transfer

By classifying and calculating the single land use degree of different land types and combining it with a comprehensive land use degree analysis, this paper explores the relationship between the changes of different land types in the Greater Bay Area and the intensity of their changes. The calculation results are shown in Table 3. For instance, the period from 1995 to 2000 showed the most significant changes in land movement attitudes, with a comprehensive land use rate of 1.40%, the highest in 37 years. The comprehensive land use rate from 2015 to 2020 was 0.27%. From 2020 to 2022, due to the shorter study period compared to other periods, the integrated land use rate was the lowest at 0.11%.

The area of cultivated land showed a decreasing trend for most of the period from 1985 to 2015, especially from 1995 to 2000, with a decrease as high as 2.95%. However, since 2015, the area of cultivated land has recovered, with a growth rate of 0.40% from 2015 to 2020 and a further growth of 0.25% from 2020 to 2022. The forest area shows an overall slight downward trend from 1985 to 2020, especially from 2005 to 2010, with a decline rate of 1.07%, followed by a slight increase of 0.10% between 2020 and 2022. Shrublands show more fluctuating changes, with a high growth rate of 5.47% during 1995-2000. After 2000, the overall trend is unstable, with a decrease of 0.30% during 2020-2022.

The area of grassland changed dramatically, with growth rates as high as 7.02% from 1990 to 1995 and 1.88% from 1995 to 2000. However, there was a significant increase of 10.74% between 2005 and 2010, and 9.92% between 2010 and 2015. After 2015, there was a downward trend again, with a decrease of 12.23% between 2015 and 2020, and a small recovery of 4.55% between 2020 and 2022. Wetland area as a whole shows fluctuations and no significant trend of increase or decrease, with an increase of 4.97% from 1995 to 2000, an increase of 3.36% from 2015 to 2020, and a continued small decrease of 0.69% from 2020 to 2022.

Impervious surface areas increased rapidly between 1985 and 2000, with their growth rate increasing from 6.08% to 16.01%. After 2000, they continued to increase, albeit at a slower rate, until 2015, when they began to decrease slightly, with a reduction of 0.16% between 2015 and 2020, and a further reduction of 0.19% between 2020 and 2022. Changes in bare land may be related to urbanization or land development, with an overall trend of decreasing land use in bare areas as cities become more rational about land use, with a larger decrease from 1990 to 2020.

**Table 3.** Single land use and Comprehensive land utilization rate

| Land type | 1985-1990 | 1990-1995 | 1995-2000 | 2000-2005 | 2005-2010 | 2010-2015 | 2015-2020 | 2020-2022 |
|---|---|---|---|---|---|---|---|---|
| **Cropland** | -0.40% | -1.16% | -2.95% | -0.68% | -0.12% | -0.59% | 0.40% | 0.25% |
| **Forest** | -0.20% | -0.15% | -0.59% | -0.94% | -1.07% | -0.44% | -0.49% | 0.10% |
| **Shrubland** | -0.13% | -0.25% | 5.47% | 0.78% | 2.86% | 1.99% | 0.88% | -0.30% |
| **Grassland** | 1.93% | 7.02% | 1.88% | 4.36% | 10.74% | 9.92% | -12.23% | 4.55% |
| **Wetland** | -3.78% | -1.28% | 4.97% | 1.34% | 1.63% | -3.62% | 3.36% | -0.69% |
| **Impervious surface** | 6.08% | 9.73% | 16.01% | 5.21% | 1.93% | 0.84% | -0.16% | -0.19% |
| **Bare areas** | -2.00% | -8.87% | -2.11% | -7.31% | -1.05% | -3.41% | -8.93% | -1.94% |
| **Water body** | 3.43% | 3.38% | -1.72% | -0.65% | -1.74% | 1.64% | -1.23% | -0.69% |
| **Comprehensive utilization** | 0.32% | 0.54% | 1.40% | 0.64% | 0.56% | 0.41% | 0.27% | 0.11% |

The comprehensive land use degree shows a trend of growth and then decline, and the overall change is gradually decreasing. It slows down from a significant increase of 1.40% during the period from 1995 to 2000 to a slight increase of 0.11% from 2020 to 2022. The increase is more pronounced from 1995 to 2000, marking the most significant period of land use change with a substantial rise in the degree of integrated land use. This trend may be attributed to the expansion of agriculture, infrastructure development, and the urbanization process. From 2015 to 2022, the slowdown in growth may be due to the urbanization phase reaching a point of saturation, accompanied by the implementation of more conservation policies and sustainable development measures.

Figure 3 shows a gradual decline in cropland (red bars) and its conversion to various other land types, including impervious surfaces and grasslands, from 1985 to 2020. There are signs of recovery in the data from 2015 to 2020. The area of cropland has increased, possibly due to adjustments in agricultural policy or restoration projects. The forest map indicates a steady decline in forest area (blue bars), particularly with conversion to cropland and impervious surfaces. In some periods, the rate of forest loss has slowed, likely due to the implementation of conservation measures.

Impervious surfaces exhibit a significant increase (green bars), reflecting the accelerated process of urbanization. At several points in time, other land types (e.g., agricultural land and forest) were converted to impervious surfaces. This increase is directly related to urban expansion and infrastructure development, marking a clear long-term trend.

Grasslands show the most significant fluctuations, sometimes increasing rapidly and at other times decreasing abruptly. These fluctuations reflect changes in land use, such as the conversion of grassland to agricultural land, as well as possible land degradation and restoration processes. The conversion of grassland into different types, such as shrubland and cropland, over different periods indicates a more resilient use.Shrubland, especially from 1995 to 2000, showed a significant increase in area, possibly due to conversion from degraded farmland or grassland. Shrubland area remained relatively stable for most of the period. Wetland area has generally fluctuated, but the overall trend is not significant. This may include increases or decreases due to temporary bare ground from natural causes or human activities.Water bodies have changed relatively little and, despite minor fluctuations, have remained relatively stable overall.

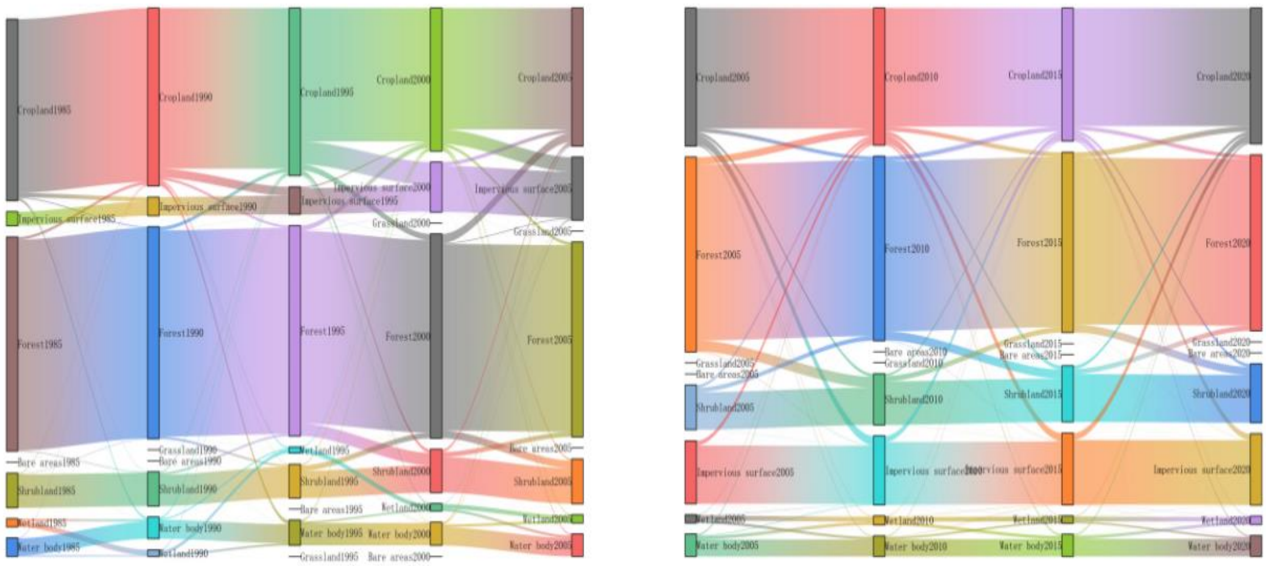


**Fig. 3** Sankey diagram of single land use intensity from 1985 to 2020

And the changes over time can be seen in Figure 2. From 1985 to 2005 (left panel), early land use changes are slower, mainly influenced by agricultural expansion and initial urbanization. However, from 2005 to 2020 (right panel), the amount of change between land types increases significantly, reflecting the accelerated urbanization process and more pronounced impacts of human activities on land use.

The main drivers of these changes are analyzed as follows:

1） Urbanization: Human population growth and urban expansion lead to the conversion of agricultural land and forests into impervious surfaces.

2）Agricultural Expansion: As demand for food increases, more forests and grasslands are cleared for farmland.

3） Climate Change and Environmental Policies: These factors influence the implementation of land-use management and conservation measures, leading to a slower conversion of land types.

4） National Economic Reform Policies: Intensive economic development in the region has led to a significant increase in the area of impervious land.

These factors collectively illustrate the complex interplay between human activities and land use changes over the studied periods.

### 3.2. Spatial Coordination Characterization Model

As shown in Table 4 [15-20], the Dada Bay area was in the low coordination stage in 2000 and 2005, characterized by high and moderate levels of uncoordination. Starting from 2010, the area reached a medium coupling state. By 2020 and 2021, it attained a strong coupling state, entering a high coordination level.From 2000 to 2021, the degree of coupling increased significantly from 0.216 to 0.921, indicating a substantial improvement. The coordination index also grew markedly, from 0.169 to 0.890, reflecting significant enhancements in system coordination. Similarly, the coordination degree of the coupling rose from 0.191 in 2000 to 0.895 in 2021, demonstrating a qualitative leap in the overall coordination ability of the system.

**Table 4.** 2000-2021The Calculation Results of Coupling Coordination Degree

| **Year** | **Coupling Degree C Value** | **Coordination Index T Value** | **Coupling Coordination Degree D Value** | **Coupling Coordination Degree D Value** | **Coupling Coordination Extent** |
|---|---|---|---|---|---|
| 2000 | 0.216 | 0.169 | 0.191 | 2 | Highly Non |
| 2005 | 0.461 | 0.202 | 0.305 | 4 | Moderately Non |
| 2010 | 0.691 | 0.380 | 0.601 | 8 | Moderately Coupled |
| 2015 | 0.775 | 0.624 | 0.780 | 8 | Moderately Coupled |
| 2020 | 0.812 | 0.879 | 0.874 | 10 | Strongly Coupled |
| 2021 | 0.921 | 0.890 | 0.895 | 10 | Strongly Coupled |

From 2000 to 2021, the Greater Bay Area's coupling and coordination have improved significantly. Initially characterized by a low-coupling and low-coordination state, the region has gradually progressed to a strong-coupling and high-coordination state by 2020 and 2021. This development indicates that the Greater Bay Area has achieved a high degree of integration in the synergistic development of science and technology, the economy, and transportation. As a result, the overall system demonstrates good coordination and high efficiency, as illustrated in Figure 4.

This change reflects the remarkable results achieved by a series of measures in infrastructure, policy implementation, and resource allocation in the Greater Bay Area. Maintaining this strong linkage and high degree of coordination in the future will help to further enhance the level of regional integration and development. By continuing to focus on these areas, the Greater Bay Area can further solidify its position as a leading region in terms of synergistic development and overall efficiency.

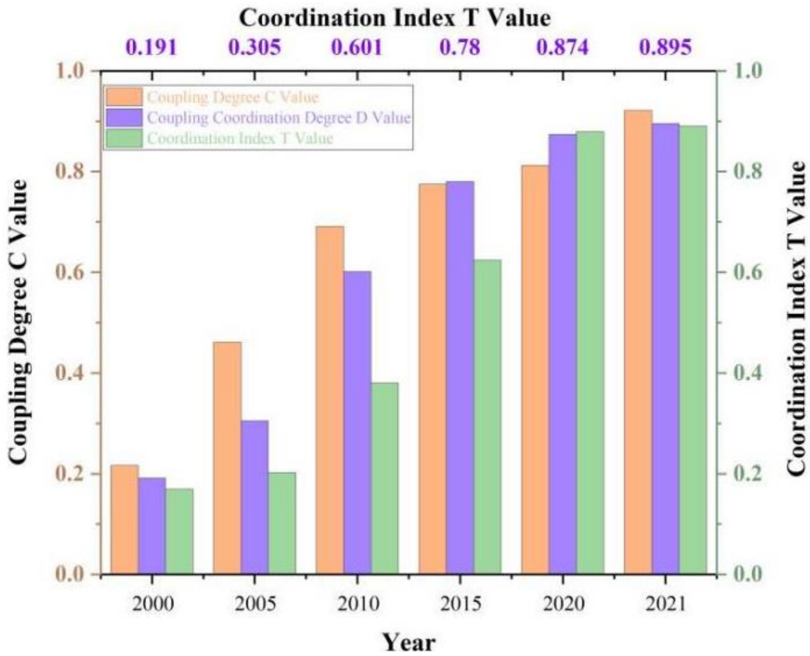


**Fig. 4** 2000-2021 Coupling Coordination Bar Chart

## 4. Research Conclusions

(1) The land use pattern within the Greater Bay Economic Zone is characterized by a central core consisting of forest land, cultivated land, and impermeable surfaces, with other land types interspersed throughout. The area exhibits a high degree of spatial clustering and dispersion. Forested areas are predominantly located in the northwestern region, while cultivated land is concentrated in the southwestern and central areas. Impermeable surfaces, on the other hand, predominantly emanate outward from the core cities of Guangzhou, Shenzhen, Dongguan, and Foshan, serving as connecting axes that enhance regional connectivity and radial expansion. Over the period from 1985 to 2022, there has been a noticeable increase in the proportion of impermeable surfaces, particularly in the core cities of the Greater Bay Area and their immediate environs.

(2) The degree of spatial coupling of land use in the Greater Bay Area has become more and more standardized, and the synergistic development of the Greater Bay Area in terms of science and technology, economy and transportation has achieved a high degree of integration, with the overall system showing good coordination and high efficiency. A series of measures in infrastructure, policy implementation and resource allocation have achieved remarkable results. Maintaining this strong linkage and high degree of coordination in the future will help to further improve the level of integrated regional development.

(3) The primary driver of changes in land use is predominantly tied to the economic progress of a region. From 1985 to 2022, the evolving characteristics of various land categories during this timeframe vividly illustrate the interconnectedness between land utilization and urban economic advancement. The process of urbanization and industrialization within the Greater Bay Area has significantly impacted agricultural and forested areas, particularly evident in the general decline of agricultural and forest lands and the rise in impervious surfaces between 1990 and 2005. Recent years have seen a shift in agricultural policies and an increase in forest conservation measures, resulting in the restoration of agricultural and forested lands. This underscores the pivotal role of environmental policies in the management of resources.

## References

[1] Wu L, Zhou Z F, Zhang L, et al. Response of landscape pattern change to habitat quality in karst area [J]. Environmental Science & Technology, 2023, 46(9): 206-217.

[2] Zhang S L. The construction of Guangdong-Hong kong-Macao Greater Bay Area: Theoretical asis, current problems and enlightenment from international Experience [J]. Journal of Lanzhou University of Finance and Economics, 2018, 34(5): 12-21.

[3] Luo Z Q, Zhang H B. Necessity and feasibility of tax co-operation among Guangdong Province, Hong Kong and Macao [J]. Foreign Taxation, 2012, (12): 64-67

[4] Zhiyong Chen, Yaowei Wu, Gangte Lin, Jianzhou Gong. Spatial Relationship between Ecological Environmental Quality and Land Use Change in the Guangdong-Hong Kong-Macao Region Based on Remote Sensing Ecological Index [J/OL] .Environmental Science, 1-21.2023-10-27

[5] Jie Zhang, Qingquan Li, Xiangyin Wu, Chenchen Zhang, Jingzhe Wang, Guofeng Wu. Analysis of the Evolution of Ecosystem Service Value and Carrying Capacity in the Guangdong-Hong Kong-Macao Greater Bay Area Based on Land Use. Acta Ecologica Sinica, 2021, 41(21): 8375-8386.

[6] YIN Nannan, TANG Jun, YANG Yuanwei, et al. Variations of shoreline and land use in Guangdong-Hong Kong-Macao Greater Bay Area from 1989 to 2021[J]. Marine Geology Frontiers, 2023, 39(5): 1-11. DOI: 10.16028/j.1009-2722.2022.158

[7] LIU Zhitao, WANG Shaojian, FANG Chuanglin. Spatiotemporal evolution and influencing mechanism of ecosystem service value in the Guangdong-Hong Kong-Macao Greater Bay Area. Acta Geographica Sinice, 2021, 76(11): 2797-2813 doi:10.11821/dlxb202111014

[8] Haojian DENG, Hengkai LI, Yongzhu XIONG, Chunyan ZHEN, Yingshuang LI. Temporal-spatial evolution of urban agglomeration in Guangdong-HongKong-Macao Greater Bay Area in recent 20 years[J]. World Regional Studies, 2020, 29(6): 1181-1189.

[9] Zhang, X., Zhao, T., Xu, H., Liu, W., Wang, J., Chen, X., and Liu, L.: GLC_FCS30D: the first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method, Earth Syst. Sci. Data, 16, 1353–1381, https://doi.org/10.5194/essd-16-1353-2024, 2024.

[10] Yongyong Song, Dongqian Xue, Lanhai Dai, et al. Land Use Change and Ecological Response in the Typical Fossil Energy Development Area in Shanxi, Shaanxi, and Inner Mongolia. Arid Zone Research, 2018, 35(5): 1199-1207.

[11] Yang Z W, Chen Y B, Wu Z F, et al. The coupling between construction land expansion and urban heat island expansion in Guangdong-Hong KongMacao Greater Bay [J]. Journal of Geo- information Science, 2018, 20(11): 1592-1603.

[12] Ding M M, Cao W D, Zhang D P, et al. Study on the measurement and coordination of road traffic and economic development in Anhui Province [J]Resources and Environment in the Yangtze Basin, 2018, 27(3): 503-513.

[13] Zhang Y, Cao W D, Liang S B, et al. A comparative study on the evolution process of urbanization and industrialization in the underdeveloped areas of western China: a case study of Qinghai Province [J]. Economic Geography, 2017, 37(2): 61-67.

[14] Zhou Jun, Ma Shipeng. SPSSAU Research Data Analysis Methods and Applications. 1st Edition [M]. Electronics Industry Press, 2024.

[15] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2010 (Electronic Edition) [M]. Beijing: China Statistics Press, 2010.

[16] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2005(Electronic Edition) [M]. Beijing: China Statistics Press, 2005.

[17] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2010 (Electronic Edition) [M]. Beijing: China Statistics Press, 2010.

[18] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2015(Electronic Edition) [M]. Beijing: China Statistics Press, 2015.

[19] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2020 (Electronic Edition) [M]. Beijing: China Statistics Press, 2020.

[20] Guangdong Yearbook Compilation Committee. Guangdong Statistical Yearbook 2021 (Electronic Edition) [M]. Beijing: China Statistics Press, 2021.