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Original Research

What Accounts for the Disparity in Cultivated Land Conversion across Different Periods? An Empirical Analysis of Guangdong Province

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Abstract

With rapid industrialization and urbanization in China, cultivated land conversion (CLC) has posed a significant threat to food security. Understanding the spatiotemporal patterns and drivers of CLC is crucial for promoting sustainable land use and economic development. However, existing research on CLC driving mechanisms has notable limitations: temporal studies often neglect spatial heterogeneity, while spatiotemporal analyses struggle to establish clear causal relationships. Therefore, this study aims to elucidate the causal mechanisms of CLC from a spatiotemporal perspective. Using land use data from Guangdong Province (2001–2020), we identified CLC patterns and applied geographical convergent cross mapping to examine causality. Results show that CLC in Guangdong expanded until 2012, then sharply declined and stabilized. Spatially, changes were more intensive along the coast and milder inland. We found that CLC drivers vary across stages, but socioeconomic factors consistently dominate. GDP growth, population increase, and urbanization emerged as primary drivers. Physical geography also constrained CLC distribution, while cultivated land endowment showed no significant impact. These insights from a rapidly developing Chinese province provide valuable implications for global cultivated land conservation and sustainable development.

Keywords: cultivated land conversion, spatiotemporal evolution, causal mechanisms, geographical convergent cross mapping

Introduction

Cultivated land conversion (CLC) refers to the transformation of farmland into land designated for construction purposes [1, 2]. This represents the most severe form of cultivated land degradation, posing the most significant threat to grain production [3, 4]. While the supply of land for non-agricultural construction can support rapid development in urban secondary and tertiary industries, the loss of cultivated land negatively impacts food security [5]. Consequently, there is an urgent need to deepen our

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understanding of this conversion process. Furthermore, complex phenomena such as population growth, capital investment, and the depletion of cultivated land resources can exacerbate non-agricultural conversion [6, 7]. Therefore, research on the driving mechanisms behind CLC is crucial for safeguarding national food security and sustaining socio-economic development.

As a dramatic and far-reaching type of land use change, the spatiotemporal patterns and evolutionary dynamics of farmland conversion have garnered extensive academic attention. To date, research on farmland conversion has yielded a wealth of theoretical and practical explorations.

Theoretically, frameworks such as land use transition theory, the dual structure theory of urban-rural land markets, and institutional economics provide robust theoretical support for the study of land use change. Land use transition theory offers a macro-level perspective for understanding the phased characteristics of farmland conversion, positing that land use change results from the interplay of multiple factors, necessitating a shift from analyzing dominant morphology to recessive morphology [8]. The dual structure theory of urban-rural land markets elucidates the institutional roots of the conversion process. Under China's unique land system, this theory highlights the structural differences and fragmentation between urban and rural land markets in terms of institutional design, operational mechanisms, rights allocation, and price formation [9]. Institutional economics focuses on the role of institutions in economic development and their broader implications. This perspective requires integrating economic factors with institutional changes to examine their combined driving effects on farmland conversion [10].

In terms of empirical research, current studies on the driving mechanisms of CLC can be broadly summarized into two major research perspectives. The first approach is based on a time series perspective. It analyzes statistical data from multiple years. Methods such as time series correlation analysis or time series causality analysis are used to explore the temporal relationship between CLC and its influencing factors. Time series correlation analysis typically employs models like linear regression, grey relational analysis, and fixed-effect models to examine whether there is a correlation between two time series datasets [11-13]. Time series causality analysis, on the other hand, uses methods such as the Granger causality model and simultaneous equation models to clarify the causal relationships between two time series datasets [14, 15]. Although the time series approach can identify driving factors associated with the temporal changes in CLC, it is based on the assumption of independent and identically distributed data [16]. However, as a typical geographical phenomenon, CLC exhibits significant spatial clustering, sequencing, and spatial differentiation, which does not align with the assumption of complete randomness [17, 18]. Therefore, time series-based studies on the driving mechanisms of CLC overlook the issue of spatial correlation.

The second perspective is the tempo-spatial viewpoint, which builds upon the time series approach by incorporating spatial correlation. This perspective recognizes that spatial data exhibit dependency or autocorrelation [19]. Research often employs spatial methods, such as the spatial error model, spatial lag model [20], geographically and temporally weighted regression model [21], and geographical detector model [22], to establish statistical relationships between CLC and potential driving factors. Overall, tempo-spatial studies on the driving mechanisms of CLC address the limitations of time series research that neglect spatial characteristics [23]. However, these studies often remain at the level of spatial correlation. They reveal the spatial association between factors and CLC, but are insufficient to prove that these factors are the true drivers of CLC.

Because correlation does not imply causation, the occurrence of a high correlation coefficient between two variables that are not causally related leads to the issue of "spurious correlation." This can affect the accuracy of driving mechanism studies of CLC [24-26]. Specifically, this manifests in two ways. Firstly, another factor may interfere, leading to misleading correlations between the two variables [27, 28]. Secondly, the correlation coefficient may reverse the causal relationship between the variables [29]. Particularly for CLC, which is a complex geographical phenomenon, the interactions between CLC and its influencing factors make the causal relationship unclear. Overall, the issue of "spurious correlation" in the tempo-spatial driving mechanisms of CLC can be attributed to the limitations of spatial statistical models. These models cannot directly control for potential variables, identify temporal sequences, or capture complex causal chains [30-32]. As a result, studies on the relationship between CLC and potential factors can only reveal spatial distribution correlations between variables, without clearly identifying causal relationships. Therefore, there is an urgent need to uncover the causal driving mechanisms of CLC from a tempo-spatial perspective.

This study seeks to reveal the causal driving mechanisms of cultivated land conversion from a tempo-spatial perspective. The study first uses Landsat-4/5/7/8 to identify the tempo-spatial patterns of CLC in Guangdong Province from 2001 to 2020 and applies Moran's I index to determine whether CLC exhibits spatial autocorrelation. Subsequently, the study will use a spatial causality analysis method called the Geographical Convergent Cross Mapping (GCCM) to identify the causes of CLC, focusing on natural conditions, socioeconomic factors, and cultivated land resource endowment. In addition, the study will compare the results of the GCCM with those of the Geographic Detector to comprehensively unveil the causal mechanisms of CLC, providing scientific evidence for the high-quality development of the economy and society.

Materials and Methods

Study Area

The study selects Guangdong Province as the research area (Fig. 1). Located at the southernmost tip of mainland China, Guangdong Province comprises four subregions: Pearl River Delta (PRD), Northern Guangdong (NG), Eastern Guangdong (EG), and Western Guangdong (WG). As China's most populous and economically significant province, Guangdong has led the nation in economic output for 35 consecutive years since 1989 [33]. In 2023, its GDP amounted to 13.5 trillion yuan, representing 11% of the national total, while the population stood at 127 million. Driven by rapid urbanization and industrialization, Guangdong's built-up land area expanded from 4,260 km² in 2000 to 9,120 km² by 2020, indicating a growth rate of 114% [34]. Additionally, the province features complex terrain, with extensive mountainous regions and limited plains, resulting in scarce cultivable land resources. Cultivated land accounts for only 10.57% of the province's total area. From 2000 to 2020, the cultivated land area in Guangdong declined from 27,425 km^2 to 21,952 km^2, a reduction of approximately 19.96% [35], posing a serious threat to regional food security. These dynamics highlight the intense demand for built-up land and the scarcity of cultivated land resources, creating a pronounced conflict between economic development and farmland protection. Consequently, Guangdong Province serves as an ideal case study for exploring CLC.

Data

Selection of Driving Factors for CLC

CLC is a complex geographical phenomenon shaped by a mix of natural geographic conditions, socio-economic influences, and resource endowments (Table 1).

Natural geographic conditions form the foundation for production and living activities. Elevation and slope are important factors limiting production and construction activities, as most projects tend to be located in flat areas [36]. Water resources, as the most rigid constraint for urban development, determine the degree of land resource development and population carrying capacity, making them key considerations in development decisions [37]. Therefore, three natural geographical factors – elevation (DEM), slope (SLO), and rainfall (RAIN) – need to be considered in the study of CLC.

Cultivated land use transformation is closely aligned with the level of economic and societal progress. Regions with concentrated economic activities and populations are more likely to experience CLC [38]. Consequently, Gross domestic product (GDP) and population (POP) are used to reflect regional economic development levels and population-carrying pressure. The financial scale of local governments also impacts CLC. Land transfer revenue is a key fiscal source for local governments, and owing to the dual nature of urban and rural land markets, the price for converting cultivated land is usually lower than that for state-owned construction land. This price disparity may incentivize governments to convert cultivated land into construction land to increase fiscal

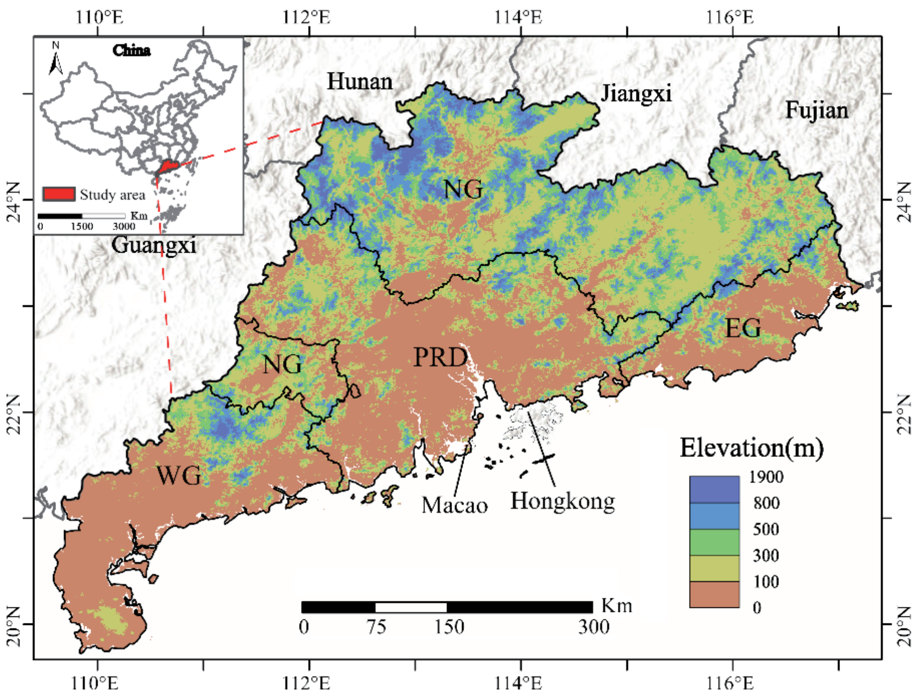

Fig. 1. Elevation Map of the Study Area

revenue and meet land demand, thus driving CLC [39, 40]. Therefore, public budget income (INC) is chosen as an indicator to measure financial scale and its impact on CLC. The transformation and upgrading of industrial structure may generate new demand for construction land, thereby influencing CLC [41]. Therefore, this study adopts the secondary and tertiary industry indices (SI, EI) to represent regional industrial structure, calculated as the ratio of industrial value-added to gross domestic product. As urbanization progresses with the massive migration of agricultural populations to urban areas, it intensifies non-agricultural construction activities [42]. Accordingly, the night-time light index (NTL) is utilized to reflect regional urbanization levels.

The abundance of regional cultivated land resources is a prerequisite for CLC. Regions with abundant resources tend to experience faster rates of CLC. Moreover, in the pursuit of efficiency, low-yield land is more likely to be converted into more profitable construction land, especially under the influence of market and policy drivers [1, 6]. Therefore, indicators such as Cultivated Land Area (CLA), Food Production (FP), and Unit Area Yield (UAY) are used to measure the impact of resource endowments on CLC.

Data Source and Processing

This study uses 124 districts and counties in Guangdong Province as basic units, with data sourced as follows:

CLC is defined as land that was cultivated in the previous year and converted to construction land in the current year. This study initially employed deep learning methods to extract Guangdong Province's cultivated land dataset (2000-2019) and construction land dataset (2001-2020) from Landsat imagery on the Google Earth Engine (GEE) platform (Fig. 2). CLC data for 2001–2020 were obtained by comparing and overlaying data from consecutive years. The cultivated land dataset was constructed by retrieving Vegetation Luxuriance Period (VLP) and Vegetation Dormant Period (VDP) images from the GEE platform and training a ResUNet model. The LandTrendr long-term sequence correction algorithm was then applied to generate annual cultivated land maps for 2000–2019, achieving an overall accuracy between 0.91 and 0.93, with a kappa coefficient ranging from 0.80 to 0.83 [31]. The construction land dataset was generated from raw Landsat data using an improved ResUNet++ model on the GEE platform, resulting in construction land distribution maps for 2001–2020 in Guangdong Province. This dataset achieved an overall accuracy of 0.99 and a kappa coefficient of 0.96 [32].

Among the driving factor data, socio-economic data were obtained from the statistical bureaus of various prefecture-level cities and the China County Statistical Yearbook. These data include GDP, population, general public budget revenue, value added in the secondary and tertiary industries, and food production. Raster

Table 1. Details about the data used in this study.

Driving factors			Spatial resolution	Data Source	Time Range
Natural geographic conditions		Elevation (m)	30 m	Geospatial data cloud (https://www.gscloud.cn/)	2020
		Slope (°)	30 m		2020
		Rainfall (mm)	1 km	National Tibetan Plateau / Third Pole Environment Data Center (https://data.tpdc.ac.cn/)	2001-2020
Socioeconomic	Economic development	Gross domestic product (hundred million yuan)	-	Guangdong Statistical Yearbook (http://stats.gd.gov.cn/gdtjnj/)	2001-2020
	Population pressure	Population (ten thousand people)	-		2001-2020
	Financial scale	Public budget income (hundred million yuan)	-		2001-2020
	Industrial structures	Secondary industry structure index (%)	-		2001-2020
		Tertiary industry structure index (%)	-		2001-2020
	Urbanization level	Night-time light index	1 km	Earth Observation Group (https://eogdata.mines.edu/products/vnl/)	2001-2020
Resource endowment		Cultivated land area (hectares)	-	-	2001-2020
		Food production (tons)	-	Guangdong Statistical Yearbook (http://stats.gd.gov.cn/gdtjnj/)	2001-2020
		Unit area yield (tons / hectares)	-	Calculated by "Food production / cultivated land area"	2001-2020

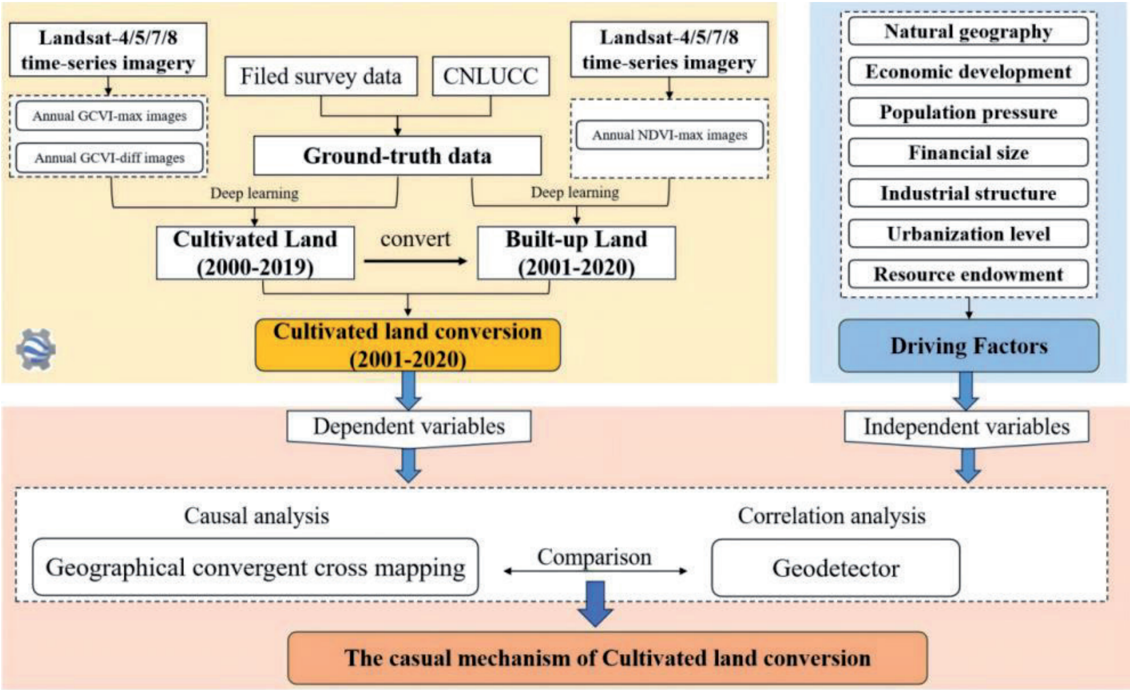

Fig. 2. The technical flowchart of CLC tempo-spatial causal mechanism.

data comprised elevation, slope, rainfall, and night-time light index, with slope calculated from elevation data. All raster datasets were aggregated to each district and county through zonal statistics. Comprehensive details regarding these datasets can be found in Table 1.

Methods

Spatial Autocorrelation Analysis

(1) Spatial Autocorrelation Analysis

This study employs the global Moran's I to reveal the overall clustering patterns of CLC spatial distribution and to test whether CLC exhibits global spatial autocorrelation [43]. This analysis provides the basis for selecting appropriate methods to investigate the driving mechanisms. The calculation formula is Eq. (1).

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

Where x represents the CLC values for different counties in Guangdong Province, $\bar{x}$ is the sample mean, S^2 is the sample variance, and w_{ij} denotes the elements of the spatial weight matrix $W = [w_{ij}]_{n\times n}$. The Moran's I index ranges between [−1,1], with higher absolute values indicating stronger spatial autocorrelation of CLC across counties in Guangdong. An index value of 0 indicates a random spatial distribution, implying no spatial autocorrelation of CLC.

(2) Analysis of CLC Trends

This study employs a linear regression model to quantify the temporal trend of CLC during each period using the regression coefficient (slope). A positive slope value indicates an increasing trend in CLC, whereas a negative value signifies a decreasing trend in regional CLC. The calculation formula is as follows:

$$m=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2}$$

Where x denotes the year, y represents the CLC area, and n indicates the number of years in the fitting period.

(3) Analysis of CLC Intensity

This study measures CLC intensity using the ratio of CLC area to total regional area. Higher values indicate greater severity of CLC during the study period.

Geographical Convergent Cross Mapping

GCCM is a method for spatial causal inference. It is grounded in dynamical systems theory and the generalized embedding theorem. This study uses GCCM to explore the causal link between CLC Y and its drivers X. The goal is to reveal the complex dynamics behind CLC [44].

GCCM reconstructs the state space of a dynamical system using spatial lags. It predicts one variable based on another variable's trajectory. The prediction accuracy is evaluated using the Pearson correlation coefficient ρ, defined in Eq. (3). When ρ approaches 1, it indicates a significant linear relationship.

$$\rho=\frac{Cov(Y,\hat{Y})}{\sqrt{Var(Y)\,Var(\hat{Y})}} \tag{3}$$

Here, Cov() represents covariance and Var() represents variance. Y is the observed value, and Y is the predicted value. The prediction Y at a spatial unit s is calculated as Eq. (4).

$$\hat{Y}_s|M_x=\sum_{i=1}^{L+1}(\omega_{si}Y_{si}|M_x) \tag{4}$$

In this equation, M_x is the state space from variable X and L is the embedding dimension. ω_{si} is the weight of the nearest neighbor in M_x, given by Eq. (5). Y_{si} is the observed value at si, also the first component of state $\psi(y,s_i)$.

$$\omega_{si}|M_x=\frac{\text{weight}[\psi(x,s_i),\psi(x,s)]}{\sum_{i=1}^{L+1}\text{weight}\,[\psi(x,s_i),\psi(x,s)]} \tag{5}$$

Where weight(* ,*) is the weight function between two states in the shadow manifold, defined as Eq. (6).

$$\text{weight}\left(\psi(x,s_i),\psi(x,s)\right)=\exp\left(-\frac{\text{dis}\left(\psi(x,s_i),\psi(x,s)\right)}{\text{dis}\left(\psi(x,s_1),\psi(x,s)\right)}\right) \tag{6}$$

Where $\psi(x,s_i)$ represents the state vector at spatial unit x, which is composed of the observed values of variable x at spatial unit s and its neighborhood. exp refers to the exponential function, used to calculate the weight, reflecting the similarity between states. dis(*,*) denotes the distance function between two states within the manifold, employed to evaluate the difference between state vectors.

GCCM is based on Takens' embedding theorem, which posits that if X and Y originate from the same dynamical system, they are causally associated and can be mutually predicted through cross-mapping. By detecting the influence of X on Y and that of Y on X, the causal relationship between them can be inferred from the results [44]. Therefore, GCCM provides a more reliable and comprehensive reference for better understanding and comparing the strength of causal relationships between a target variable and multiple influencing variables.

By comparing the predictive skill of X to Y with that of Y to X, GCCM reveals the primary causal direction and quantifies the asymmetric causal effects. This offers a new perspective on understanding CLC. In this study, the interannual variation (or spatial distribution pattern) of CLC area serves as the dependent variable input to the model, while the variations in driving factors constitute the independent variables. For two natural factors – elevation and slope – which exhibit minimal interannual fluctuation, their spatial distribution patterns are used as input variables. The interannual variation is quantified by the slope of change over the 20-year period, and the spatial distribution level is represented by the 20-year average. A ρ value approaching 1 indicates a statistically significant linear relationship.

Geographical Detector Model

Geographical Detector introduces the "factor detection" metric in conjunction with GIS spatial overlay analysis and set theory, to identify interactions among multiple factors [29]. It has been widely applied in analyzing geographical feature patterns and spatial differentiation. In this study, Geographical Detector results are used as a comparative analysis alongside the GCCM method. The dependent variable y and independent variables A are set consistently across both experiments, where y represents changes and distribution of CLC areas, and A denotes the changes and distributions of driving factors.

The study presents the factor q explanatory power metric to examine the driving factors of CLC. A higher q value suggests a significant impact of that factor on CLC. y is represented by a grid system composed of sampling units i (i = 1, 2, 3, …, n, where n is the total count of sampling units). It is assumed that A = {Ah} constitutes a set of factors potentially influencing the spatial differentiation of CLC, where h = 1, 2,…, L and L is the number of factor categories. Each type Ah is linked to one or more spatial subregions. To analyze the spatial correlation between factor A and y, the y layer is overlaid on top of the A layer. For the h type of factor A (corresponding to one or more subregions), the discrete variance of y is denoted as σh2. The determination power q of factor A on y is defined as Eq. (7).

$$q=1-\frac{1}{N\sigma^2}\sum_{h=1}^{L}N_h\sigma_h^2 \tag{7}$$

In the formula, N_h represents the number of samples in the h category of factor A (corresponding to one or more subregions). N represents the total number of sampling units in the entire region, where $N = \sum^{L}_{h=1}N_h$. L denotes the classification hierarchy of factor A, while σ^2 signifies the discrete variance for the whole region.

Results and Discussion

Tempo-Spatial Evolution of CLC

During the study period, Guangdong Province exhibited fluctuating trends in CLC, characterized by three distinct phases: a gradual increase (2001-2012), a sharp decline (2012-2014), and a stabilized rise (2014-2020). The cumulative CLC area reached 7,208.20 km². The Pearl River Delta, western Guangdong, and northern Guangdong regions showed comparable CLC magnitudes, each approximately 2,000 km², whereas eastern Guangdong recorded a significantly lower CLC area of only 716 km².

Nevertheless, all four regions followed trajectories consistent with the overall trend, aligning with the three-phase pattern described above. In the initial phase, the expansion of CLC was closely associated with investment-driven construction activities. Major events such as China's accession to the WTO in 2001 boosted economic confidence, triggering a new wave of investment and land acquisition. Following the 2008 Asian Financial Crisis, governmental macroeconomic stimulus measures relaxed land use restrictions and promoted large-scale infrastructure development, leading to a surge in CLC during 2009-2011. The second phase (starting 2012) marked China's transition to a new development paradigm. In economic terms, the logic of the Chinese government's economic policy has shifted from scale-oriented expansion toward quality and efficiency-oriented development, and the growth model has transitioned from extensive to intensive. This shift reflects a reduced dependence of economic growth on land resources, thereby significantly curbing the scale of farmland conversion to non-agricultural uses. With regard to cultivated land protection, the Chinese government introduced a "Quantity–Quality–Ecology" trinity management and control system through the Circular on Enhancing Cultivated Land Protection and Comprehensively Strengthening Cultivated Land Quality Management and Construction. This system incorporates cultivated land productivity into the core indicators of the requisition–compensation balance framework, marking a policy shift from a singular focus on total amount control to a comprehensive enhancement of effectiveness. Overall, the Chinese government has further strengthened the principle of sustainable development by implementing the strictest cultivated land protection system and establishing a comprehensive framework that coordinates the protection of quantity, quality, and ecology. Consequently, Guangdong's CLC area plummeted in 2012, effectively curbing the previous upward trend and entering an adjustment phase. Subsequently, CLC activities maintained relative stability during the 2014-2020 period.

From a spatial perspective, regional differences in the trends of CLC are marked across Guangdong Province from 2001 to 2020 (Fig. 3b) and in the multi-year average distribution (Fig. 3c). Moran's I index tests show that both Moran's I values exceed 0, and the P-values are below 0.01. This indicates that the Moran's I index is statistically significant at the 1% level, suggesting spatial clustering in the changes and distribution of CLC in Guangdong Province. On one hand, the CLC pattern in Guangdong shows an increase in the central and northern areas and a decline in the western areas. Counties with significant increases in CLC are concentrated in the rapidly developing areas on the outskirts of the PRD and in NG. To facilitate the integrated development of the Guangdong–Hong Kong–Macao Greater Bay Area, peripheral areas in the PRD, such as Jiangmen and Huizhou, have functioned as satellite cities of the region's core

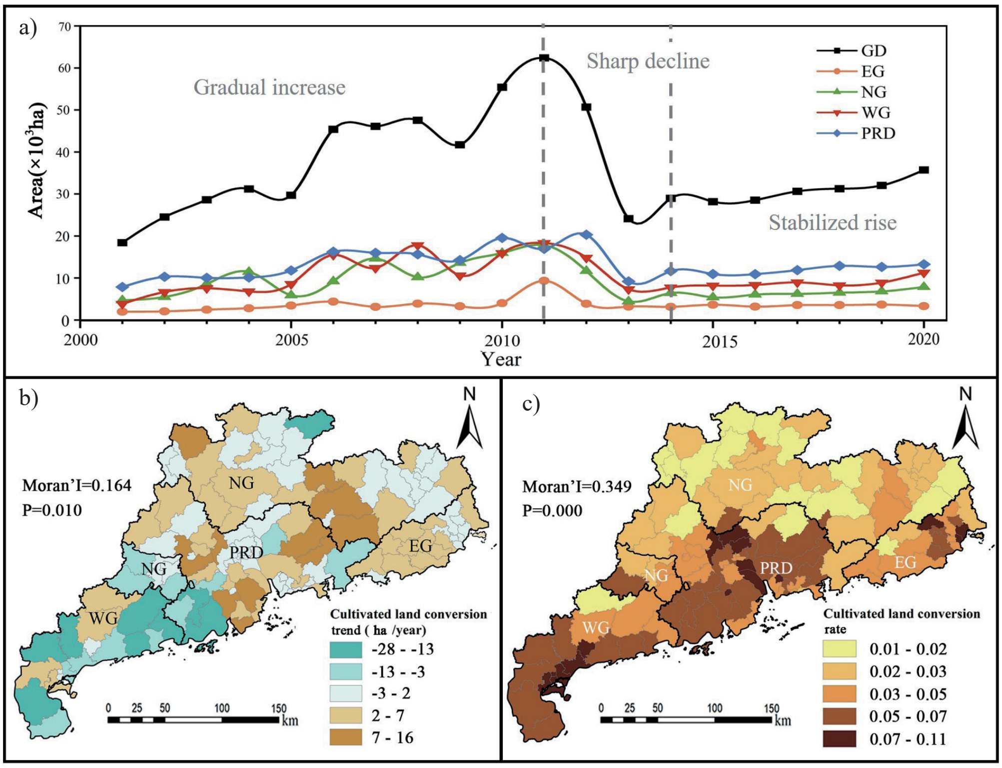

Fig. 3. Changes in Cultivated Land Conversion Area in Guangdong Province a). Spatial Distribution of Overall Trends b) and Multi-Year Average Spatial Distribution c) of Cultivated Land Conversion across Counties in Guangdong Province.

cities, undertaking industrial transfer from the core areas, which has led to a rapid increase in farmland conversion to non-agricultural uses. In contrast, the growth of farmland conversion in NG, including cities such as Heyuan and Qingyuan, is associated with infrastructure development in mountainous areas. Policy implementation has necessitated the improvement of the transportation network in NG to promote the integrated development of transportation and industrial sectors, which, to a certain extent, has intensified the pressure of farmland conversion in peri-urban areas. Regions with relatively stable CLC levels each year include highly urbanized areas such as Guangzhou and Shenzhen, as well as ecologically protected areas in mountainous regions, such as Zhaoqing and Meizhou. Regions where the trend of farmland conversion has slowed are primarily concentrated in WG. Benefiting from its clear positioning as a grain production base within the "Modern Agriculture Demonstration Zone," the effective implementation of cultivated land protection policies in this region has led to a sustained reduction in the scale of farmland conversion.

On the other hand, Guangdong Province's CLC scale generally exhibits a spatial pattern of higher concentrations in coastal areas and lower levels in inland regions. The most severe CLC is concentrated in coastal cities of WG, the PRD, and ED, with Maonan District showing the most intensive conversion, reaching 0.11 km² of CLC area per square kilometer of land. Simultaneously, a noticeable radiation effect is observed, where CLC intensity gradually decreases in peripheral areas surrounding core cities. The regions with relatively minimal CLC during the study period are predominantly concentrated in northern Guangdong. These northern counties typically feature mountainous terrain, extensive land areas, and limited non-agricultural conversion, resulting in low CLC rates. For instance, in Lianshan Zhuang and Yao Autonomous County, where land development is constrained by topographic limitations and water conservation requirements, the CLC rate remains as low as 0.013.

Driving Mechanism Analysis

Results of Spatial Causal Detection

The causal inference results of CLC are shown in Fig. 4. At the 95% confidence level, factors significantly influencing CLC include elevation (ρ = 0.34), slope (ρ = 0.17), rainfall (ρ = 0.22), GDP (ρ = 0.44), population (ρ = 0.44), public budget income (ρ = 0.26), and night-time light index (ρ = 0.27). Conversely, factors exhibiting changes driven by CLC feedback include DEM (ρ = 0.23), SLO (ρ = 0.18), GDP (ρ = 0.31), POP (ρ = 0.36), and CLA (ρ = 0.35).

The findings reveal three key insights: Firstly, socioeconomic conditions exert the most significant influence on CLC. GDP growth and population increase are identified as the primary drivers of CLC changes in Guangdong Province, while CLC conversely contributes to regional GDP and population growth to some extent. The positive correlation between local fiscal revenue and CLC intensification indicates that local governments' reliance on land finance has accelerated the conversion process. Furthermore, urbanization development level demonstrates a clear positive effect on CLC, suggesting that an advancing urbanization level encroaches upon agricultural production spaces, leading to reductions in cultivated land area. Secondly, natural geographic conditions substantially constrain CLC occurrence. The ρ value of 0.34 for elevation confirms that physical terrain limitations naturally restrict CLC, explaining the comparatively lower conversion rates observed in Northern Guangdong's mountainous areas. The relatively weaker impact of CLC on natural geographic conditions factors represents a subordinate effect within a strong correlation framework [21]. Finally, factors representing cultivated land resource endowment, including cultivated land area and food production, show no significant influence on CLC. Instead, CLC occurrence significantly affects changes in cultivated land area (ρ=0.35), indicating that conversion activities drive subsequent alterations in agricultural land resources rather than being predetermined by existing resource conditions.

Results of Stratified Heterogeneity Test

During the study period, CLC exhibited distinct phase-specific characteristics. Focusing solely on the overall change trend may lead to discrepancies between analytical results of driving factors and actual conditions in specific years. Therefore, based on the temporal evolution features of CLC in Guangdong Province, the study period was divided into three phases to examine the impacts of dynamic socioeconomic factors and cultivated land resource endowment on CLC within each phase, thereby conducting an in-depth investigation of the driving mechanisms behind CLC in different periods, with the results presented in Fig. 5.

During the phase of accelerated growth (2001-2012), GDP and population served as the primary drivers of CLC, with causal coefficients reaching 0.47 and 0.48 respectively. This reflects the substantial pressure exerted by rapid economic development and population growth on cultivated land resources. The influence of public budget income on CLC was relatively weaker (ρ=0.29), though it represented the highest value among all three phases before gradually diminishing in subsequent periods. The ρ values for cultivated land area and food production were 0.33 and 0.16 respectively, indicating that cultivated land resource endowment moderately contributed to CLC during this phase. Overall, as Guangdong Province served as a pioneer in reform and opening-up during this period, economic expansion and population growth triggered unprecedented urban sprawl and infrastructure demands, substantially accelerating CLC.

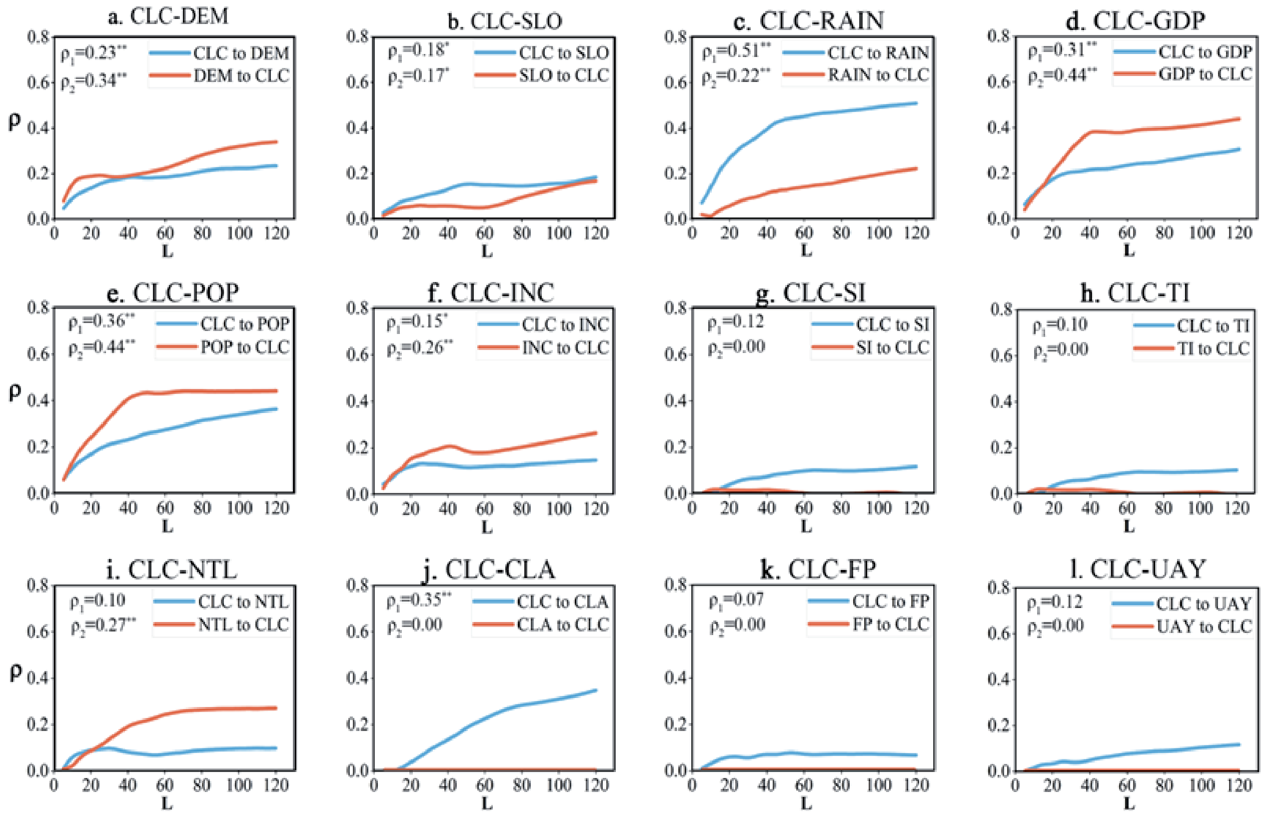

Fig. 4. Causal inference of cultivated land conversion changes. Figs a-b present the cross-mapping predictions between the average CLC area and the mean values of elevation and slope at the county level in Guangdong Province. Figs c-j display the cross-mapping predictions between CLC trends and the changing patterns of rainfall, GDP, population, fiscal revenue, secondary industry index, tertiary industry index, night-time light index, cultivated land area, food production, and unit area yield at the county level. Note: ρ² represents the ρ-value at maximum library size for the influence of factor variations on CLC changes (orange curves), while ρ¹ denotes the ρ-value for the reverse impact of CLC changes on factor variations (blue curves). ** correlation is significant at the 0.01 level, * correlation is significant at the 0.05 level.

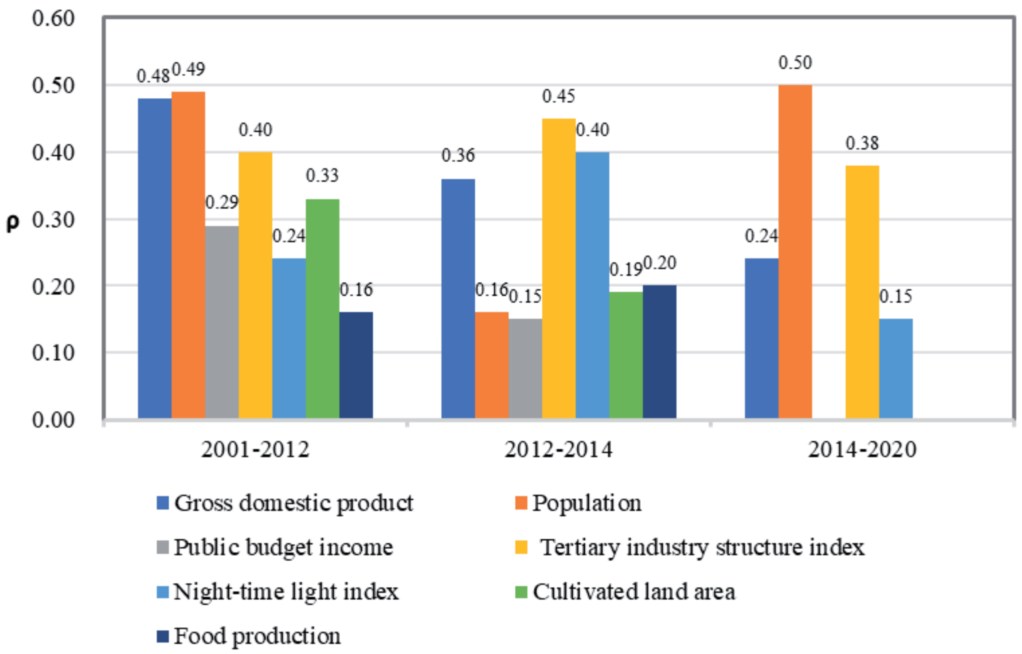

Fig. 5. Causal Inference of Cultivated Land Conversion (CLC) Changes Across Different Phases. Note: Driving factors with p-values greater than 0.05 are considered statistically non-significant, and their values are displayed as 0 or have been entirely removed.

During the adjustment phase (2012-2014), the influence of GDP, population, and public budget income significantly diminished, with their ρ values declining to 0.36, 0.16, and 0.15 respectively. Simultaneously, the impact of the tertiary industry structure index and night-time light index intensified, with ρ values increasing from 0.40 to 0.45 and from 0.24 to 0.46 respectively, indicating that tertiary industry development and urbanization development level became the primary drivers during this phase. The effects of cultivated land area and food production remained relatively weak (ρ=0.19, 0.20), with the promoting role of resource endowment further weakening. This shift reflects how, against the backdrop of economic restructuring, land use gradually tilted toward service industries and high-value-added sectors, while accelerated urbanization further prompted the conversion of cultivated land to non-agricultural uses.

During the stable growth phase (2014-2020), the influence of GDP continued to diminish (ρ = 0.24), representing approximately half of its impact during the initial phase. However, the effect of population reemerged as a prominent factor, reaching a ρ value of 0.50 and becoming the most influential variable, indicating that population growth and mobility served as key drivers during this period. Although the tertiary industry structure index decreased to ρ=0.38, it remained the second most significant factor, demonstrating the sustained driving force of tertiary sector development. The night-time light index showed a notable decline in influence (ρ = 0.15), reflecting the weakened direct positive effect of urbanization on CLC. These shifts mirror Guangdong's deepened economic transformation and industrial upgrading during this stage, where the development of service industries and high-tech sectors attracted substantial labor forces, consequently driving the demand for construction land.

Geographical Detector Results

This section employs the factor detection method of Geographical Detector to examine the influence of driving factors on CLC (Table 2). The night-time light index (q = 0.42) demonstrates the highest significance, indicating that spatial expansion and economic activities during urbanization serve as the primary drivers of CLC. Furthermore, rainfall (q = 0.20) and cultivated land area (q = 0.19) also exhibit relatively high significance, suggesting that climatic conditions and cultivated land resource endowment significantly influence CLC changes. Although GDP (q = 0.13) and population size (q=0.10) show statistical significance, their lower q-values imply comparatively limited effects on CLC. Other factors show no significant impact on CLC. The factor detection results thus identify urbanization level as the most crucial factor influencing CLC changes, revealing that urbanization characterized by spatial expansion continuously encroaches upon cultivated land resources.

Table 2. Factor Detection Results of Geographical Detector.

Detect factors	Cultivated land conversion	
	q	P value
DEM	0.02	0.59
SLO	0.03	0.34
RAIN	0.20	0.00**
GDP	0.13	0.01**
POP	0.10	0.01**
INC	0.01	0.79
SI	0.01	0.89
TI	0.00	0.94
NTL	0.42	0.00**
CLA	0.19	0.00**
GO	0.03	0.37
PUAGO	0.01	0.80

Note. ** correlation is significant at the 0.01 level, * correlation is significant at the 0.05 level.

Discussion

Comparative Analysis of Driving Mechanisms

Divergence between Overall and Phase-Specific Driving Factors of Cultivated Land Conversion

Comparative analysis between the overall drivers and phase-specific drivers of CLC in Guangdong Province reveals notable inconsistencies. For instance, while the tertiary industry structure demonstrated significant impacts in phase-specific analyses, its influence was not statistically significant in the overall analysis. Similarly, fiscal revenue showed significance in the overall analysis but exhibited progressively weakening effects across phases. Furthermore, GDP maintained relatively high explanatory power in the overall analysis yet displayed declining influence in phase-specific examinations, whereas population demonstrated stronger phase-specific impacts despite its modest overall effect. This discrepancy indicates the inherent complexity of CLC phenomena. Neither standalone overall analysis nor segmented phase analysis can comprehensively unveil its driving mechanisms. Consequently, investigating CLC drivers requires adopting long-term dynamic analytical approaches rather than relying solely on fixed-interval studies. Failure to account for temporal dynamics may lead to misinterpretation of driving factors, ultimately compromising the scientific validity and effectiveness of policy formulation.

A Contrast between Causal Research and Correlational Study

Both Geographical Convergent Cross Mapping (GCCM) and the Geographical Detector method provide valuable insights into revealing the driving mechanisms of Cultivated Land Conversion (CLC). While both approaches demonstrate the significant promotive effect of urban development on CLC, they differ in the following aspects:

Discrepancies in Identifying Natural Factors. The causal driving mechanism analysis reveals that regional variations in elevation (DEM, $\rho = 0.340$) and slope (SLO, $\rho = 0.167$) significantly influence CLC, consistent with findings that low-elevation flat farmland constitutes the most concentrated areas for CLC [45]. In contrast, the Geographical Detector method suggests no statistically significant relationship between DEM/slope and CLC. Evidently, the latter demonstrates weaker capability in identifying the impacts of natural factors on CLC.

Given that GCCM is capable of identifying causal relationships that remain undetected by GD and remains effective even in the absence of significant correlations [46], it can overcome the mirroring effect in contexts where cultivated land conversion (CLC) is influenced by the synergistic effects of multiple factors, thereby effectively avoiding bias in the analysis of drivers affecting CLC [46]. In this study, although natural factors such as DEM exert a certain causal influence on CLC, the magnitude of such influence is relatively weak. Consequently, compared with the analytical results derived from GD, GCCM enables a more precise estimation of the extent to which each influencing factor contributes to CLC.

Discrepancies in Economic Factor Driving Forces. In investigating the determinants of CLC spatial distribution, the GCCM model demonstrates strong driving forces from GDP ($\rho = 0.534$), population (POP, $\rho = 0.204$), and fiscal revenue (INC, $\rho = 0.509$), all statistically significant ($p<0.01$). This indicates that economic expansion directly promotes cultivated land conversion through increased land demand, aligning with findings from other studies [47]. Conversely, Geographical Detector results show substantially lower explanatory power for these economic factors ($q = 0.09$-0.14), with some failing to reach statistical significance. Therefore, GCCM proves more effective in revealing the comprehensive driving effects of economic factors.

Disparities in Driving Forces of Cultivated Land Resource Endowment. The Geographical Detector results indicate a significant correlation between changes in cultivated land area and CLC ($q=0.19$). In contrast, the GCCM model clarifies that variations in cultivated land area do not drive CLC ($\rho=0.00$), but rather CLC induces changes in regional rainfall and cultivated land area ($\rho = 0.35$). This demonstrates that the driving mechanism results based on Geographical Detector may potentially suffer from confounding causality issues, whereas GCCM effectively delineates the reverse causal relationship between CLC and cultivated land area changes.

Policy-Driven Analysis

In this study, the significant effects of core driving factors – namely GDP, population, local fiscal revenue, and urbanization level – on the intensity of CLC at various stages are inseparable from the influence of policy interventions and institutional changes. Since the beginning of the 21st century, the evolution of farmland conversion in Guangdong Province has served as a concrete manifestation of the aforementioned driving factors operating within the policy and institutional framework. During the period of economic expansion-oriented development from 2001 to 2011, policy priorities leaned toward the expansion of construction land. Under the policy orientation of "prioritizing economic growth," local governments generated fiscal revenue and investment capital through land management [48]. Concurrently, the growth of permanent population accelerated urbanization and increased the demand for converting cultivated land into construction land [49]. A mutually reinforcing cycle emerged among GDP growth, urban expansion, and farmland occupation, exerting a significant and stable driving effect on farmland conversion.

The period from 2011 to 2020 marked a phase of policy adjustment concerning farmland conversion in China. Under the framework of high-quality development, the fundamental shift in policy logic transformed the mechanisms through which various driving factors affected the intensity of cultivated land use. Since 2012, as economic development transitioned from scale-oriented expansion toward quality- and efficiency-oriented development, the source of local fiscal incentives gradually shifted from land dependence to industrial upgrading and innovation-driven growth [50]. Consequently, the marginal dependence of GDP growth on land resources significantly decreased. The land demand arising from the expansion of permanent population also came under structural control to a certain extent, owing to intensified requirements for intensive use of construction land. Concurrently, the cultivated land protection system was upgraded from a single focus on quantity control to a comprehensive "Quantity–Quality–Ecology" trinity governance framework, incorporating cultivated land productivity into the core indicators of the requisition–compensation balance. This raised the cost and tightened the constraints of farmland conversion from an institutional perspective [51].

Implications for Cultivated Land Protection

Cultivated land constitutes the fundamental basis for grain production and is crucial to ensuring national food security. Since the 21st century, the Chinese government has implemented stringent measures to prevent non-agricultural use of cultivated land. Based on the research findings, this study proposes the following policy recommendations for cultivated land protection:

Transforming the Economic Development Model. Research indicates that Guangdong Province's previous economic growth followed an extensive pattern heavily reliant on land supply, resulting in significant cultivated land loss. Therefore, to curb non-agricultural use of cultivated land, it is imperative to shift the economic growth model from extensive to intensive and efficient patterns, accelerate the transition from investment-driven to innovation-driven economic engines, and achieve effective substitution of real estate-dependent development with a robust real economy [52].

Breaking Local Governments' Dependence on "Land Finance". Land conveyance revenue constitutes the largest proportion of local fiscal income, with local governments relying on land finance to meet essential expenditures and performance evaluation targets. Therefore, it is imperative to simultaneously diversify revenue sources and streamline expenditures: on one hand, improve the tax structure and expand tax categories; on the other hand, optimize expenditure allocation and enhance the efficiency of public fiscal spending. Furthermore, the performance evaluation mechanism should be refined to prioritize the quality and sustainability of economic development over mere quantitative growth metrics [53].

Proactively Advancing New-Type Urbanization. Research confirms that urbanization inevitably contributes to cultivated land conversion. However, given the growing scarcity of cultivated land resources, urbanization patterns must be transformed. First, large cities should shift from incremental expansion to stock regeneration by promoting urban renewal initiatives, revitalizing inefficient existing land use and avoiding excessive demolition and construction in new urban development. Second, small towns should enhance infrastructure development and industrial supporting facilities to strengthen their capacity for driving rural development, foster coordinated urban-rural integration, and encourage "in-situ" or "nearby" urbanization of rural populations [54, 55].

Research Limitations and Future Prospects

This study has certain limitations regarding the selection of driving factors. The CLC drivers considered in this research remain relatively limited, primarily due to incomplete historical data in county-level statistical yearbooks and changes in governmental statistical standards. Consequently, critical factors such as fixed-asset investments and road area could not be fully considered. Meanwhile, although policy factors profoundly influence CLC, this study only provides theoretical analysis without further empirical investigation, mainly because policy variables are challenging to quantify.

In summary, this study employs the GCCM model to analyze the driving mechanisms of CLC in Guangdong Province, effectively identifying causal relationships and overcoming potential misjudgments arising from high correlations. It reveals that cultivated land area is not a driver but rather an outcome of CLC. However, using the GCCM model to investigate CLC driving mechanisms also has limitations. Specifically, when the model indicates interrelationships between variables, it remains challenging to distinguish whether such relationships stem from strong causal subordinate effects or bidirectional causality between variables. In future research, the authors plan to further deepen the understanding of CLC driving mechanisms and explore additional data and methodologies to address the current study's limitations.

Conclusions

Key Findings

Based on continuous spatiotemporal data from 2001 to 2020, this study analyzes the spatiotemporal patterns and causal driving mechanisms of cultivated land conversion (CLC) in Guangdong Province, drawing the following conclusions:

From 2001 to 2020, the CLC process in Guangdong Province underwent three distinct phases, marked by 2012 as a critical turning point. Prior to 2012, the scale of CLC demonstrated a phased growth trend; it entered an adjustment phase in 2012 characterized by a sharp decline in conversion scale; post-2014, the non-agricultural conversion scale maintained relative stability. This transition aligns with China's shift toward a green and sustainable development philosophy. Spatially, Guangdong's CLC exhibited growth in central-northern regions, decline in western areas, intense conversion along coastal zones, and milder manifestations inland.

While interactive relationships exist between CLC and economic activities, the driving effects of economic factors on CLC significantly outweigh the feedback effects of CLC on economic factors. Gross domestic product and population serve as primary influencing factors of CLC, with public budget income and urbanization level also exerting moderate influence. Simultaneously, the spatial distribution of CLC is constrained by natural geographic conditions, where elevation, slope, and rainfall exert weaker influences on CLC distribution. Regional cultivated land resource endowments demonstrate no significant impact on CLC, and notably, changes in cultivated land area are identified as outcomes rather than causes of non-agricultural conversion.

The driving factors of CLC varied across different phases: from 2001 to 2012, it was primarily driven by economic development and population pressure; during 2012-2014, urbanization level and tertiary industry development became the dominant drivers; after 2014, fewer driving factors remained significant, with population growth and tertiary industry structure index emerging as the main influencing factors.

Research Contributions

The innovations of this study are mainly reflected in three aspects: First, in terms of research perspective, it breaks through previous analytical approaches based on fixed intervals or fragmented time nodes by introducing long-term continuous observation methods, systematically revealing the evolution patterns and phase characteristics of CLC and enhancing the continuity and robustness of conclusions. Second, in driving mechanism research, it introduces the GCCM model to shift from traditional correlation analysis to causal identification, clarifying the causal direction and operational mechanisms of driving factors through state space reconstruction and cross-mapping techniques. Third, it divides the evolution phases according to actual turning points in CLC and analyzes the driving causes of each stage, which aligns more closely with actual processes compared to traditional fixed-interval analysis, providing more reliable theoretical foundations for causal interpretation and policy formulation.

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AI Usage Disclosure Statement

The authors acknowledge the use of deep learning models (ResUNet/ResUNet++) for land use data extraction and AI-assisted tools(Grammarly and ChatGPT) for language polishing. All AI-generated outputs were reviewed and verified by the authors, who take full responsibility for the content.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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