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A new multi-dimensional framework considering environmental impacts to assess green development level of cultivated land during 1990 to 2018 in China

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ABSTRACT

China has achieved food security in the last three decades through massive use of fertilizers, pesticides, and irrigation water, resulting in negative environmental impacts to the cultivated land use system (CLUS). Hence, it is urgent to assess the green development level of cultivated land (GDL-CL). The objective of this study was to develop a new multi-dimensional framework considering environmental impacts to assess GDL-CL based on "elements – processes – dimensions – goals – drivers" according to the interaction between the soil-water-plant-atmosphere system (SWPAS) and CLUS. The entropy weight method, spatial autocorrelation analysis, and the Geodetector method were applied to provincial data in China from 1990 to 2018 to determine the spatiotemporal evolution, correlation, and quantitative attributes, respectively, of GDL-CL. The results indicated that the changing agricultural input-output farming patterns in China during 1990–2018 followed U-shaped trend in GDL-CL that reached an inflection point in 1998. In addition, GDL-CL differed significantly between the eastern and western regions in China, with the eastern areas showing an obviously high-high agglomeration and the western areas showing an apparently low-low agglomeration. The reason behind this phenomenon is that climate and socio-economic factors such as temperature, precipitation, sunshine, assets, markets, education, employment, and policies profoundly and extensively influenced GDL-CL in different regions during 1990–2018. However, the contribution of climate factors to GDL-CL overtook the socio-economic factors in 2010–2018. Therefore, this study suggests that priority should be given to optimizing production modes of cultivation, coordinating regional GDL-CL contradictions, and warning of climate change to sustainably manage cultivated land.

1. Introduction

As one of the most critical elements of the land ecosystem, cultivated land supports the food, fodder, fuel, nutrition, and fiber needs of nearly eight billion human beings around the world (Cassman, 1999; Foley et al., 2011; Li and Liu, 2021). However, increasing demand for grains has led to excessive production inputs that have resulted in a series of serious negative environmental impacts occurring concurrently in cultivated land (Zambon et al., 2017). From 1990 to 2018, the per hectare input of irrigation water, chemical fertilizers, and pesticides has increased by 44.6%, 41.4%, and 71.6%, respectively, in the world's cultivated land (FAO, 2011; FAO, 2018), resulting in soil pollution, biodiversity loss, land degradation, and freshwater pollution (Rasmussen et al., 2018). With the introduction of the UN Sustainable Development Goals (SDG) (specifically goals 12 and 13) and the "green" transformation of the food system (Yue et al., 2022), there is no time to delay green development as it relates to the world's cultivated land.

Over the past three decades, China has achieved food security by making large investments in labor and technology as applied to the use of cultivated land. However, massive element inputs have resulted in

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increasingly serious negative environmental impacts to cultivated land (Zhou et al., 2021). For example, from 1990 to 2018, the growth rate of fertilizer and pesticide use in China was 5.4 and 1.7 times that of the world, respectively (FAO, 2018). This growth in fertilizer and pesticide applications has caused soil erosion, soil pollution, agricultural non-point source pollution, and other negative environmental impacts (Ye et al., 2022). Cultivated land production systems in China face increasingly severe environmental risks in situations where production inputs of various elements are constrained to a point where their capacity to meet current and future needs is immeasurably jeopardized. Therefore, there is an urgent need to comprehensively evaluate and promote the green development level of China's cultivated land (Bryan et al., 2018).

The research on green development of cultivated land (GD-CL) is mainly aimed at increasing grain yield while reducing negative environmental impacts (Note: In this paper we use GD-CL when referring to green development of cultivated land, and GDL-CL when referring to the level of green development of cultivated land as we quantify changes in GD-CL). At present, a great deal of previous research on framework construction has focused on the soil-plant-atmosphere continuum (SPAC) (Philip, 1966; Shen et al., 2011) and the soil-water-plant-atmosphere system (SWPAS) (Aftab and Roychoudhury, 2022), among which SWPAS was the continuation and extension of SPAC. In green agricultural systems, whether they have been SPAC or SWPAS, studies on the correlation between the internal components have mainly focused on environmental alteration, greenhouse gas releases, and carbon sequestration (Aftab and Roychoudhury, 2022). However, there is no consensus on how SPAC and SWPAS relate to external environmental systems, such as land use systems, to affect environmental sustainability. On the other hand, many studies related to the concept of GD-CL have assessed and investigated soil health, cultivated land health (CLH), sustainable intensification of cultivated land (SICL), and ecological intensification of cultivated land (EICL). Due to differences in research priorities and purposes, the evaluation of related research on GD-CL has had different emphases. However, the focus has been on the selection of relevant indicators by measuring the conceptual relationship between environmental threat, function, or ecosystem services of cultivated land (Rinot et al., 2019; Ye et al., 2022). Generally speaking, there have been three main indicators: (1) The static indexes of inherent physical, chemical, and biological soil properties of cultivated land have been selected and associated with the cultivated land Ecosystem Service Value (ESV), mainly including physical aspects of soil permeability resistance, soil texture, and soil volume density (Askari and Holden, 2015; Bünemann et al., 2018); chemical available nutrients nitrogen (N), phosphate (P_2O_5), potash (K_2O), and soil pH value (Lu et al., 2021 Ahmad et al., 2021); and biological aspects of microbial content and soil respiration intensity (Zambon et al., 2017). (2) The health status of cultivated land systems was determined by selecting the level of social environmental governance and technical control attached to the cultivated land system. This mainly included irrigation and drainage conditions, field road accessibility, disaster prevention and control level, agricultural mechanization level, and land fragmentation degree (Liu et al., 2020a; Zhang et al., 2022; Ye et al., 2022). (3) The cultivated land input and output relationship was used to reflect the human land use or intensive sustainable degree or efficiency by screening the flow elements in cultivated land systems (labor, technology, capital, etc.). These elements mainly included the intensity of chemical fertilizer or pesticide use, effective irrigation area, multiple crop indexes, grain yield, agricultural output, and carbon emissions (Kumar et al., 2020; Liu et al., 2020b; Wu et al., 2021).

As reflected in the above indicators, the dimensions of edaphic conditions, resource utilization, and green production have been extensively considered. However, cultivated land is an artificial utilization system with multiple attributes such as natural, social, and economic environments (Li and Liu, 2021). The flow of elements between cultivated land systems is accelerating along with human activities. To a large extent, cultivated land environmental governance and output productivity should also be considered in the indicator system (Chen et al., 2015; Zambon et al., 2017; Cunha-Zeri et al., 2022), such as the control area of waterlogging disaster or soil erosion (Chen et al., 2018; Pretty et al., 2018; Ma et al., 2021), grain output per capita/land, and labor/land productivity (Uisso and Tanrıvermiş, 2021; Yue et al., 2022). In order to understand GDL-CL at the macro scale over a long time period, the inherent static attributes of cultivated land can no longer be a scientific evaluation index. Instead, there should be more comprehensive indicators of environmental factor flow and human utilization efficiency (Li and Liu, 2021).

In summary, there is no reasonable theoretical framework and index system considering environmental impacts to comprehensively evaluate GDL-CL over a long timescale. Contributing substantially to global food availability and sustainability, GD-CL plays a key role in meeting the UN SDG and Food System Transformation. China has nearly 9% of the world's cultivated land, but feeds nearly 20% of the world's population (Zhou et al., 2021). Therefore, China provides a good example for the UN SDG. However, the use of large amounts of element inputs has produced immeasurable negative environmental impacts on the cultivated land system (Hussainzada and Lee, 2022). Over time, China has also carried out many different cultivated land protection practices, such as the policy referred to as the"14th Five-Year Plan for National Agricultural Green Development", the "strategy of storing grain in land and technology" in the 13th Five-Year Plan, and the three aspects of protection related to cultivated land quantity, quality, and ecology (Zhou et al., 2021). Nevertheless, GDL-CL in China has been unclear over the past three decades. In order to explore various aspects of how and why GDL-CL in China has changed over time, this study had three main objectives: (1) According to the comparison of concepts related to GD-CL and the existing theoretical foundation, propose a new multi-dimensional theoretical framework considering environmental impacts based on the interaction between SWPAS and CLUS, and construct a comprehensive evaluation index system based on the framework. (2) Applying the entropy weight method, the polynomial fitting method, and the spatial autocorrelation analysis method, determine the spatio-temporal evolution patterns and spatial differentiation characteristics using data based on 31 provinces/autonomous regions/municipalities in China (hereafter referred to as provinces) from 1990 to 2018, respectively. (3) Using the Geodetector method, determine the driving factors behind GDL-CL from the three dimensions of climatic, economic, and social environments.

Section 2 compares the meanings of GD-CL, and describes framework development, methodologies, and data sources. Section 3 provides the results associated with spatiotemporal evolution patterns, differentiation characteristics, and driving factors. Section 4 provides the possible innovations, policy implications and suggestions, shortcomings, and future prospects. Section 5 presents the main conclusions.

2. Materials and methods

2.1. Comparison of studies related to GD-CL

As mentioned in the introduction, correlational studies regarding the meaning and evaluation of GD-CL have mainly focused on soil health, CLH, SICL, and EICL (Fig. 1). Specifically, (1) based on the balance of physical, chemical, and biological processes, soil health focuses on the dynamic change process of soil elements from the perspective of macro elements such as nitrogen, phosphorus, and potash. However, soil health rarely considers the interaction between soil and cultivated land systems (Cassman, 1999; Bünemann et al., 2018; Rinot et al., 2019). (2) Cultivated land health has been extensively studied by Chinese scholars over the last ten years, generally on the strength of cultivated land to resist invasion with human assistance (Han and Zhang, 2020). The ability of cultivated land to prevent soil erosion, resist natural disasters, and maintain stable quality under external environmental threats has been

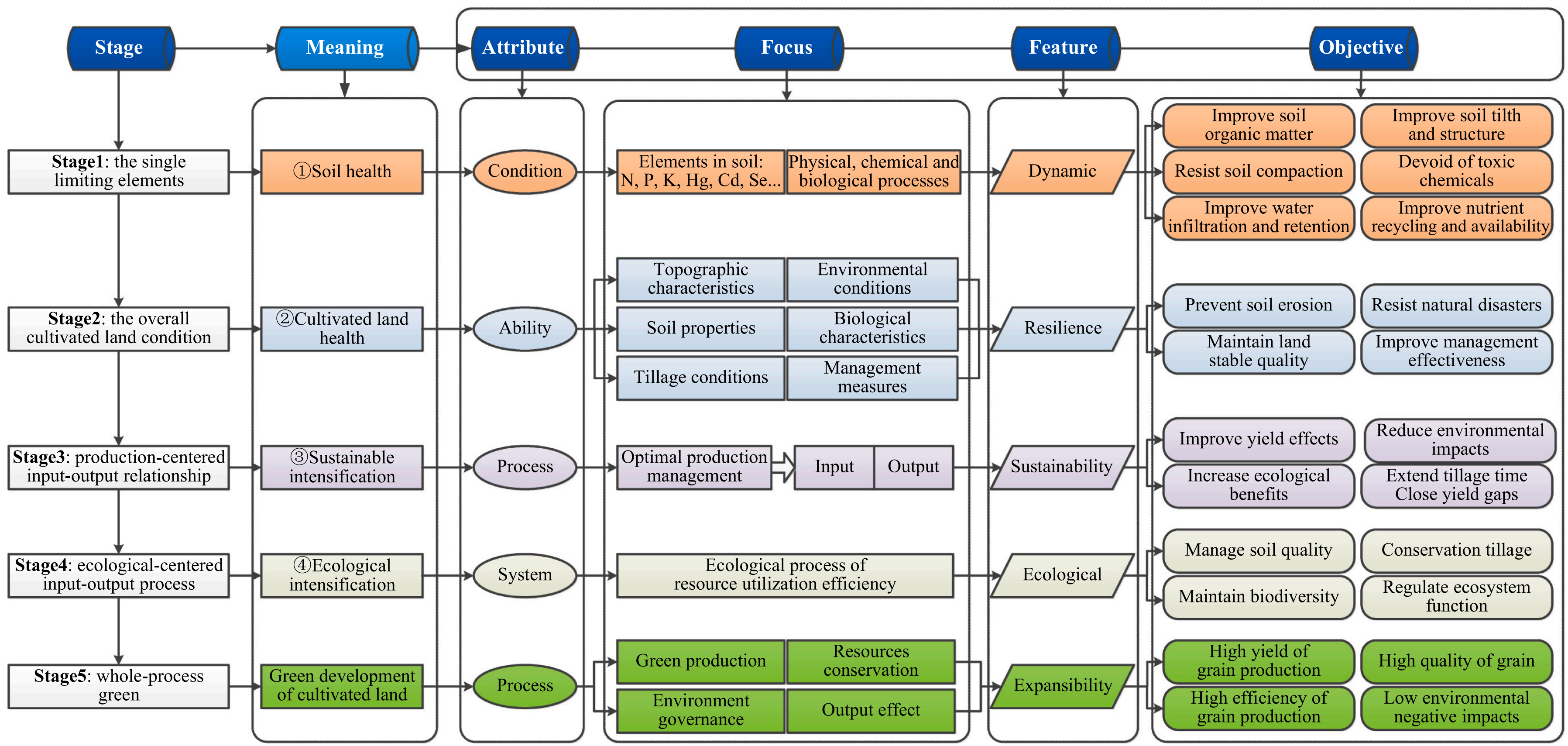

Fig. 1. Comparison of the meanings of soil health, cultivated land health, sustainable intensification, ecological intensification, and green development of cultivated land (GD-CL) based on stage, attribute, focus, feature, and objective. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

considered Liu et al. (2020a). (3) Studies on both sustainable intensification or ecological intensification of cultivated land have emphasized effects rather than means (Cassman and Grassini, 2020). SICL is defined as a process or system where increases in food production occur without expansion of cultivated land and without adverse environmental impacts (Tilman et al., 2011; Pretty and Bharucha, 2014). The optimal management of inputs and outputs of cultivated land production, including yield effects, environmental impacts, and ecological benefits of element inputs such as herbicides, pesticides, fertilizers, and mechanization is considered (Liao and Brown, 2018; Jayne et al., 2019). (4) In contrast, EICL focuses on the ecological process of resource utilization efficiency (Matson et al., 1997; Kassam et al., 2011), including soil quality management, conservation tillage, biodiversity maintenance, ecosystem function regulation, and other cultivated land use processes (Cassman, 1999; Bommarco et al., 2013; Gurr et al., 2016).

In summary, research on GD-CL has gone through different developmental stages with different areas of emphasis (Fig. 1): (1) Single limiting elements (such as nitrogen and carbon); (2) Overall cultivated land condition; (3) Comprehensive input-output relationship (emphasis on production); (4) Integration of ecosystem service processes with the input-output process (emphasis on ecological investigations). However, the perspective of cultivated land system theory has been sorely neglected. It is critical and essential to comprehensively and multidimensionally consider production input, resource protection, environmental governance, and output benefits with regard to GD-CL.

2.2. Developing a new multi-dimensional framework considering environmental impacts to assess GDL-CL

2.2.1. Theoretical analysis of the new multi-dimensional framework to assess GDL-CL

SWPAS is made up of four different components (soil, water, atmosphere, and plants) that interact with each other all of the time (Cornelis et al., 2009). In SWPAS, plants absorb carbon and release oxygen into the atmosphere through photosynthesis, and transport water into the atmosphere through transpiration. A variety of nutrient (C, N, P, K, etc.) cycles are constantly carried out between the soil and plants. Soil is constantly eroded and degraded due to the interaction of various components (Aftab and Roychoudhury, 2022). The dynamic distinctions of water as rainfall in the atmosphere, infiltration in the soil, runoff on the land, and transpiration from plants are triggered and maintained by the water cycling (Boyd, 2020). Plants are constantly undergoing physiological metabolism in the nutrient cycle.

Different from the previous focus on the interaction between components or the overall flow process of SWPAS, this study emphasized the interaction between SWPAS and CLUS, as well as paid more attention to GD-CL caused by unreasonable input and management of cultivated land, affecting the normal operation process of SWPAS. Specifically, this investigation analyzed the theoretical framework considering environmental impacts to assess GDL-CL based on “elements – processes – dimensions – goals – drivers”. This framework focused on the six key ecological processes of SWPAS: photosynthesis, nutrient cycling, soil erosion and degradation, hydrologic cycling, physiological metabolism, and transpiration. Additionally, the framework encompassed the four

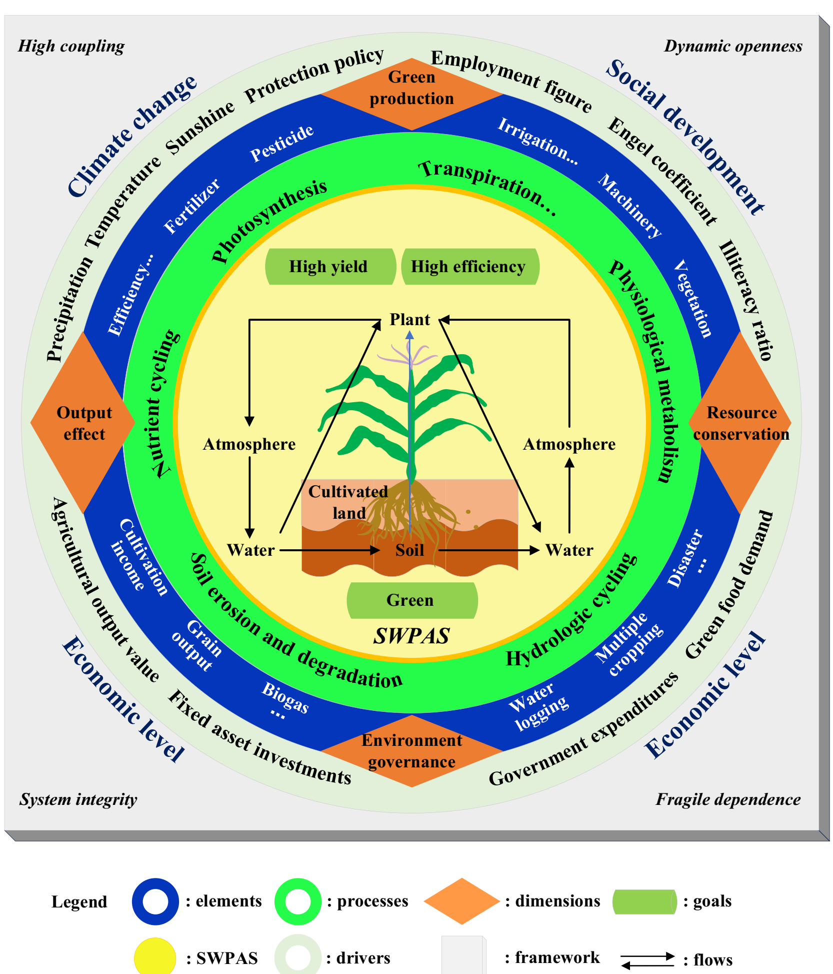

Fig. 2. The theoretical analysis of the multi-dimensional framework considering environmental impacts to assess green development level of cultivated land (GDL-CL) based on “elements – processes – dimensions – goals – drivers” based on the interaction between CLUS and SWPAS. CLUS represents the cultivated land use system. SWPAS represents the soil-water-plant-atmosphere system (Aftab and Roychoudhury, 2022), which is a continuation and extension of SPAC (soil-plant-atmosphere continuum) (Philip, 1966). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Evaluation index system and data sources for quantifying the green development level of cultivated land (GDL-CL) in China.

First-level	Second-level	Third-level	Attribute	Computational formula	Data source
Green production	Production Consumption	Intensity of fertilizer use	−	Chemical fertilizer input amount / cultivated land area (kg/ha)	①China Rural Statistical Yearbook 1990–2018 ②Statistical Yearbook of 31 provinces in China 1990–2018
		Intensity of pesticide use	−	Pesticide input amount / cultivated land area (kg/ha)	
		Intensity of agricultural film	−	Agricultural film input amount / cultivated land area (kg/ha)	
		Intensity of diesel use	−	Diesel input amount / cultivated land area (kg/ha)	
		Intermediate consumption	−	Intermediate consumption value / total value of agricultural output (%)	
	Technical contribution	Mechanical power	+	Total mechanical power / cultivated land area (kW/ha)	
		Electricity consumption	−	Rural electricity consumption / cultivated land (kW/ha)	National Bureau of Statistics of China (http://www.stats.gov.cn/)
Resource conservation	Resource condition	Conversion rate of cropland to forest	+	Original data (%)	
		Cultivated land per capita	+	Cultivated land area / number of rural residents (ha/person)	
	Utilization extent	Multi-cropping index	−	Cropping land area / cultivated land area (%)	
		Irrigation efficiency	+	Effective irrigation area / cultivated land area (%)	①China Rural Statistical Yearbook 1990–2018 ②Statistical Yearbook of 31 provinces in China 1990–2018 ③China Environmental Statistics Yearbook 1990–2018
Environmental governance	Production guarantee	Waste methane utilization	+	Total gas produced by biogas digester / Number of township (10,000 m^3)	
		Crop disaster rate	−	Crop disaster area / cultivated land area (%)	
	Governing efficiency	Waterlogging area rate	+	Waterlogging area / cultivated land area (%)	
		Soil erosion control rate	+	Soil erosion control area / cultivated area (%)	
Output effect	Production level	Grain output per capita	+	Total grain output / number of agricultural workers (t/person)	
		Grain output per land	+	Total grain output / total cultivated land area (t/ha)	①China Statistical Yearbook 1990–2018 ② National Bureau of Statistics of China (http://www.stats.gov.cn/)
		Labor productivity	+	Agricultural production value / number of agricultural workers (yuan/person)	
		Land productivity	+	Agricultural production value / cultivated land area(yuan/ha)	
	Income Level	Cultivation income per capita	+	Farmer's household business income from crop production (yuan/person)	China Rural Statistical Yearbook 1990–2018

Note: The data for cultivated land area from 2009 to 2018 came from the China Land and Resources Statistical Yearbook and the China Land and Resources Bulletin of the Ministry of Land and Resources. The remaining data from 1990 to 2008 were based on the results of China's second land survey. Missing data were supplemented by SPSS.26 software using the methods of sequence mean value, mean value of adjacent points, median value, linear interpolation, or linear trend of adjacent points. Due to a lack of data, this study inculudede 31 provinces (autonomous regions/municipalities) in China, Hong Kong, Macao, and Taiwan were not stuided.

links of green production, resource conservation, environmental governance, and output effect, and also covered the three drivers of climate change, economic level, and social development. GD-CL is produced by the combined effects of the input of pesticides and fertilizers, mechanical power, irrigation efficiency, vegetation coverage, waterlogging control, yield, income, production efficiency, and other elements. Furthermore, GD-CL has the development ability to meet human needs for high yield, high efficiency, and "green" grain production. In addition, GD-CL is also readily driven by exogenous factors such as climate, production value, investment, markets, education, employment, and policy. Meanwhile, the interaction between these factors is often greater than the driving effect of individual factors on GD-CL (Fig. 2).

By giving more attention to green attributes while emphasizing the lowering of negative environmental impacts, GD-CL focuses on whether the production and ecological processes of cultivated land are green and healthy. Fig. 2 also shows that GD-CL has the characteristics of high coupling, system integrity, dynamic openness, and fragile dependence. (1) High coupling means that GD-CL plays an explicit or implicit role in the land ecosystem, the production management system, and the environmental management system, and that the roles among these systems are highly similar. (2) System integrity reflects the importance of green production, resource conservation, environmental governance, and output effect. (3) Dynamic opening means that the internal elements of GD-CL are constantly flowing and reorganizing while being impacted and harmed by the external environment. (4) Fragile dependence refers to the development and production processes of the GD-CL system that depend on environmental changes (such as the driver of climate change) and human activities (such as the drivers of economic level and social development) to a large extent, and can be vulnerable to damage and difficult to reprocess.

2.2.2. *Construction of evaluation index system for GDL-CL*

Based on a theoretical analysis and the indicators of CLH, SICL, EICL, green transformation of food systems and UN SDGs, considering the greenness and environmental impact of cultivated land production processes (Rohr et al., 2021), and combining the theoretical and practical experiences of various countries, this study identified four first-level indicators: green production (Garnett et al., 2013; Bellarby et al., 2014; Gunton et al., 2016; Han and Zhang, 2020; Rohr et al., 2021; MacLaren et al., 2022), resource conservation (Garnett et al., 2013; Yuan et al., 2021; Soergel et al., 2021), environmental governance (Firbank et al., 2013; Bellarby et al., 2014; Soergel et al., 2021), and output effect (Garnett et al., 2013; Firbank et al., 2013; Kumar et al., 2020; Yuan et al., 2021) (Table 1). The four first-level indicators are interlinked, but each has its own focus. GD-CL requires that cultivated land has the output effect to meet human needs while maintaining green production and balancing resource conservation and environmental management. Then eight second-level indexes are classified (Table 1). Specifically, high pollution and high emission inputs (e.g., materials such as fertilizers and pesticides, and energy such as machinery and electricity) (Kumar et al., 2020; Yuan et al., 2021) need to be controlled in the production processes used on cultivated land. Therefore, it is necessary to promote the greening process by continuously upgrading the production technology used on cultivated land (Garnett et al., 2013; Kuang et al., 2020) and improving the production efficiency (Soergel et al., 2021). Meanwhile, resource conservation in the cultivated land production process is essential. Only with a clear understanding of resource condition (Pretty et al., 2018; Hussainzada and Lee, 2022) and utilization extent (Gunton et al., 2016; Hussainzada and Lee, 2022; MacLaren et al., 2022) can production be carried out in a more energy-efficient and low-carbon manner (Wu et al., 2021). Indisputably, the generation of negative environmental products in the process of cultivated land production is inevitable. Negative environmental impacts must be compensated for or avoided through reasonable production guarantees (Pretty et al., 2018; Hussainzada and Lee, 2022) and governing efficiencies (Gunton et al., 2016; Rohr et al., 2021). Critically, while cultivated land production is green and sustainable, it must meet normal human food needs and the productive business income of farmers. Therefore, it is particularly important to measure the output efficiency of GD-CL in terms of production (Gunton et al., 2016; Yue et al., 2022; Uisso and Tanrıvermiş, 2021) and income levels (Chen et al., 2018; Kalibata, 2021).

In consideration of the relations, restrictions, objectivity, rationality, and availability of index data and previous interrelated studies, 20 third-level indicators are screened (Table 1). In terms of cultivated land input production consumption, the intensities of use of high energy consumption inputs including fertilizers, pesticides, agricultural films, diesel fuel, and intermediate consumption have been taken into account (Han and Zhang, 2020; Kuang et al., 2020; Kumar et al., 2020; Yuan et al., 2021; Hussainzada and Lee, 2022). Energy consumption, such as mechanical power as well as electricity (Kumar et al., 2020; Yuan et al., 2021), has been applied to measure the technical contribution to green production. For resource conservation, resource conditions have been characterized by forest cover (Cunningham et al., 2015; Tasser et al., 2007; Pretty et al., 2018) and per capita cultivated land (Hussainzada and Lee, 2022), and the extent of resource utilization has been probed by multiple cropping indexes (MacLaren et al., 2022) and irrigation efficiency (Pretty et al., 2018; Kumar et al., 2020). In terms of environmental governance, the security guarantees of green production and yield have been reflected through the utilization of clean energy (such as methane) and the crop disaster rate (Hussainzada and Lee, 2022). The rates of waterlogging (Pretty et al., 2018) and soil erosion control (Firbank et al., 2013; Chen et al., 2018) have also been applied to measure the governing efficiency. In terms of output effect, the production level under green production has been viewed through a series of productivity calculations (Kumar et al., 2020; Yuan et al., 2021), and the income (Kalibata, 2021) from GD-CL has been reflected through the cultivation income of farmers.

2.3. Methodologies

2.3.1. Entropy weight method to calculate GDL-CL score

The entropy weight method has been successfully and widely used in the fields of environmental impact assessment, sustainable development, and resource quality evaluation. Compared with subjective weighting methods such as Analytic Hierarchical Process, Additive Ratio Assessment, Redundancy Analysis, and Expert Opinion, it can avoid the interference of subjective factors and assign more scientific weights from an objective perspective (Cunha-Zeri et al., 2022). The entropy weight method was used to determine the objective weight according to the index variability. Generally speaking, the smaller the information entropy of an indicator is, the greater the difference coefficient of the indicator is. The greater the contribution is in the comprehensive evaluation, the greater the weight is. In contrast, the smaller the role, the smaller the weight (Zambon et al., 2017). The steps of the entropy weight method are as follows.

2.3.1.1. Range Normalization. For positive indicators,

$$Y_{ij} = \frac{X_{ij} - min\left(X_{1j}, X_{2j}, \dots, X_{nj}\right)}{max\left(X_{1j}, X_{2j}, \dots, X_{nj}\right) - min\left(X_{1j}, X_{2j}, \dots, X_{nj}\right)} \tag{2-1}$$

For negative indicators,

$$Y_{ij} = \frac{max\left(X_{1j}, X_{2j}, \dots, X_{nj}\right) - X_{ij}}{max\left(X_{1j}, X_{2j}, \dots, X_{nj}\right) - min\left(X_{1j}, X_{2j}, \dots, X_{nj}\right)} \tag{2-2}$$

where i= 1, 2, …, m ; j= 1, 2, …, n. X_{ij} represents indicator j of object i. Y_{ij} represents the value after data standardization.

2.3.1.2. Quantification of the same dimension of indicators

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \tag{2-3}$$

$$E_j = -(lnm)^{-1} \times \sum_{i=1}^{n} P_{ij} ln\left(p_{ij}\right) \tag{2-4}$$

$$g_j = 1 - E_j \tag{2-5}$$

where P_{ij} indicates the proportion of the object i in the indicator j, if $P_{ij} =$ 0, we define $\lim_{p_{ij}\to 0} p_{ij} ln\left(p_{ij}\right) = 0$. E_j indicates the information entropy value of the indicator j. g_j indicates the difference coefficient of the term j.

2.3.1.3. Normalization of the difference coefficient and weight calculation

$$W_j^E = \frac{g_j}{\sum_{j=1}^{n} g_j} (j = 1, 2, \dots, n) \tag{2-6}$$

$$W^E = \left(W_1^E, W_2^E, W_3^E, \dots, W_n^E\right) \tag{2-7}$$

$$L_i = \sum_{j=1}^{n} Y_{ij} W^E \tag{2-8}$$

where W_j^E indicates the weight of the indicator j. W^E indicates the entropy weight vector. L_i indicates the evaluation score of the object i.

2.3.2. Polynomial fitting method for analysis of temporal GDL-CL

In this study, the representative polynomial fitting method was selected to fit a curve to China's total GDL-CL time series from 1990 to 2018. The polynomial fitting method assumes that the given time sample sequence satisfies the form of a polynomial function, and then fits a curve to the data. Its expression is as follows:

$$S_f = a + b_1 S_t + b_2 {S_t}^2 + \cdots + b_n {S_t}^n \tag{2-9}$$

where $a, b_1, b_2, \cdots, b_n$ are the parameters to be solved for. S_f is the score of China's GDL-CL after successful curve-fitting. S_t is the score of China's GDL-CL in different years ($1990 \le t \le 2018$, $t \in Z^+$).

2.3.3. Spatial autocorrelation analysis to explore spatial-temporal differentiation of GDL-CL

Spatial autocorrelation analysis is used to determine the spatial dependence of adjacent spatial units. Furthermore, it is used for testing the similarity between the values of attributes or observations of variables related to spatial position, i.e., to determine whether there is a spatial dependency (Liu et al., 2020b). Compared with traditional correlation analysis, such as correlation analysis, regression analysis, and multivariate analysis (Ma et al., 2021), spatial autocorrelation analysis considers the geospatial relationship between observations and their neighbors when measuring geospatial similarity (Liao et al., 2021). This study used the global Moran index and the local Moran index to analyze global and local spatial autocorrelation statistics, respectively. For the global spatial autocorrelation analysis, the Moran index ranges from −1 to 1. Positive values indicate positive spatial autocorrelation, and negative values indicate negative spatial autocorrelation. However, there is no significance measurement of agglomeration in the global Moran index, and it cannot evaluate spatial autocorrelation in local areas. The Local Indicator of Spatial Association (LISA) statistics can measure significance of each province, and decompose the global spatial autocorrelation Moran's I statistics to quantify the contribution of each spatial unit observation. The specific calculation equations are:

2.3.3.1. Global Moran Index

$$①Moran's\ I = \frac{N}{S_0}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i-\overline{y})(y_j-\overline{y})}{\sum_{i}^{N}(y_i-\overline{y})^2}, \tag{2-10}$$

$$②S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$$

where N represents the number of observed values. y_i represents the observed value of the variable y in cell i. $\overline{y}$ represents the mean of the variable y. w_{ij} represents the element in the spatial weight matrix. S_0 represents the sum of all the elements of the spatial weight matrix.

2.3.3.2. Local Moran Index

$$①Local\ Moran's\ I_i = \frac{y_i-\overline{y}}{S_i^2}\sum_{j=1, j\neq i}^{N} w_{ij}(y_i-\overline{y}), \tag{2-11}$$

$$②S_i^2 = \frac{\sum_{j=1, j\neq i}^{N} w_{ij}}{N-1} - (\overline{y})^2$$

where N represents the number of observed values. y_i and y_j represent observations of the variable of interest. $\overline{y}$ and w_{ij} are the same as in Eq. 2-10 above. S_i^2 is defined as shown above.

2.3.4. Geodetector method to detect driving factors of spatial-temporal differentiation on GDL-CL

Geodetector is a new spatial statistical method to detect the driving factors behind spatial differentiation. Compared with traditional regression models such as geo-weighted regression and spatial econometric models, Geodetector is good at detecting not only numerical data but also qualitative data. It can also determine the strength and direction of linear and non-linear relationships of the interaction between two factors. The basic assumption of the model is that the important influence of an independent variable on the dependent variable is closely related to the spatial distribution between them (Wang et al., 2016). The factor detector and the interactive detector in this study were chosen to explore the driving factors behind the spatial differentiation of China's GDL-CL from 1990 to 2018 (Wang et al., 2018).

2.3.4.1. Factor detector. Factor detector mainly detect the spatial differentiation of the property Y. A factor detector is measured by detecting how strongly a factor X interprets the spatial differentiation of an attribute Y. Generally, it is measured by the q value (Wang et al., 2016). The range of the q value is 0–1. The larger the q value is, the stronger the driving force is.

$$q = 1 - \frac{\sum_{h=1}^{L} N_h\sigma_h^2}{N\sigma^2} \tag{2-12}$$

where L represents a classification or partition, i.e., a strata of variables or factors. $h = 1, 2, 3, \cdots$, N_h and N are the number of units of layer h and the entire region, respectively. σ_h^2 and σ^2 are the variances of layer h and the Y value of the entire region, respectively.

2.3.4.2. Interactive detector. The interactive detector is used to identify interactions between different risk factors, i.e., to determine whether the forces on Y between different factors of X are independent of each other. Furthermore, the interactive detector is used to evaluate whether the combination of factors X1 and X2 increases or decreases the explanatory power of attribute Y. The evaluation steps are as follows: ①Calculate q (X1) and q(X2) ; ②Calculate the interaction q(X1∩X2); ③Compare q (X1), q(X2), and q(X1∩X2). The interaction of different influencing factors is shown in Fig. A1.

2.4. Driving factors of GDL-CL screening and data sources

GDL-CL is affected by multiple factors. GDL-CL depends on the conditions of agricultural resources and the natural environment (Kumar et al., 2020). In recent years, climate change has increasingly become a key constraint that threatens food security and the green transformation of cultivated land (Garnett et al., 2013; Bellarby et al., 2014; Pugh et al., 2016; Rohr et al., 2021; Soergel et al., 2021). In addition, the socio-economic environment, as the "enabler" of GDL-CL, also profoundly influences the GD-CL process (Gunton et al., 2016; Kumar et al., 2020; Soergel et al., 2021). Therefore, taking into account the UN SDGs, data availability, typicality and previous studies, this study selected three types of drivers, namely climate change, economic level, and social development, to detect the causes of GDL-CL over the past three decades (Table 2). In terms of climate change (SDG13), temperature (1) (Pugh et al., 2016; Uisso and Tanrıvermiş, 2021), precipitation (2) (Uisso and Tanrıvermiş, 2021; Soergel et al., 2021), and sunshine (3) (Ma et al., 2021; Rohr et al., 2021) are indispensable natural elements for cultivated land production that are positively correlated with crop growth. However, in recent years, the frequent occurrence of extreme weather events such as high temperature or excessive precipitation have resulting in frequent droughts or floods (Heikkinen et al., 2021) which in turn have caused irreversible losses to resources and to the environment with regard to production and output of cultivated land (Garnett et al., 2013). (4) According to the United Nations' Food and Agriculture Organization, agricultural output per person has increased by 50% since 1960 (Michael, 2020). Meanwhile, the value of agricultural output has been rising. From the farmer's perspective, an increase in agricultural output per capita drives farmers to use green technologies to improve the productivity of their farmland and to focus on greening their farmland in order to achieve higher yields, higher efficiency, and greener crops (Michael, 2020; Liu et al., 2020b). (5) Farmers' investments in fixed assets reflect the SDG9 (Nabieva and Davletshina, 2015). The efficient use of fixed assets is a major factor in improving agricultural production and agricultural efficiency, and profoundly affects the process of greening cropland. (6) From the government perspective, government agricultural expenditures are a constant driver of GDL-CL that play a role in stabilizing agricultural production and efficiency (Soergel et al., 2021). (7) From the market perspective, the demand for green food is an effective driving force for GDL-CL, constantly stimulating and promoting green production and economical use of resources (Bellarby et al., 2014; Gunton et al., 2016; Kalibata, 2021; Rohr et al., 2021). (8) Illiteracy rate is an important component of SDG4, representing the level of education and literacy of farming households (Béné and Obirih-Opareh, 2009; Rasmussen et al., 2018; Soergel et al., 2021). The higher the level of

Table 2
Driving factors and data sources for quantifying the green development level of cultivated land (GDL-CL) in China.

Driving factor		Variable definition	Computing method	Source
Climate change	Temperature (Temp) (X1)	Annual mean temperature	Interpolation: IDW and Kriging (in ArcGIS 10.7 software) (°C)	China Meteorological Administration station (http://data.cma.cn/)
	Precipitation (Pre) (X2)	Annual average precipitation	Original data (mm)	
	Sunshine (Sun) (X3)	Annual sunshine hours	Original data (hours)	
Economic level	Agricultural output value (AOV) (X4)	Per capita agricultural output value of rural residents	Agricultural output value/number of rural residents (yuan/person)	National Bureau of Statistics of China (http://www.stats.gov.cn/)
	Fixed asset investments (FAI) (X5)	Fixed asset investments of rural households	Original data (100 million yuan)	
	Government expenditures (GE) (X6)	Government expenditures on agriculture, forestry, and water affairs	Original data (100 million yuan)	
	Green food demand (GFD) (X7)	Market demand for green food	Green Food Sales (100 million yuan)	China Green Food Development Center (http://www.greenfood.agri.cn/ztzl/tjnb/lssp/)
Social development	Illiteracy ratio (IR) (X8)	Illiteracy ratio of labor force in rural households	Illiteracy number/ rural workers (%)	China Rural Statistical Yearbook 1990–2018
	Engel coefficient (EC) (X9)	Engel coefficient of rural households	Food/total consumption expenditure (%)	
	Employment fig. (EF) (X10)	Number of rural individuals employed	Original data (1000 persons)	National Bureau of Statistics of China (http://www.stats.gov.cn/)
	Protection policy (PP) (X11)	National cultivated land protection policy	The cumulative value of investment from national land comprehensive consolidation projects (100 million yuan)	China Land & Resources Almanac 1990–2011 China Land & Resources Statistical Almanac 2012–2018 Finance Yearbook of China 1991–2018

knowledge acquired by farmers, the more awareness of using green technologies and of producing environmentally friendly products. (9) The Engel coefficient combines the SDG1 and 2 (Soergel et al., 2021). The lower the Engel coefficient, the higher the income level and quality of life of farmers, and the higher the probability of green production on farmland (Rasmussen et al., 2018). (10) The employment figure is closely related to the SDG8. The stability of rural employment also contributes to a healthy investment in cultivated land production to a certain extent (Garnett et al., 2013; Soergel et al., 2021). (11) The government's cultivated land protection policy regulates the "ungreening" of cultivated land, and protects the sustainable intensification of cultivated land (Gunton et al., 2016; Rohr et al., 2021).

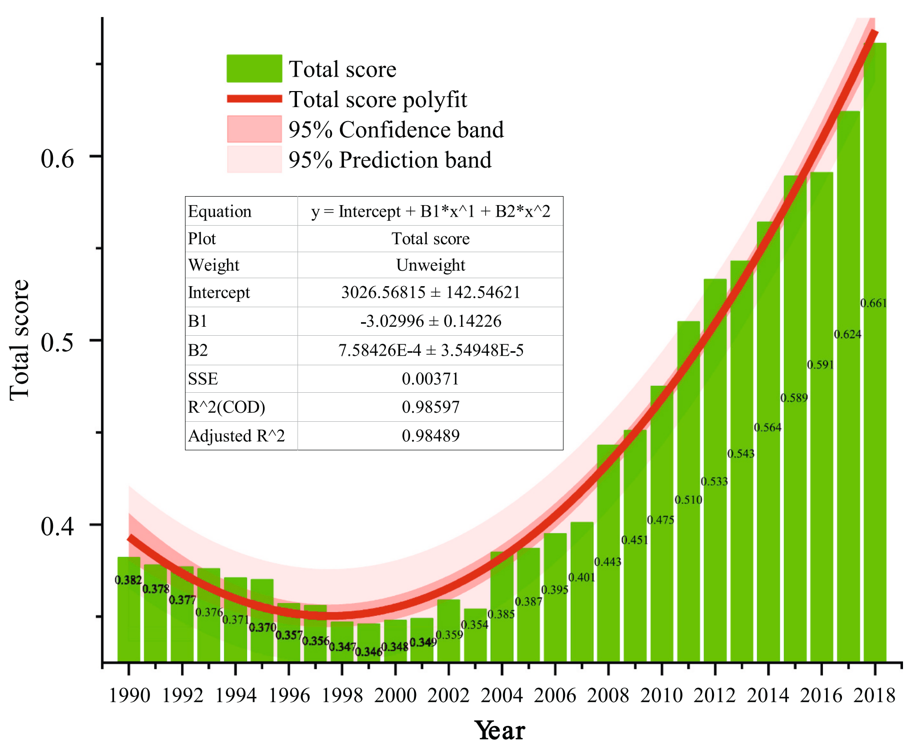

Fig. 3. The total score and its polynomial fitting curve for green development level of cultivated land (GDL-CL) in 1990–2018 in all of China. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Analysis of the spatial-temporal evolution patterns of GDL-CL in China

3.1.1. Temporal patterns of GDL-CL in China during 1990–2018

Fig. 3 shows that the polynomial curve-fitting of GDL-CL scores resulted in a "U-shaped" pattern in China from 1990 to 2018. The inflection point occurred in 1998. The R^2 value of the polynomial fitting curve was nearly 0.99, indicating a very good degree of fitting. During 1990 to 2000, the total GDL-CL score decreased steadily from 0.382 to 0.348. From 2000 to 2010, the total GDL-CL score increased from 0.348 to 0.475, showing a trend of gradual growth. During 2010 to 2018, the total GDL-CL score showed an increasingly positive trend compared with the previous two decades, rising from 0.475 to 0.661, and showing a trend of rapid growth. To some extent, the curve showed the effectiveness of the Chinese government's use of a series of measures to promote green development and sustainable intensification of cultivated land. Additionally, the issued land policies and institutional provisions have also been effectively implemented.

Fig. 4 shows that: (1) In 1998, when the marginal score was 0, the total score reached its inflection point (minimum value). (2) In 2008, the marginal score curve exceeded the average score curve, meaning that the total score added for each additional year was greater than the total score averaged over each year (a total of 29 years). In 2008–2018, the total score began to rise faster and faster. Based on the above results and the implementation intensity of related policies, GDL-CL in China will continue to show a rising trend in the future. Although there may be a minor pullback due to the combined impact of COVID-19 and extreme climate, the overall trend of GDL-CL in China is positive and moving upward.

3.1.2. Spatial patterns of GDL-CL in China in 1990, 2000, 2010, and 2018

Table 3 shows the specific scores and comprehensive ranking of GDL-CL in different provinces in China. Fig. 5 shows the spatial-temporal evolution pattern of GDL-CL from 1990 to 2018. Overall, the values of GDL-CL in China showed significant spatial differences among the provinces from 1990 to 2018, and these differences had a pattern similar to that observed for economic level and technological level of each province. Specifically, the high value zones were concentrated in the eastern developed regions, such as Beijing, Shanghai, and Guangdong in 1990, 2000, and 2010. However, as cultivated land was converted to construction land, the values of GDL-CL in Beijing, Shanghai, and Guangdong plummeted by 54.7%, 34.7%, and 28.4%, respectively, from 2010 to 2018. The medium value zones were concentrated in the central and northeastern regions. In contrast to the declining trend in GDL-CL of the eastern developed regions in recent years, most of the central regions saw increasing GDL-CL. For example, the values in Hubei, Hunan, and Henan increased by 4.5%, 11.1%, and 15.2%, respectively, from 1990 to 2018. This indicated that the original middle-efficiency provinces focused on cultivated land protection and strengthened their compliance with national policies to pursue continuous GDL-CL and healthy conditions. Also, it is important to be alert to the fact that GDL-CL in the northeast was slowly decreasing due to a combination of shrinking black soil quantity and declining quality. Low-value zones were concentrated in the western regions. Unfortunately, except for a few regions (Sichuan, Guangxi, and Chongqing) where GDL-CL was rising, most western regions were declining, which may be due to the low-level trap brought about by the combination of resource shortages, harsh climate, and lack of good socio-economic conditions.

Of the four years analyzed, the spatial differences of GDL-CL in 2000 were the largest (C.V. = 0.303, maximum = 0.680, minimum = 0.206), and in 2018 were the smallest (C.V. = 0.216, maximum = 0.588, minimum = 0.243). Although the regional differences showed a weakening tendency, the annual regional average value was going down. Additionally, the maximum value was decreasing rapidly and the minimum value was increasing slowly. This showed that the leading factors affecting GDL-CL are increasingly uncontrollable. Overall, during 1990–2018, GDL-CL presented the following patterns and tendencies in China: (1) High-level regions have moved from the Bohai Rim (Beijing, Tianjin, Hebei, and Shandong) to the middle and lower reaches of the Yangtze river (Jiangsu, Zhejiang, Fujian, Hubei, and Hunan). (2) Middle-level regions have shifted from the central provinces (Shaanxi, Shanxi, Hebei, and Henan) to the southwest provinces (Chongqing, Sichuan, Guizhou, Yunnan, and Guangxi). (3) Low-level regions have remained relatively unchanged, and were mainly concentrated in the western provinces (Xinjiang, Tibet, Qinghai, Gansu, Ningxia, and Inner Mongolia). The central provinces of Shaanxi and Shanxi tended to shift to the low-level classification over time.

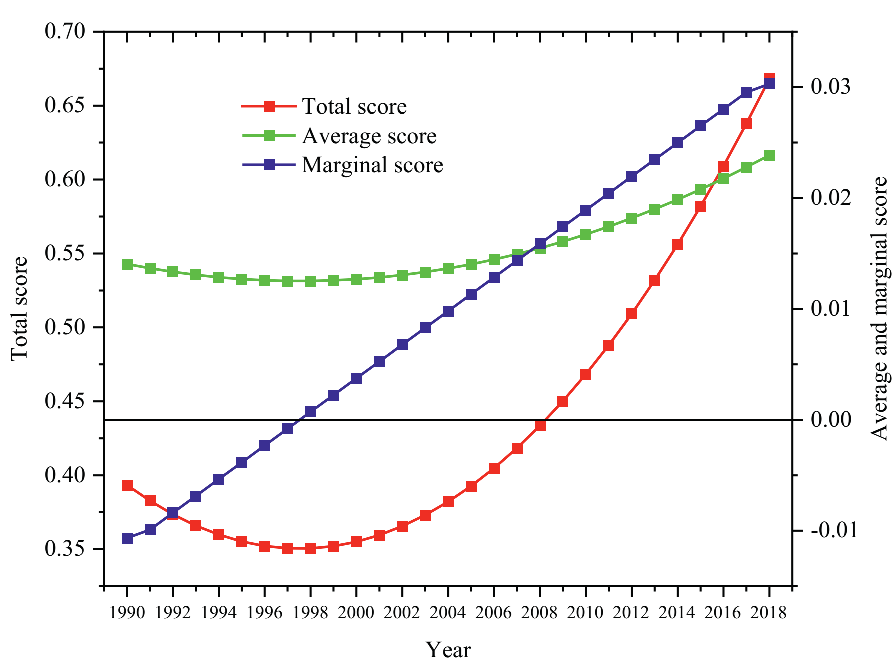

Fig. 4. The total, marginal, and average scores of green development level of cultivated land (GDL-CL) during 1990 to 2018 in China. The total score is the sum of scores of green development level of cultivated land in every year during 1990 to 2018. The marginal score is defined as how much the total score increased for each additional year. The average score represents the score based on the average annual score of GDL-CL (29 years in total). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
The score and comprehensive ranking of green development level of cultivated land (GDL-CL) for individual provinces in China in 1990, 2000, 2010, and 2018.

Province	Area	1990	2000	2010	2018	Average	Comprehensive ranking
Beijing	Eastern	0.652	0.680	0.580	0.308	0.555	1
Tianjin	Eastern	0.621	0.595	0.491	0.449	0.539	2
Jiangsu	Eastern	0.468	0.525	0.520	0.588	0.525	3
Shanghai	Eastern	0.532	0.498	0.445	0.325	0.450	5
Zhejiang	Eastern	0.510	0.545	0.455	0.416	0.482	4
Shandong	Eastern	0.399	0.468	0.466	0.455	0.447	6
Guangdong	Eastern	0.488	0.500	0.395	0.358	0.435	8
Fujian	Eastern	0.439	0.494	0.407	0.418	0.440	7
Hebei	Eastern	0.362	0.446	0.453	0.394	0.414	10
Hainan	Eastern	0.333	0.347	0.365	0.430	0.369	17
Hubei	Central	0.426	0.375	0.421	0.445	0.417	9
Jiangxi	Central	0.412	0.400	0.428	0.399	0.410	11
Hunan	Central	0.380	0.414	0.407	0.422	0.406	12
Henan	Central	0.349	0.395	0.437	0.402	0.396	14
Anhui	Central	0.397	0.371	0.384	0.407	0.390	15
Shaanxi	Central	0.363	0.308	0.315	0.288	0.319	21
Shanxi	Central	0.395	0.279	0.259	0.225	0.289	26
Sichuan	Western	0.312	0.314	0.327	0.354	0.327	20
Guangxi	Western	0.317	0.298	0.345	0.368	0.332	19
Chongqing	Western	–	0.285	0.323	0.334	0.314	24
Xinjiang	Western	0.343	0.320	0.309	0.300	0.318	22
Yunnan	Western	0.335	0.277	0.289	0.357	0.315	23
Inner Mongolia	Western	0.318	0.298	0.307	0.300	0.306	25
Tibet	Western	0.287	0.262	0.259	0.306	0.279	27
Ningxia	Western	0.304	0.237	0.304	0.265	0.278	28
Guizhou	Western	0.271	0.235	0.241	0.284	0.258	29
Gansu	Western	0.275	0.236	0.237	0.225	0.243	31
Qinghai	Western	0.278	0.206	0.245	0.244	0.243	30
Heilongjiang	Northeast	0.451	0.350	0.378	0.407	0.397	13
Jilin	Northeast	0.460	0.353	0.366	0.346	0.381	16
Liaoning	Northeast	0.411	0.366	0.347	0.313	0.359	18
Average		0.396	0.377	0.371	0.359	–	–
Coefficient of variation (C.V.)		0.240	0.303	0.230	0.216	–	–

Note: The results of regional division refer to Liao et al. (2021). Chongqing did not have a value in 1990 because it was separated from Sichuan Province to become a municipality in 1997.
Note: "GDL-CL" is "green development level of cultivated land".

3.2. Spatial correlation analysis of GDL-CL in China in 1990–2018

3.2.1. Analysis of spatial global autocorrelation of GDL-CL in China in 1990, 2000, 2010, and 2018

Due to the adjacency characteristics of the 31 provinces in China, we used the "Queen" 0–1 adjacency matrix that defined two provinces as neighbors when their boundaries or nodes were adjacent to each other. Based on the "Queen" 0–1 adjacency matrix, we used Stata software to calculate the spatial autocorrelation Moran index and to draw the Moran's I scatter plots for 31 provinces in 1990, 2000, 2010, and 2018 (Fig. 6). The results showed that the global Moran index of GDL-CL from 1990 to 2018 fluctuated up and down between 0.30 and 0.65, and the p-value was <0.01, indicating that the Global Moran indexes all passed the $P = 0.01$ significance test. Thus, the spatial correlation of GDL-CL from 1990 to 2018 showed a regular distribution, having a strong positive correlation and obvious spatial dependence in China's 31 provinces. Additionally, the value of Moran's I showed an inverted V-shape fluctuation trend during the study period. Specifically, spatial agglomeration increased gradually during the first three periods, but decreased significantly in 2018. This indicated that the mutual influence of GDL-CL among provinces was weakening, and that the level of green factor mobility of cultivated land within provinces was greater than that inter-provincial mobility.

3.2.2. Analysis of LISA spatial agglomeration of GDL-CL in China in 1990, 2000, 2010, and 2018

Fig. 7 shows the strong spatial stability and clear polarization of GDL-CL for provinces in China over the past 30 years (mostly low-low and high-high agglomeration). The P-values (significance) of spatial agglomeration results are shown in Table B1. Specifically, during 1990–2018, the core low-low agglomeration area of Sichuan radiated its influence to western provinces. This was mainly due to an increase in the concentration of food demand due to population growth, and to relatively barren and harsh arable land production resources and environment that led to high inputs to cultivated land while neglecting the negative environmental impacts in western regions. The high-high agglomeration areas were mainly concentrated in the eastern provinces and moved to the south. This was mainly attributed to the good ecological resources and climatic conditions, strict agricultural environmental management and protection policies, and the large-scale application and promotion of green cultivation technology in eastern regions. Additionally, the GDL-CL in China showed a clear spatial spillover effect between provinces during 1990–2018. For example, Hebei changed from a low-high agglomeration area in 1990 to a high-high agglomeration area in 2000. Anhui transformed from a low-high agglomeration area in 2000 to a high-high agglomeration area in 2010. This indicated that Hebei and Anhui were positively influenced by the surrounding higher-level areas such as Beijing and Jiangsu, respectively. Overall, from 1990 to 2018, we observed the coexistence of spatial correlation and spatial heterogeneity in China's provinces. Specifically, spatial correlation was mainly concentrated in the inner western regions, such as Xinjiang, Qinghai, and Gansu (low-low cluster) in 2000, 2010, and 2018, and in the inner eastern regions such as Jiangsu, Shanghai, and Zhejiang (high-high cluster) in 1990, 2000, 2010, and 2018. Spatial heterogeneity was reflected in the difference between eastern and western regions, forming a significant high-high clustering and low-low clustering, respectively, from 1990 to 2018.

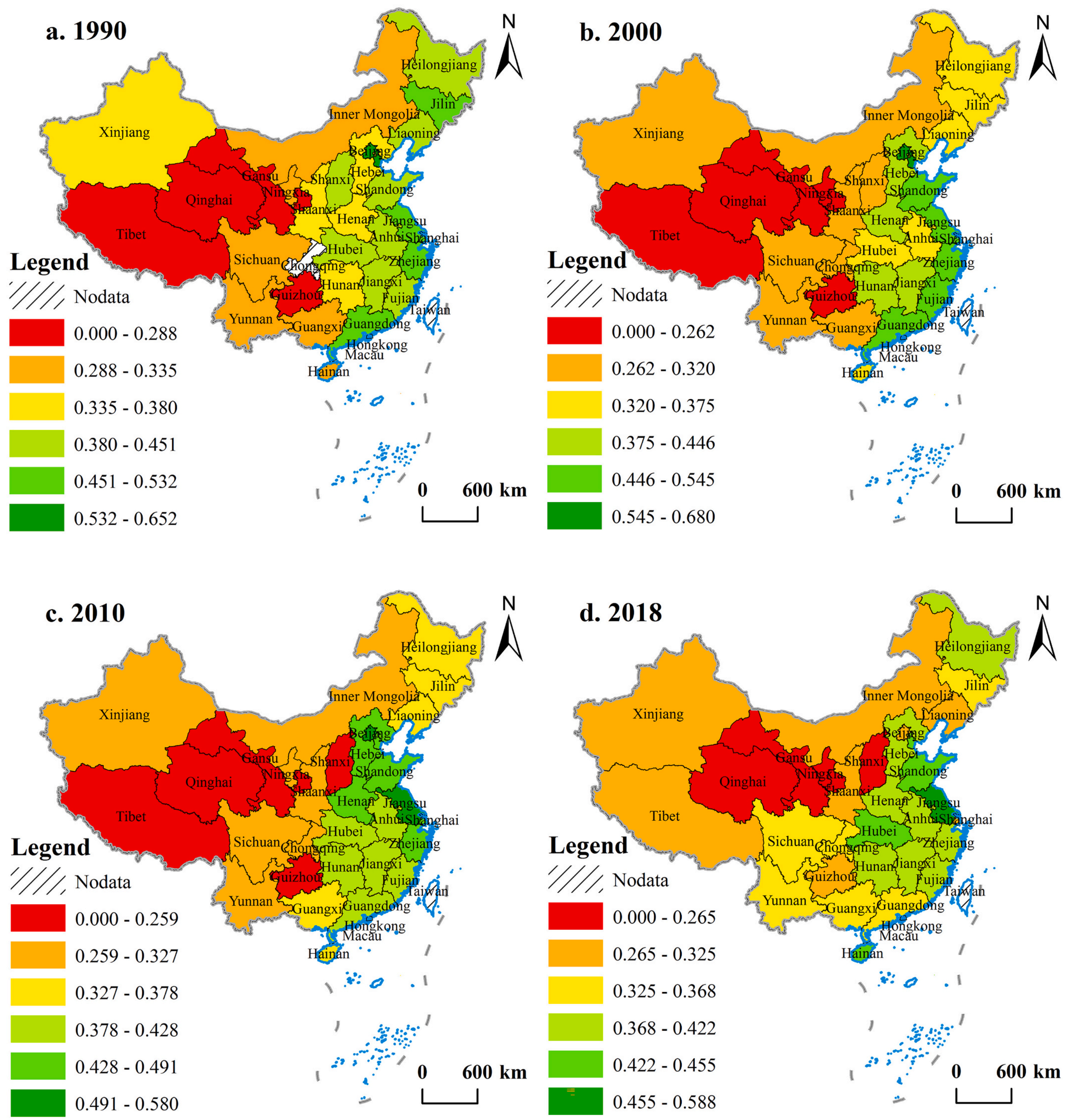

Fig. 5. The spatial pattern of green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018. The colors red, orange, yellow, chartreuse, light green, and dark green represent level 1, 2, 3, 4, 5, and 6, respectively; level 1 and 2 represent low level; level 3 and 4 represent middle levels; level 5 and 6 represent high level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.3. Quantitative attribution of spatial-temporal differentiation of GDL-CL in China

3.3.1. Factor detection results for spatiotemporal differentiation of GDL-CL in China

Table 4 shows that the q value for each variable were significant ($p = 0.01$). Fig. 8 shows that the driving force of the 11 exogenous variables for the spatial differentiation of GDL-CL in China was different in the past 30 years. For the dimension of climate change, the q value (q value represent driving force affecting spatial differentiation of GDL-CL) of Temp and Pre increased from 0.090 to 0.450 and from 0.130 to 0.494, respectively, as year increased from 1990 to 2018, showing a strong dominant force and climbing range. This result indicated that the uncertainty, disastrousness, and normalization of climate conditions were increasingly hindering the greening of arable land in different regions. The driving force of the Sun factor was comparatively stable, always remaining above 0.370 during the last three decades. This was mainly due to the irreplaceable role of sunshine conditions on crop growth. For

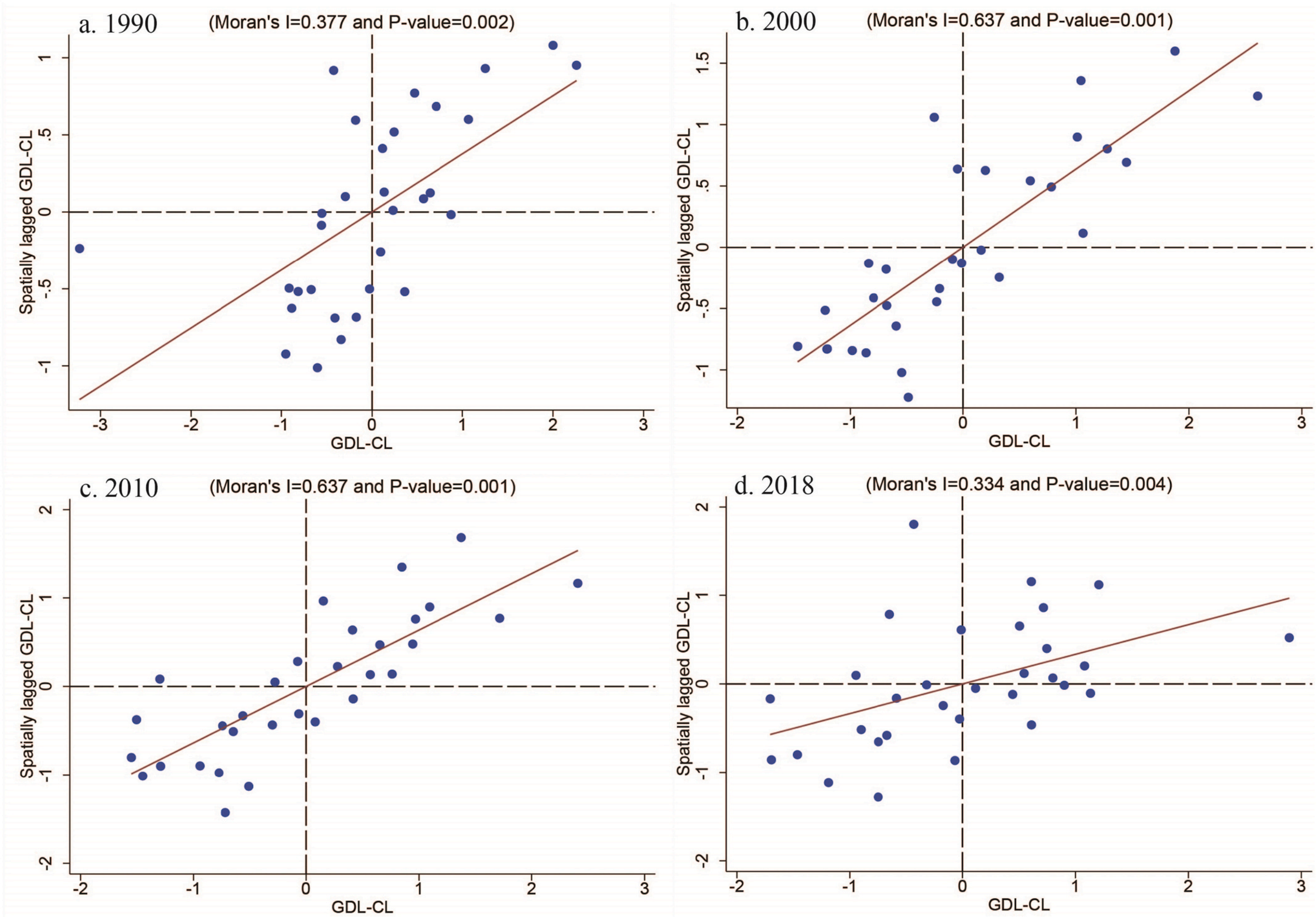

Fig. 6. Scatter plots of Moran's I and spatial autocorrelation of Moran index of green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the dimension of economic level, the driving force of the four variables showed an increasing trend in 1990–2010 followed by a decreasing trend in 2010–2018, with values hovering mostly around 0.25–0.60. This finding was attributed to the high yield, high efficiency, and greening of food production brought about by the increase in farmers' financial investment in arable land, stable government financial support, and high market demand for green products in different areas during 1990–2010. Investment in cultivated land production from 2010 to 2018 was neglected due to the large number of migrant farmers moving to urban areas in China. On the other hand, the difficulties in regulating and managing the market for green agricultural products made the green transformation of cultivated land less driven by economic factors. For the dimension of social development, the driving force of the IR factor increased from 0.329 to 0.665 in 1990–2000, and then decreased to 0.293 in 2018. This may be due to the fact that the quality of farming methods used by farmers has increased significantly since 1986 when compulsory nine-year education became universal. The "education dividends" have faded in different regions since 2010, thus reducing the spatial driving force for GDL-CL. In addition, the driving force of the EF factor moved upward from 0.220 to 0.582 in 1990–2010 and then downward to 0.432 in 2018. This may be due to the fact that before 2010, most farmers were full-time farmers and had a higher investment in arable land production and a sense of social responsibility. After 2010, most farmers in each region began to gradually leave the primary sector for the secondary and tertiary sectors and became part-time farmers, resulting in slowly increasing neglect of arable land production. Additionally, the driving force of the protection policy factor was always >0.200 and had been above 0.300 in the last 20 years. This indicated that cultivated land protection policies have been playing a stable supporting role for GDL-CL in different regions.

3.3.2. Interaction detection results for spatiotemporal differentiation of GDL-CL in China

Fig. 9 shows that only two types of GDL-CL driving factor interaction forces (nonlinear enhancement and bivariate enhancement) were observed in China. That is, the combined action of any two factors was greater than the action of a single factor. Specifically, the proportion of nonlinear enhanced types accounted for 85.5%, 34.5%, 38.2%, and 67.3% of the two types in 1990, 2000, 2010, and 2018, respectively. However, the interaction forces of factors were more intense in 2000 and 2010. For these years, the interaction intensity of most factors was >0.700 (q value≥0.700). In particular, the synergy effects between X3 and X7 (q value = 0.952) in 2000, between X1 and X4 (q value = 0.989) in 2010, between X3 and X4 (q value = 0.920) in 2010, and between X3 and X9 (q value = 0.965) in 2010 were nearly 1.000. Therefore, interaction forces among climate change (especially reasonable temperature, precipitation, and sunshine), economic level (especially higher agricultural output, government expenditures, and green food demand), and social development (especially lower Engel coefficient, higher employment, and good protection policies) had a significant positive impact on GDL-CL. The results showed that the interaction of various factors on GDL-CL is dynamic and complex. Therefore, China must give attention to the synergistic effect of various factors affecting spatial differentiation of GDL-CL in an integrated manner. (For interpretation of the references

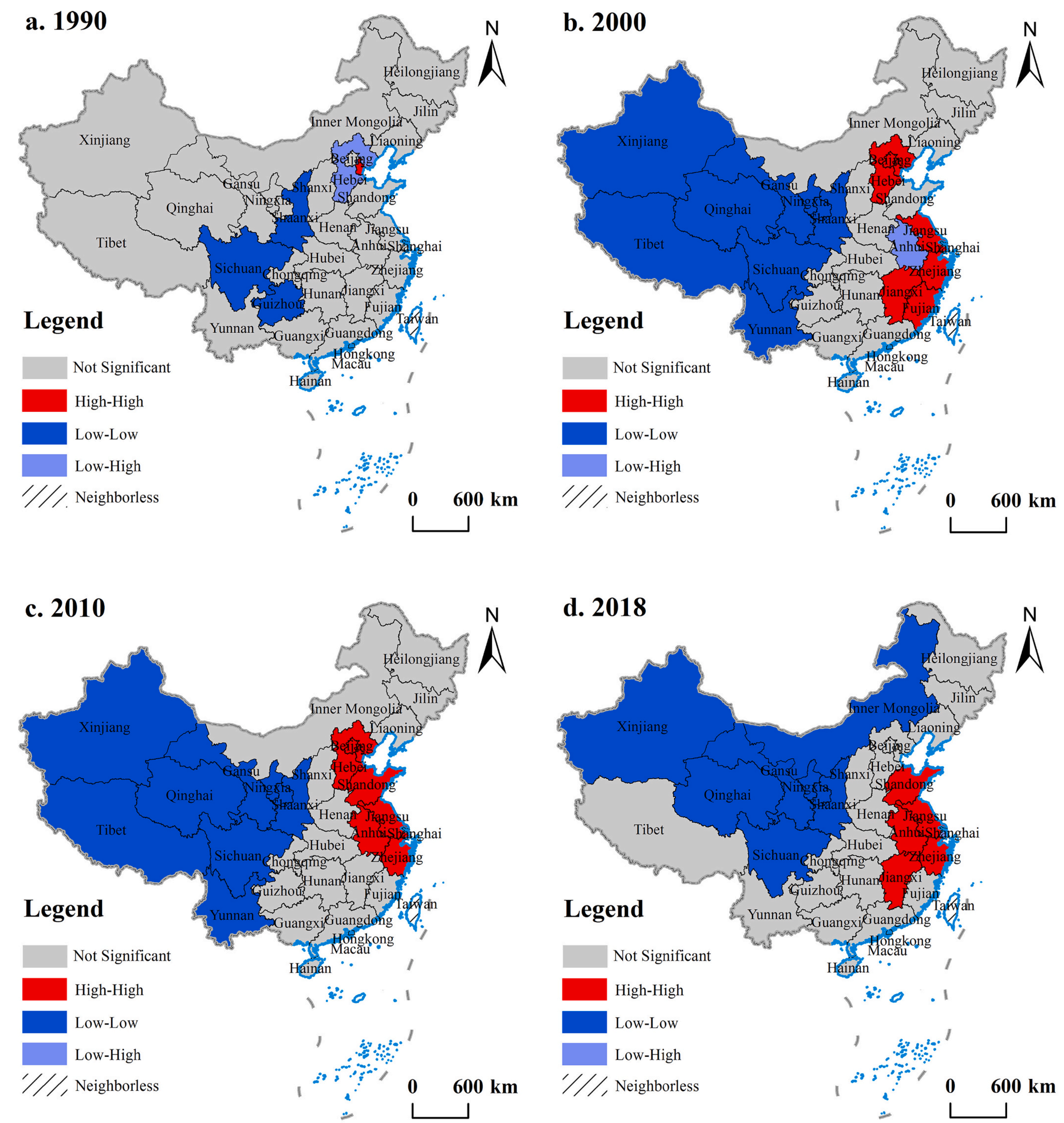

Fig. 7. LISA agglomeration map of green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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4. Discussion

Previous studies on sustainable management of cultivated land have mainly focused on regional quantity protection, use change, quality construction, soil health, and sustainable intensification. Unlike these previous studies, the current study had a green-development perspective comprised of three components: (1) proposal of a new perspective to construct a multi-dimensional framework and evaluation index system for assessing GDL-CL that considered environmental impacts; (2) application of effective mathematical, geographical, and economic methods to explore spatial-temporal evolution patterns and differentiation characteristics; and (3) detection of driving factors of GDL-CL from climatic, economic, and social environments. Furthermore, unlike the previous focus on the circular flow between internal components of SWPAS and the unidimensional, short-term, and micro-scale nature of

Table 4
Statistical table of q values and their significance and rank for driving factors of green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018.

Driving factors		1990		2000		2010		2018	
		q	rank	q	rank	q	rank	q	rank
Climate change	Temperature (X1)	0.090***	11	0.296***	10	0.289***	9	0.450***	3
	Precipitation (X2)	0.130***	9	0.312***	9	0.460***	5	0.494***	1
	Sunshine (X3)	0.411***	1	0.385***	6	0.539***	4	0.381***	6
Economic level	Agricultural output value (X4)	0.124***	10	0.577***	3	0.263***	10	0.339***	8
	Fixed asset investments (X5)	0.295***	5	0.590***	2	0.616***	1	0.401***	5
	Government expenditure (X6)	0.320***	4	0.396***	5	0.456***	6	0.267***	10
	Green food demand (X7)	0.147***	8	0.382***	7	0.612***	2	0.454***	2
Social development	Illiteracy ratio (X8)	0.329***	3	0.665***	1	0.422***	7	0.293***	9
	Engel coefficient (X9)	0.363***	2	0.289***	11	0.159***	11	0.184***	11
	Employment fig. (X10)	0.220***	6	0.528***	4	0.582***	3	0.432***	4
	Protection policy (X11)	0.215***	7	0.321***	8	0.379***	8	0.344***	7

Note: ***indicates statistical significance at $p = 0.01$.

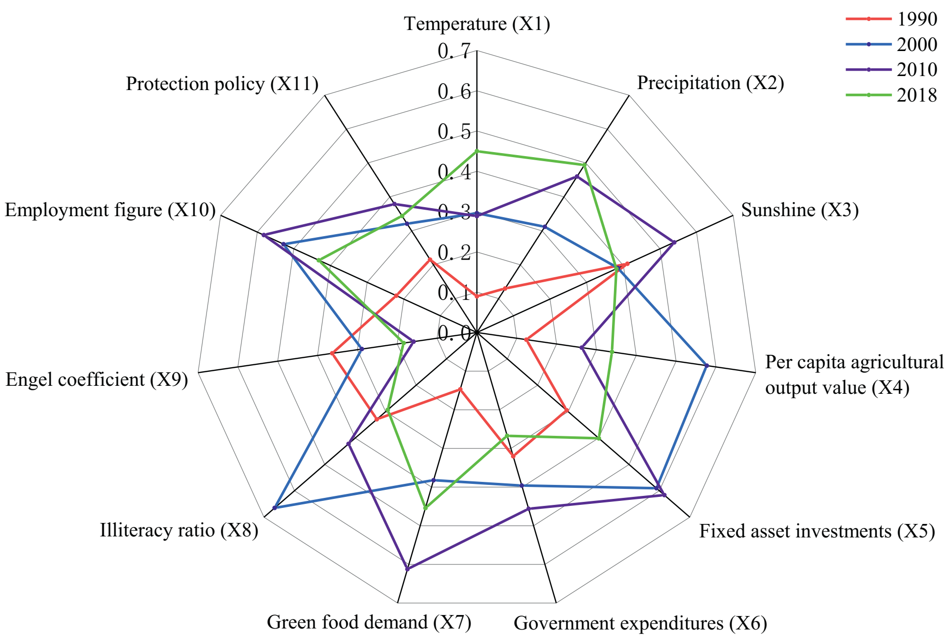

Fig. 8. Radar map of q values for factor detection results for green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

evaluation indicators, this study focused more on the interaction between SWPAS and CLUS and on the construction of multidimensional, long-term, and macro-scale evaluation indicators.

4.1. Effect of production mode changes on GDL-CL

According to the results of spatial-temporal evolution, GDL-CL was highly correlated with the input-output relationship of cultivated land in China. GDL-CL experienced a difficult period from 1998 to 2003, and entered a period of rapid improvement after 2008 (Fig. 3 and Fig. 4), indicating that China's tillage method had shifted from the model of low input-low output in 1990–1998 to high input-low output in 1998–2008, followed by a period of high input-high output after 2008. Meanwhile, serious surpluses occurred in the nutrient content of cultivated land. The soil nutrient budget in China increased from 172.9 kg/ha to 244.1 kg/ha from 1990 to 2018, which was 5.9 times the global level (FAO, 2018). High negative environmental impacts were subsequently generated due to agricultural production inputs. For example, soil compaction was caused by excessive fertilizer inputs, soil pollution was caused by excessive pesticide inputs, soil salinization was caused by basin irrigation, and large amounts of mechanical inputs led to rapid increases in agricultural carbon emissions (Bellarby et al., 2014; Wu et al., 2021). Therefore, cultivated land must shift to the low input-high output production model in China by incorporating biotechnology, digital agriculture, and other green technologies (Zhou et al., 2021). Additionally, the conflict between population growth and area of cultivated land has become seriously obvious in China. The cultivated land area per capita decreased from 0.103 to 0.082 ha/person from 1990 to 2018 (FAO, 2018). Thus, it is also very important to integrate cultivated land resources for moderate scale management and deep integration of agriculture, industry, and service industries (Zhang et al., 2022).

4.2. Coordination of regional differences in GDL-CL

Although GDL-CL in China has been constantly improving from 1990 to 2018 and regional differences have narrowed (Fig. 5), spatial heterogeneity has been significant, manifesting as high-high agglomeration in the east and low-low agglomeration in the west (Fig. 7). Fortunately, effective implications can be obtained from spatial autocorrelation and clustering results. GDL-CL in eastern China was promoted by the core areas (Tianjin, Jiangsu, and Zhejiang), showing a clear positive diffusion that resulted in GDL-CL of Shandong, Anhui, and Jiangxi continuing to

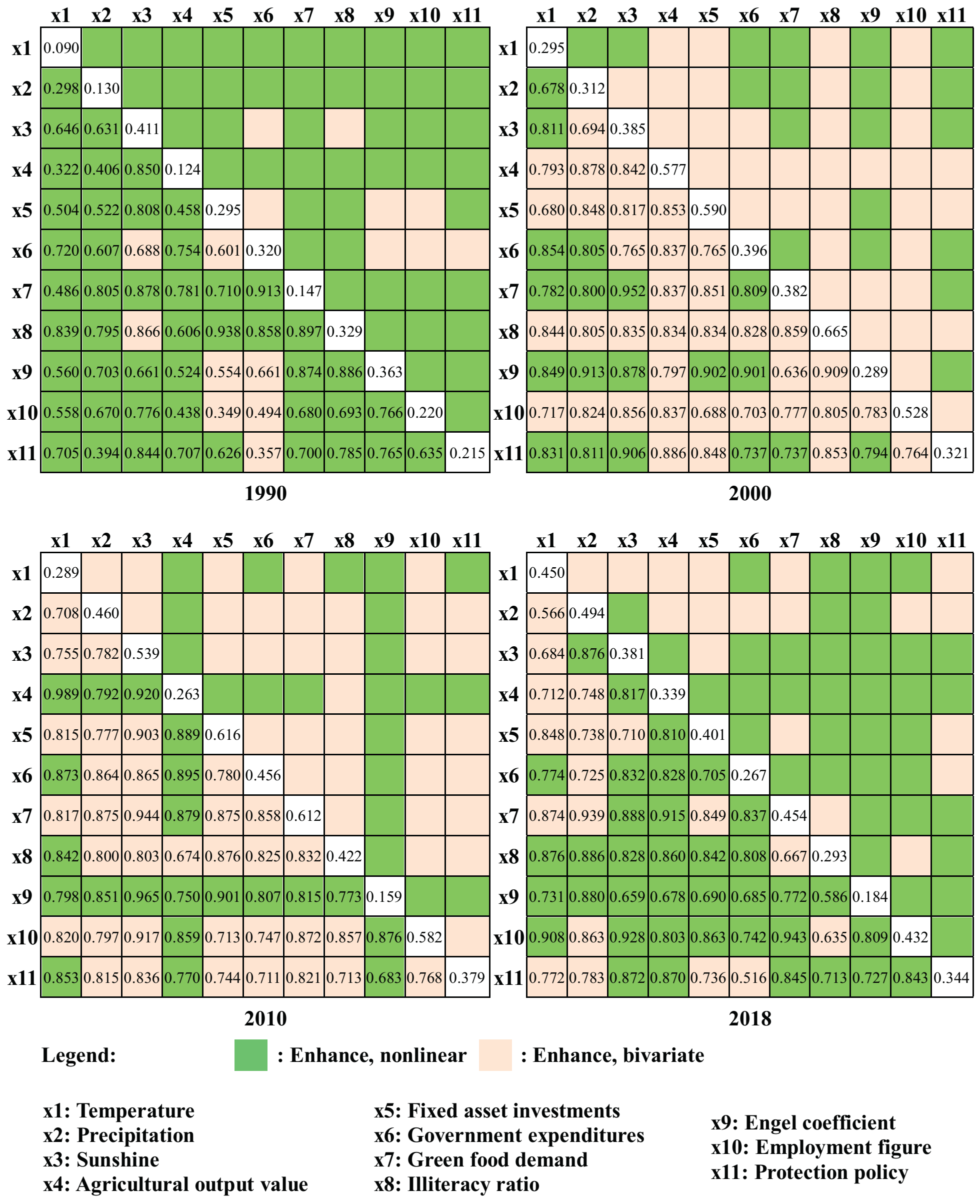

Fig. 9. The interaction effects (green and beige squares) and corresponding q values and single factor q values (white squares) for green development level of cultivated land (GDL-CL) in China in 1990, 2000, 2010, and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increase (Fig. 7). Therefore, the positive spatial spillover effect of GDL-CL must be captured. The flow of elements such as green technologies, capital, labor, and models of arable land production should be intentionally guided from high-level eastern regions to central and western regions (Liu et al., 2020b). Furthermore, the western and central regions show spatial spillover effects of low-low agglomeration and are constrained by resources and climatic conditions. Unfortunately, western provinces (such as Sichuan, Qinghai, Ningxia, Gansu, and Xinjiang) that have long been in the lower level of GDL-CL may gradually fall into the abyss of the "poverty trap" of GDL-CL. Thus, distribution of government subsidies and "one-on-one" support from eastern regions are necessary for low-level regions (Zhou et al., 2021). In addition, sufficient attention should be given to regional contradictions in GDL-CL. There have been many different negative environmental impacts on cultivated land in different regions of China (Ye et al., 2022), e.g., decreasing soil organic matter content in northeast China's cultivated land; soil acidification in southwest China; soil erosion of cultivated land in western China; and heavy metal pollution in cultivated land in eastern China. Therefore, any specific action must be tailored to local conditions, classification, and treatment of the symptoms.

4.3. Beware of extreme climate effects on GDL-CL

Unlike the results associated with many previous research discoveries where the impact of climate factors on agricultural productivity became less and less with the increased use of artificial exploitative and technical production methods (Fu et al., 2018; Wang et al., 2018; Han and Zhang, 2020), the drivers affecting GDL-CL gradually changed from socio-economic factors to climatic factors in this study (especially temperature and precipitation) (Fig. 8). Additionally, the interaction results showed that the synergy of climate change with other factors on spatial differentiation became stronger and stronger over time (Fig. 9). Both results suggest that the impacts of extreme climate such as droughts and floods should be given added attention in the future. In particular, the strongest impacts on flooding and drought were the precipitation amount during the warmest quarter of the year and elevation. In extreme cases associated with these factors, incalculable negative impacts on GDL-CL have been observed. Floods tend to occur in southern China, while droughts are concentrated in western China (Fu et al., 2018; Wang et al., 2018). However, flood areas in China have been gradually moving northward, from Anhui to Henan and Shanxi from 2020 to 2021. Furthermore, climate change and inconsistent use of cultivated land have together been destroying biodiversity, resulting in a corresponding threat to yield and GDL-CL (Heikkinen et al., 2021). Due to the difficulty in modifying natural conditions and the frequent occurrence of drought and flood disasters in China, a dynamic warning mechanism and emergency management measures should be quickly applied to the green development management of cultivated land. Meanwhile, we must not ignore the long-term and stabilizing forces of social-economic impacts on GDL-CL while paying attention to extreme natural elements (Fig. 8 and Fig. 9).

5. Conclusions and further research

The interwoven food security and environmental challenges can be effectively mitigated and addressed by GD-CL (Foley et al., 2011). In this study, a new multi-dimensional framework considering environmental impacts for assessing GDL-CL was proposed based on “elements – processes – dimensions – goals – drivers” according to the interaction between SWPAS and CLUS. An evaluation index system was built multidimensionally based on that framework. Overall, GDL-CL showed a U-shaped trend, with 1998 as an inflection point and 2008 as a rapid growth point in China. Regionally, there was obvious spatial heterogeneity between the eastern and western regions of China, with the eastern regions showing a high-high agglomeration and the west showing a low-low agglomeration. Meanwhile, the gap in GDL-CL between different regions has been narrowing from 1990 to 2018. However, the values of most of the high-level areas have decreased over time, and the rate of decline far exceeded the growth rate of the low-level areas. Using the Geodetector method, we found the reason for these phenomena: GDL-CL across regions has always been driven by socio-economic factors such as agricultural output, farmers’ assets, food markets, farmers’ education, employment, and government policies. Particularly, climate factors have gradually become the dominant factors during 2010–2018. Therefore, to promote the policy strategy of “storing food in the land and technology”, it will be necessary to enhance GDL-CL by relying on integrating green production, resource conservation, environmental governance, and output effect. Additionally, there is an urgent need to continuously optimize the production model of cultivation based on green technological progress, production factor allocation, and industrial structure upgrading. Furthermore, the “14th Five-Year Plan for National Agricultural Green Development” proposes that by 2025, 1.075 billion mu of continuous high-standard farmland will be built nationwide. Thus, it will be necessary to enhance GDL-CL in low-level areas such as the central and western regions that lack resources and are more affected by environment. Specifically, regional differences can be effectively coordinated through policies such as subsidy distribution, improvement of green food certification systems and regulatory mechanisms, education enhancement, employment stabilization, and one-on-one assistance. In particular, mitigating adverse impacts of climate change such as droughts or floods on GDL-CL in each region will be indispensable through real-time early warning mechanisms and comprehensive emergency measures.

This study developed a new framework and evaluation index system for GD-CL, and conducted a series of empirical analyses using mathematical, economic, and geographical methods from the last three decades in China. Therefore, the results of this study have both theoretical value and practical significance, and can effectively provide scientific and reasonable suggestions for the sustainable management of cultivated land. However, readers should be aware that due to the scale of data used in this study, the results may have had some precision limitations that were partially remedied by using the scientific missing value supplement and spatial interpolation method. On the other hand, this study discussed the spatial-temporal evolution, differentiation characteristics, and driving factors of GDL-CL at the provincial level in China, and may have limited accuracy. In the future, it will be crucial to analyze and discuss GDL-CL at a finer scale (municipal- or county-level). Accordingly, after clearly determining the spatiotemporal differentiation and regularity of GDL-CL, there will also be a need to clarify the multi-dimensional linkages affecting GDL-CL. For example, understanding the related effects of farmers’ behaviors, food market prices, consumer demand, and industrial upgrading will also need to be one of the directions for future investigations. Furthermore, emphasis should be placed on the influence of legislation, procedure, practices, and governance of environmental impact assessments on GDL-CL in the future.

CRediT authorship contribution statement

Chaoqing Chai: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Investigation, Writing – original draft, Writing – review & editing. **Bangbang Zhang:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Visualization, Writing – review & editing. **Yuanyuan Li:** Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Investigation, Writing – review & editing. **Wenhao Niu:** Data curation, Methodology, Formal analysis, Software. **Weiwei Zheng:** Formal analysis, Software. **Xiangbin Kong:** Conceptualization, Funding acquisition, Project administration, Supervision. **Qiang Yu:** Funding acquisition, Project administration, Supervision, Validation. **Minjuan Zhao:** Project administration, Supervision. **Xianli Xia:** Project administration, Supervision.

Declaration of Competing 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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Appendix A

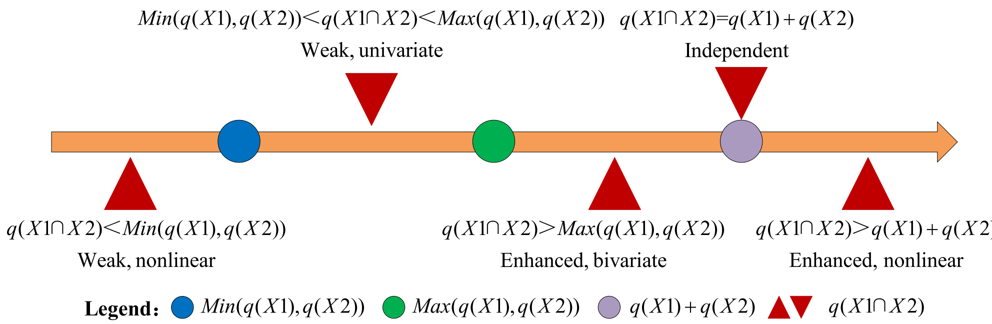

Fig. A1. Interaction of different influencing factors. Fig. A1 is modified from Wang et al., 2016.

Appendix B

Table B1
P-values for spatial agglomeration results for green development level of cultivated land (GDL-CL) for provinces in China in 1990, 2000, 2010, and 2018.

Year	$p = 0.05$	$p = 0.01$	$p = 0.001$
1990	Tianjin, Hebei, Guizhou	Shaanxi	Sichuan
2000	Beijing, Hebei, Tianjin, Jiangsu, Shanghai, Zhejiang, Fujian, Anhui, Jiangxi, Ningxia, Qinghai, Tibet, Yunnan	Shaanxi Gansu	Xinjiang Sichuan
2010	Beijing, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Ningxia, Shaanxi, Qinghai, Tibet, Yunnan	Tianjin Gansu	Sichuan Xinjiang Anhui
2018	Shandong, Jiangsu, Shanghai, Fujian, Jiangxi, Inner Mongolia, Qinghai, Ningxia, Shaanxi	Anhui, Xinjiang, Gansu, Sichuan	–

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