land

MDPI

Article

The Relationship between Farmland Abandonment and Urbanization Processes: A Case Study in Four Chinese Urban Agglomerations

Nan Zheng [1], Le Li [1,*], Lijian Han [2], Xiufang Zhu [3], Kefei Zhao [1], Ziyang Zhu [4,5] and Xiaolan Ye [1]

1 School of Management, Guangdong University of Technology, Guangzhou 510520, China; 3217003558@mail2.gdut.edu.cn (N.Z.); zhaokf@gdut.edu.cn (K.Z.); 2112108068@mail2.gdut.edu.cn (X.Y.)
2 State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China; ljhan@rcees.ac.cn
3 State Key Laboratory of Remote Sensing Science, Beijing Normal University, Beijing 100875, China; zhuxiufang@bnu.edu.cn
4 Key Laboratory of Natural Resources Monitoring in Tropical and Subtropical Area of South China, Ministry of Natural Resources, Guangzhou 510663, China; gd.airfly7@gmail.com
5 Surveying and Mapping Institute, Lands and Resource Department of Guangdong Province, Guangzhou 510663, China
* Correspondence: lilegeo@gdut.edu.cn

Abstract: Clarifying the relationship between urbanization and farmland abandonment in urban agglomerations (UAs) is crucial to guide the formulation of arable land management policies and strategies for sustainable urban development. Despite numerous studies confirming the correlation between farmland abandonment and certain urbanization factors, the exploration of the patterns and underlying mechanisms of farmland abandonment in China's UAs remains worthy of systematic investigation. In this study, we conducted an analysis of the spatiotemporal trends in farmland abandonment and examined the key drivers of farmland abandonment in four representative Chinese UAs—Beijing–Tianjin–Hebei (BTH), Chengdu–Chongqing (CC), Pearl River Delta (PRD), and Yangtze River Delta (YRD). Our findings reveal that farmland abandonment has been intensified with increasing fragmentation and aggregation patches across these UAs. Abandonment experience was the main driver of continuous abandonment. Moreover, natural conditions persistently influenced farmland abandonment in the BTH, while land urbanization and economic urbanization were predominant drivers in the CC. The abandonment in the PRD was mainly driven by population urbanization, while the abandonment in the YRD was primarily driven by economic urbanization and land urbanization. The research findings provide data support and scientific explanation for land policy-making in these typical UAs under different development strategies.

Keywords: abandoned farmland; urbanization; driving factor; urban agglomeration; landscape pattern

check for updates

Citation: Zheng, N.; Li, L.; Han, L.; Zhu, X.; Zhao, K.; Zhu, Z.; Ye, X. The Relationship between Farmland Abandonment and Urbanization Processes: A Case Study in Four Chinese Urban Agglomerations. *Land* **2024**, *13*, 664. https://doi.org/10.3390/land13050664

Academic Editors: Guohua Hu, Yilun Liu and Xiaocong Xu

Received: 20 March 2024
Revised: 3 May 2024
Accepted: 8 May 2024
Published: 11 May 2024

1. Introduction

Although China is a major grain-producing nation, with arable land covering 13% of its total land area, its production of food imposes certain pressure to achieve self-sufficiency for its population of 1.4 billion [1,2]. Farmland abandonment is a significant issue that could potentially affect food security. Farmland abandonment is characterized by a deliberate reduction or complete cessation in land utilization due to the comprehensive impact of factors such as marginalization, urbanization, and social dynamics [3,4]. It greatly reduces grain acreage, inhibits the production enthusiasm of farmers, and negatively affects food security [5,6], although it may promote regional biodiversity [7,8]. Abandoned farmlands are found in areas of poor farming conditions and frequently found in areas of rapid urbanization [9,10]. With the development of rapid urbanization, many young and middle-aged farmers have been attracted to work in cities with more job opportunities and higher incomes, resulting in a shortage of rural agricultural labor resources [11,12]. The agricultural plots in UAs are generally smaller than those in major agricultural regions, and they are more easily abandoned due to labor shortages. The negligent abandonment of arable land precipitates a diminution in sown area, weakens farmers' enthusiasm, and finally hinders efforts to maintain food security and ensure stable social development. Furthermore, agricultural development may influence the process of urbanization. Some studies indicate that the effective supply of food constrains the rapid expansion of urban populations [13,14], and there is a correlation between the proportion of urban populations in different provinces and the per capita grain output in rural areas [15]. Therefore, it is crucial to clarify the relationship between urbanization and farmland abandonment, as it informs the formulation of arable land management policies and urban sustainable development strategies.

During the process of urbanization, the advanced spatial form of urban systems emerges as interconnected and integrated entities comprising different cities. These entities, known as urban agglomerations (UAs), typically develop and consolidate in densely populated areas where cities are closely distributed [16,17]. Urban agglomerations typically consist of multiple cities with diverse populations, economic activities, and land characteristics. Due to differences in spatial location, administrative attributes, and levels of development, different UAs vary in terms of their scale and developmental strategies [18,19]. The developmental levels of different UAs are reflected in the extent of land urbanization, population urbanization, and economic urbanization [20,21]. Land urbanization refers to the constantly expanding process of urban land areas [22,23]. Land urbanization leads to an increase in farmland fragmentation and farmland costs [24]. Population urbanization refers to the agglomeration of people from rural to urban areas who look for opportunities for off-farm jobs and then become permanent residents in cities [25,26]. Population urbanization brings a shortage in agricultural labor resources, resulting in abandoned farmland without adequate management [27]. Economic urbanization refers to the agglomeration of non-agricultural industries in cities [28]. Economic urbanization results in the rapid development of the urban industrial economy, widening the gap between urban and rural income, promoting increasing agricultural production costs, inhibiting enthusiasm for farming and ultimately resulting in farmland abandonment [29]. The impact of arable land abandonment varies across UAs with different levels of urbanization [30]. Understanding the spatiotemporal distribution characteristics and pattern changes of farmland abandonment in different UAs, as well as quantitatively analyzing the driving mechanisms behind arable land abandonment in these agglomerations, serves as a crucial foundation for formulating sustainable development policies regarding arable land management within UAs.

Many studies have been devoted to the driving effect of urbanization on farmland abandonment [31–33]. A spatial analysis of farmland abandonment studies published in different regions from 2000 to 2024 on the Web of Science has been conducted [34–37]. This reveals that Europe was a hotspot for early studies on arable land abandonment, while Asia has gradually emerged as a hotspot for arable land abandonment research in recent years. Previous studies have indicated that arable land has been abandoned under different urbanization-related driving factors. Sroka et al. illustrated that the proportion of built-up and urbanized areas, and the population density were the dominant driving factors for semi-abandoned farmland in Polish metropolitan areas from 1995 to 2010 [27]. Chaudhary et al. concluded that population growth and urbanization have been the major drivers of farmland abandonment in Nepal since 1961 from the relevant literature [38]. In China, Xie et al. found that population urbanization was one of the crucial drivers of farmland abandonment in Jiangxi from 1990 to 1995, while economic development became the dominant driver from 1995 to 2005 [39]. Similarly, Hou et al. revealed that the non-agricultural economy was the main determinant of farmland abandonment from 2003 to 2018 in the Sunan economic region [40]. Despite regional and national variations, as well as variations in the stages of urbanization, empirical evidence from these studies substantiates that land urbanization, population urbanization, and economic urbanization stand out as the foremost factors contributing to farmland abandonment. As there are disparities between urbanization in China and that in Western developed countries and developing nations, the relationship between Chinese urbanization and farmland abandonment remains unclear.

Urbanization is a complex process of multi-dimensional development involving population, economy, and land [41]. And farmland abandonment is the integrated outcome of these urbanization factors acting on arable land with different cultivation conditions. First, farmland abandonment is deeply influenced by the natural conditions of farmland. Factors such as steep terrain, harsh climate, poor soil quality, high degree of fragmentation of arable land, poor irrigation conditions, and high commuting costs all contribute to the low productivity of the arable land patches [42–44]. Additionally, limited mechanization due to constraints such as terrain further hampers the efficiency of agricultural production on the land, resulting in low economic returns [45]. In order to achieve better economic benefits, farmers always prioritize abandoning arable land with poor agricultural productivity and low economic returns, leading to farmland abandonment. Secondly, land urbanization affects the occurrence of farmland abandonment by altering land use structure and land value. During the process of land urbanization, rural arable land may be allocated for urban construction, industrial use, or infrastructure development [46]. This conversion of arable land use results in a decrease in agricultural land area, which can be identified as farmland abandonment through remote sensing observations [47]. The lower value of arable land compared to urban land also prompts some farmers to willingly transfer land usage rights at a higher price due to speculative motives, leading to arable land abandonment. Furthermore, environmental pollution and the deterioration of arable land quality brought about by land urbanization also serve as driving factors for farmland abandonment [48]. Thirdly, population urbanization, manifested as labor migration from rural to urban areas, is the most direct driving factor behind farmland abandonment. With the advancement of industrialization, non-agricultural employment opportunities have increased, allowing farmers to choose to reduce labor input in agricultural production or directly abandon it, opting instead for part-time or full-time employment in non-agricultural sectors. Thus, as urban populations continue to grow and rural populations decline, agricultural labor shortages become unavoidable, ultimately resulting in farmland abandonment. In the mountainous regions of Nepal, rural populations migrating to lower-altitude urban areas contribute to the increasing urban population, fostering rapid growth in non-agricultural industries, thereby hindering agricultural development and driving more farmers to abandon agricultural production [38]. Fourthly, economic urbanization also contributes to farmland abandonment. Economic urbanization may lead to changes in rural economic structure, with farmers shifting to non-agricultural activities, resulting in an increased proportion of non-agricultural industries in the economic structure and rapid income growth for urban residents. Meanwhile, the proportion of the agricultural industry declines and the growth rate of farmers' income slows down. Such economic urbanization leads to a widening income gap between urban and rural residents. Faced with a widening income gap and decreasing agricultural income, farmers tend to abandon farmland and seek livelihoods and development in urban areas, resulting in farmland abandonment. The key driving factor behind the abandonment of rice fields in Japan is the lower agricultural economic benefits. When non-agricultural income exceeds agricultural income, farmers often abandon farmland [49]. In rapidly urbanizing coastal areas of Europe and Western Europe, the per capita GDP increases in urban areas while rural farmers' incomes decrease. The economic income gap suppresses farmers' production enthusiasm, leading to a decrease in the intensity of land use or direct abandonment of farmland [50,51]. Thus, the impact of urbanization on farmland abandonment is essentially the combined result of the four effects mentioned above. The farmland abandonment development process, and its driving mechanisms vary among different UAs due to differences in cultivation natural conditions and paths of urbanization development. It is unreasonable to formulate farmland utilization policies for different UAs based on a single factor or a unified driving mechanism outcome.

Therefore, the main objectiveness of this study are as follows: (1) to analyse the spatial and temporal characteristics of farmland abandonment in typical UAs in China; (2) to illustrate the landscape pattern of farmland abandonment in main UAs in China; and (3) to detect the dominant driving factors of farmland abandonment under different urbanization statuses and quantify the relationship between farmland abandonment and urbanization processes. The remainder of this paper consists of five parts. Section 2 introduces the study area and data. Section 3 describes the methods. Section 4 presents the results. Section 5 contains the discussion, and Section 6 summarizes the conclusions.

2. Study Area and Data

2.1. Typical Urban Agglomerations in China

The study selected four typical UAs in China as research areas, which are the Beijing–Tianjin–Hebei urban agglomeration (BTH), the Yangtze River Delta urban agglomeration (YRD), the Pearl River Delta urban agglomeration (PRD) and the Chengdu–Chongqing urban agglomeration (CC). BTH, YRD, and PRD are the three major urban agglomerations in China, with the most vibrant economies, the strongest innovation capabilities, and the highest influx of migrant population in China [52,53]. These three major urban agglomerations are located in the eastern region of China, while the CC is the largest urban agglomeration in the central and western regions. CC is designated as one of the most advanced and optimized urban agglomerations in China's "14th Five-Year Plan", and it is also a hotspot for research on farmland abandonment in China [54–57].

BTH, YRD, CC, and PRD are distributed sequentially from south to north in China, with different scales and climate conditions (Figure 1). The coverage of the UAs is based on the specific scope described in the UA development plans issued by the Chinese administrative unit (Table 1).

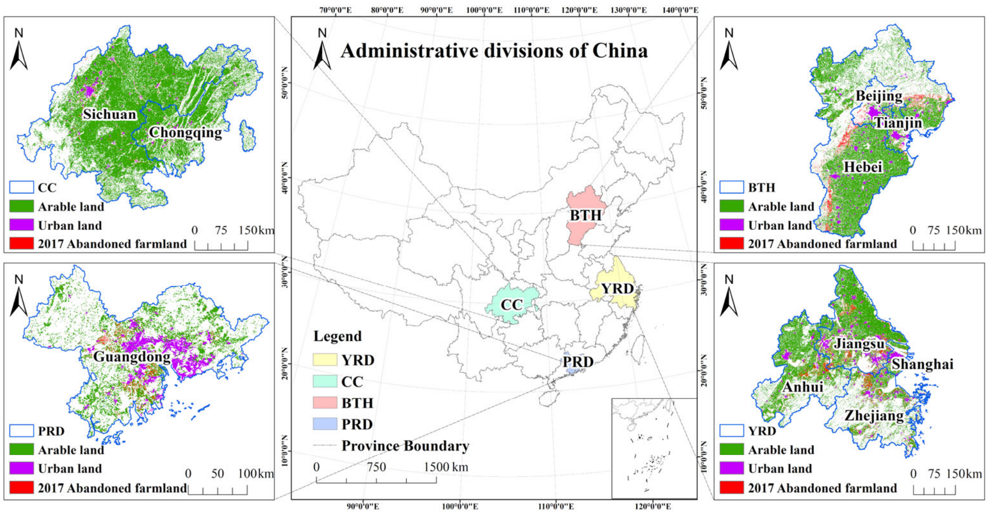

Figure 1. Farmland abandonment in 2017 in four of China's typical UAs.

Table 1. The coverage of typical UAs.

UAs	Coverage Area
BTH	Beijing, Tianjin, Hebei Province (11 cities)
CC	Chongqing (29 districts or counties), Sichuan Province (15 cities)
PRD	Guangdong Province (9 cities)
YRD	Shanghai, Jiangsu Province (9 cities), Zhejiang Province (8 cities), Anhui Province (8 cities)

BTH is a global UA as the political center in China, including Beijing, Tianjin, and 11 other cities in Hebei Province. The resident population of BTH exceeds 110 million, covering an area of 218,000 km^2. BTH is in the North China Plain, and the terrain is high in the northwest and low in the southeast. Arable land accounts for more than 40% of the area, with the major crops being wheat and corn. The gross domestic product (GDP) of BTH contributes approximately 10% of China's GDP.

CC is an important demonstration area for China to promote new-type urbanization, which includes 15 cities in Sichuan and 29 counties in Chongqing. The resident population of CC exceeds 60 million with an area of 185,000 km^2. CC is in the Sichuan Basin and is dominated by mountains and hills. Arable land resources are rich in CC, occupying more than 50% of the total area, and the grain crops are mostly rice, corn, and tubers. The GDP of CC contributes approximately 6% of China's GDP.

PRD is one of the most populated areas in China and includes 9 cities in Guangdong. PRD has a resident population of more than 70 million, covering an area of approximately 42,200 km^2. PRD is in the plain of the Pearl River Delta, and the terrain is mostly dominated by plains and impact deltas. The area of arable land accounts for more than 20% of PRD, and rice and tubers are the major products of food production. The GDP of PRD contributes approximately 9% of China's GDP; however, the per capita GDP remains among the highest in China.

YRD is the most dynamic, open, and innovative region in China, including a total of 26 cities in Shanghai, Jiangsu, Zhejiang, and Anhui Provinces. YRD has a resident population of more than 165 million and covers an area of approximately 211,700 km^2. YRD is in the lower reaches of the Yangtze River in China. The terrain is high on the edges and low in the middle, and the river network is dense. Arable land accounts for more than 40% of YRD, and the grain crops are mostly rice and wheat. The GDP of YRD contributed approximately 20% of China's GDP.

2.2. Data Source

2.2.1. Geospatial DATA

(1) Time series maps of abandoned farmland across China with 250 m spatial resolution from 2002 to 2017 were derived from Zhu, et al [4].

(2) LandScan Global Population Data with 30 arc-seconds spatial resolution for 2002, 2005, 2010, 2015, and 2017 were developed by the Oak Ridge National Laboratory (https://landscan.ornl.gov, accessed on 1 June 2022), which provides global population data annually [58–62].

(3) China's National Land Use and Cover Change (CNLUCC) for 2002, 2005, 2010, 2015, and 2017 with 1 km spatial resolution was provided by the Resource and Environment Science and Data Center (RESDC) (http://www.resdc.cn, accessed on 1 June 2022), which includes 23 land types [63]. The land use types were concluded to be arable land and urban land in this study by reclassification.

(4) The average monthly precipitation data with 1 km spatial resolution from 2002 to 2016 were released on the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn, accessed on 1 June 2022), which were calculated from the 1 km monthly temperature and precipitation dataset derived from Peng, et al. [64].

(5) The average monthly temperature data with 1 km spatial resolution from 2002 to 2016 were also released on http://www.geodata.cn (accessed on 1 June 2022), which were calculated from Peng et al. [64].

(6) Digital elevation models (DEMs) were published by RESDC and were generated from SRTM V4.1 data resampled to 250 m spatial resolution.

(7) The Chinese county-level administrative boundary data were obtained from the 1:1 Million Basic National Geographic Database, which was provided by the National Catalogue Service for Geographic Information (https://www.webmap.cn, accessed on 1 June 2022).

2.2.2. Statistical Data

The county-level statistical data for 2002, 2005, 2010, 2015, and 2017 were obtained from the China County Statistical Yearbook, which can be found at https://data.cnki.net/ (accessed on 1 June 2022). This dataset comprises a range of indicators that reflect the socioeconomic development of the counties, such as GDP, employed population, etc. [65–69].

2.3. Selecting Variables

We regarded the proportion of abandoned farmland area to arable land area in year i (Y_i) as the dependent variable and took abandonment experience factor, multiple sourced urbanization-related factors, and natural conditions factors as potential driving factors. Urbanization-related factors address population urbanization factors, economic urbanization factors, and land urbanization factors (See Appendix A).

The definition of farmland abandonment varies across the world, and FAO studies define farmland abandonment as abandoned farmland that has not been cultivated for agricultural production for at least two to four consecutive years. The spatiotemporal distribution dataset of farmland abandonment across China utilized in this study was obtained from Zhu et al. [4]. Farmland abandonment in this study was defined as arable land left uncultivated for two or more years. The average proportion of abandoned farmland area in arable land area in the past few years was regarded as the abandonment experience factor (Ae_fa). Ae_fa values for 2005, 2010, 2015, and 2017 were calculated according to the average proportion of abandoned farmland area to arable land area for 2002–2004, 2005–2009, 2010–2014, and 2015–2016, respectively.

Total population (Pu_pop), population density (Pu_pd), changing rate of population density (Pu_crpd), rural employment (Pu_re), and changing rate of rural employment (Pu_crre) in 2005, 2010, 2015, and 2017 were selected as population-urbanization-related factors. Because the statistical indicators were adjusted by the Bureau of Statistics, Pu_re in 2015 and 2017 were defined by employment in the primary industry (Pu_ep) in 2015 and 2017, while Pu_crre in 2015 and 2017 were defined by the changing rate of employment in the primary industry (Pu_crep) in 2015 and 2017, respectively.

Economic-urbanization-related factors included GDP (Eu_GDP), per capita GDP (Eu_pGDP), increased value of the primary industry (Eu_p), and the ratio of secondary industry increase value to primary industry increase value (Eu_sp). Due to a lack of county-level GDP statistical indicators before 2015, Eu_GDP and Eu_pGDP were replaced by savings deposits of residents (Eu_sd) and per capita savings deposits of residents (Eu_psd) in 2005 and 2010.

The area of urban land (Lu_ua), the proportion of urban area in total area (Lu_pua), and the changing rate of urban area proportion (Lu_crpua) were selected to present the land-urbanization-related factors.

Natural conditions involve natural topographic conditions, natural climate conditions, and the patch characteristics of arable land. Here, natural topographic conditions were indicated by the average elevation (Nc_ae), range of elevation (Nc_re), and average slope (Nc_as), while natural climate conditions were indicated by the average annual precipitation for the past few years (Nc_ap) and average annual temperature for the past few years (Nc_at). The area of arable land (Nc_area), proportion of arable land area in total area (Nc_pa), number of arable land patches (Nc_np), patch density of arable land patches (Nc_pd), landscape shape index of arable land patches (Nc_lsi), and aggregation index of arable land patches (Nc_ai) were employed to show the patch characteristics of arable land.

The dependent variable, land-urbanization-related factors, and the patch characteristics of arable land factors in 2002 and 2017 were derived from the land-use data of 2000 and 2018, respectively. Population- and economic-urbanization-related factors in 2004 were used to fill the data gaps in 2005, considering the incompleteness of statistical data.

3. Methods

The Mann–Kendall trend test, landscape index, and gravity center of migration were used to reveal the temporal characteristics and the spatial characteristics of farmland abandonment in four typical UAs during past two decades. Additionally, Geodetector was implemented to explore the urbanization drivers on farmland abandonment for 2002–2005, 2005–2010, 2010–2015, and 2015–2017 (Figure 2).

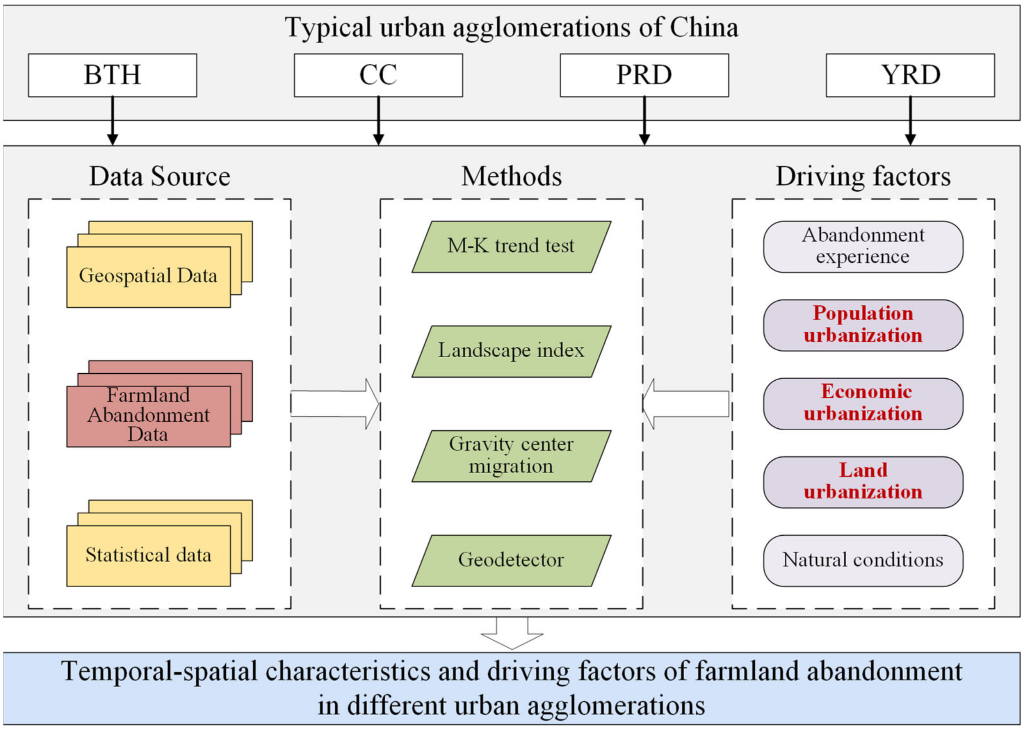

Figure 2. The flowchart of this research.

3.1. Trend Analysis Based on the Mann–Kendall Trend Test

The Mann–Kendall (M-K) trend test was used to identify the significance of the variation in farmland abandonment distributions in UAs for 2002–2010 and 2010–2017. This test has been widely used in extensive research to evaluate meteorological changes from time series data [70,71]. The M-K trend test statistics S is calculated according to Equations (1) and (2):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \tag{1}$$

$$sgn\left(x_j - x_i\right) = \begin{cases} 1, \ if \ x_j - x_i > 0 \\ 0, \ if \ x_j - x_i = 0 \\ -1, \ if \ x_j - x_i < 0 \end{cases} \tag{2}$$

where n refers to the time spans of abandoned farmland maps and x_i and x_j denote the farmland abandoned area in time series i and j ($i < j$). When $n \leq 10$, the corresponding probabilities of statistics S can be seen in the table in Gilbert [70]. While S is greater than zero and the tabled probability for S is less than the significance level specified a priori (α), this indicates that abandoned farmland area shows a remarkable increasing trend. Similarly, when S is less than zero and the corresponding probability is less than α, the abandoned farmland area shows a remarkable decreasing trend.

3.2. Landscape Pattern Indices

Four kinds of landscape indices, including the number of patches (NP), patch density (PD), landscape shape index (LSI), and aggregation index (AI) were selected to illustrate the landscape pattern of farmland abandonment in UAs, where the former three indices represent the landscape characteristics of individual farmland abandonment patches and AI represents the landscape heterogeneity characteristics of farmland abandonment patches (Table 2).

Table 2. The selected landscape indices used in this study.

Index Name	Formulas	Units	Range
Number of Patches (NP)	$NP = N$ (N = the number of abandoned farmland patches in the landscape)	None	$NP \geq 1$, without limit
Patch Density (PD)	$PD = N/A \times 10{,}000 \times 100$ (A = the area of landscape $\left(m^2\right)$)	Number per 100 hectares	$PD > 0$, constrained by cell size
Landscape Shape Index (LSI)	$LSI = \frac{0.25\sum_{k=1}^{m} e_{ik}^{*}}{\sqrt{A}}$ (e_{ik}^{*} = the total length (m) of edge in landscape between patch types i and k, type i refers to farmland abandonment, type k refers to other patches in landscape)	None	$LSI \geq 1$, without limit
Aggregation Index (AI)	$AI = \frac{g_{ii}}{max \to g_{ii}} \times 100$ (g_{ii} refers to the number of like adjacencies between pixels of abandoned farmland (patch type i) based on single-count method, $max \to g_{ii}$ refers to the maximum number of like adjacencies between pixels of abandoned farmland based on the single-count method)	Percent	$0 \leq AI \leq 100$

NP and PD reflect the fragmentation degree of the abandoned farmland patches. A greater NP represents more fragmented patches; similarly for PD. The patch shape types include regular geometric shapes and irregular shapes. A greater LSI means more protrusions around the patches, which reflects patches with irregular geometric shapes. A greater AI indicates concentrated distributions of abandoned patches. The indices were calculated at the class level.

3.3. Gravity Center of Farmland Abandonment Migration

Gravity center migration has been widely used to trace the spatiotemporal distribution variance [72] and is calculated as follows:

$$\overline{X_k} = \frac{\sum_{i=1}^{n} X_i k_i}{\sum_{i=1}^{n} k_i} \tag{3}$$

$$\overline{Y_k} = \frac{\sum_{i=1}^{n} Y_i k_i}{\sum_{i=1}^{n} k_i} \tag{4}$$

where X_i and Y_i refer to the longitude and latitude of county ith, respectively, and k_i refers to the kth indicator in the ith county. When we calculate the gravity center of farmland abandonment, k_i refers to the area of abandoned farmland in county ith, and $\overline{X_k}$ and $\overline{Y_k}$ refer to the longitude and latitude of the gravity center for farmland abandonment, respectively.

In this study, the gravity center migration model was also implemented to calculate the gravity centers of the population distribution, GDP, secondary industry product, and urban expansion in the four typical UAs for the past two decades. The trajectory of the gravity center of farmland abandonment migration was tracked with the gravity centers of population distribution migration, economic development migration, industrial development migration, and urban expansion migration.

3.4. Driving Factor Detection

The Geodetector model has been used to clarify the driving factors of farmland abandonment in UAs with different development statuses. These quantitative analysis tools can illustrate the potential driving factors by evaluating the spatial variance between the independent variable and dependent variable using the q value [73], which is calculated as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2 \quad (5)$$

where q denotes the driving forces of the independent variable on farmland abandonment, L represents the number of stratified classes, σ^2 represents the overall variance of the dependent variable, σ_h^2 represents the variance of the dependent variable in the Lth class, N refers to the number of geographic units, and N_h denotes the number of geographic units in the Lth class. The k-means cluster analysis method was used to classify each independent variable. According to the similarity between each independent variable, the k-means clustering method was used to divide all independent variables of the county-level sample into five categories for multiple iterations to minimize the loss function of the clustering result [74,75].

The range of the q value can indicate that the indicator controls the spatial distribution of $100 \times q\%$ farmland abandonment samples. The larger the q value, the stronger the forces of the factor's determination of farmland abandonment.

Additionally, the interactive effect on farmland abandonment driven by different drivers was quantitatively explored by Geodetector. This detection calculates the q values of two driving factors ($X1$ and $X2$) for the dependent variable, $q(X1)$, $q(X2)$, and the q value when $X1$ and $X2$ work together, $q(X1 \cap X2)$. Then, it determines how $X1$ and $X2$ interact by comparing the sizes among $q(X1 \cap X2)$, $q(X1)$, and $q(X2)$. The interaction mode demonstrated by the Geodetector is shown in Table A2 and the results of the interaction are shown in Appendix B.

4. Results

4.1. The Temporal Patterns of Farmland Abandonment

Urbanization accelerated farmland abandonment in the four studied UAs across the past two decades. Farmland abandonment areas in BTH and YRD were significantly greater than those in CC and PRD. The increase in farmland abandonment area in the YRD was greater than that in the other three UAs, followed sequentially by BTH, CC, and PRD. At the 95% confidence level, farmland abandonment area shows an increasing trend in all UAs after 2010.

The trend in changes in farmland abandonment area was affected by the urbanization development as indicated by the M-K trend test results (Table 3). Farmland abandonment area changed non-significantly in each UA from 2002 to 2010. The area in all UAs showed an increasing trend, except for BTH. An increasing trend was observed in farmland abandoned area in each UA from 2010 to 2017. Farmland abandonment area in BTH and PRD increased insignificantly, while the area in CC and YRD increased significantly.

Table 3. M-K trends in farmland abandonment area in the study area.

Period	Probabilities Value Corresponding to the Computed S			
	BTH	CC	PRD	YRD
2002–2010	−0.460 (ND)	0.130 (NI)	0.381 (NI)	0.022 (SI)
2010–2017	0.054 (NI)	0.016 (SI)	0.138 (NI)	0.003 (SI)

Specified significance level α = 0.05. ND refers to non-sig decrease, NI refers to non-sig increase and SI refers to sig increase.

It can be seen from Figure 3 that the farmland abandonment area of BTH and YRD was much larger than that of CC and PRD. The fastest-growing area of abandoned farmland from 2002 to 2017 was in YRD, while BTH and CC were relatively low, especially in the PRD.

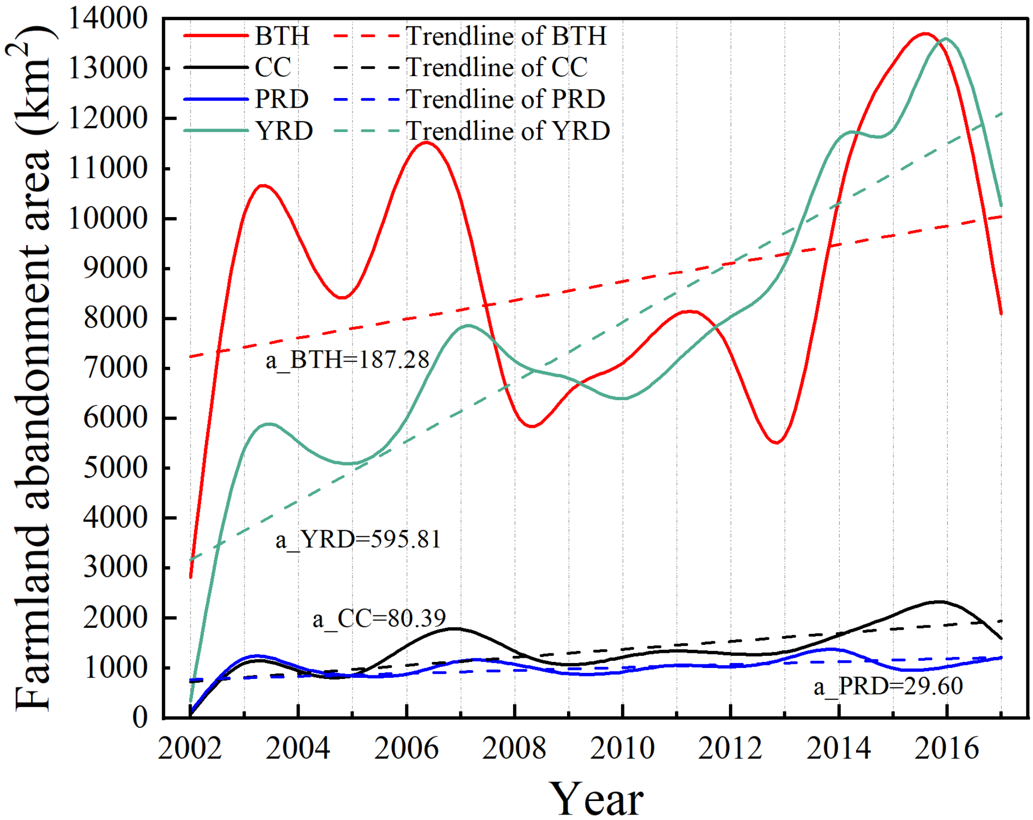

Figure 3. Changes in farmland abandonment area in typical UAs from 2002 to 2017.

The degree of abandoned farmland also exhibited an overall increasing status from 2002 to 2017, and the average degree of each UA peaked after 2010, as shown by the distribution of farmland abandonment degree in the UAs (Figure 4). According to the average degree of farmland abandonment of counties, the degree experienced increasing fluctuations and peaked in 2015 in BTH. In CC and YRD, the degree of farmland abandonment continued to increase before 2015 and began to decrease after 2015. In PRD, the average degree of farmland abandonment gradually increased over time and peaked in 2017. Among these UAs, CC had the most balanced spatial distribution of the abandonment degree, as evidenced by the smallest range of degree across counties.

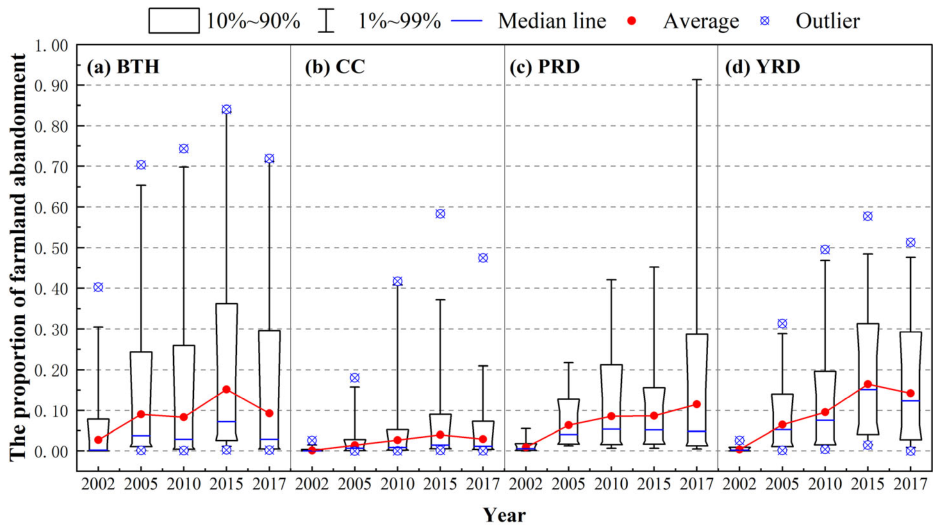

Figure 4. The distribution of farmland abandonment degree in typical UAs from 2002 to 2017.

4.2. The Landscape Pattern of Farmland Abandonment

Farmland abandonment patches showed a trend of being fragmentized and clustered in space in the four studies UAs across the past two decades, as shown by the change in landscape indices in these UAs (Figure 5). From 2002 to 2017, the abandoned farmland patches were gradually fragmented being of small size with increasing NP, PD, and LSI in the four studied UAs. Fortunately, the distribution of abandoned patches became more clustered throughout the period with increasing AI.

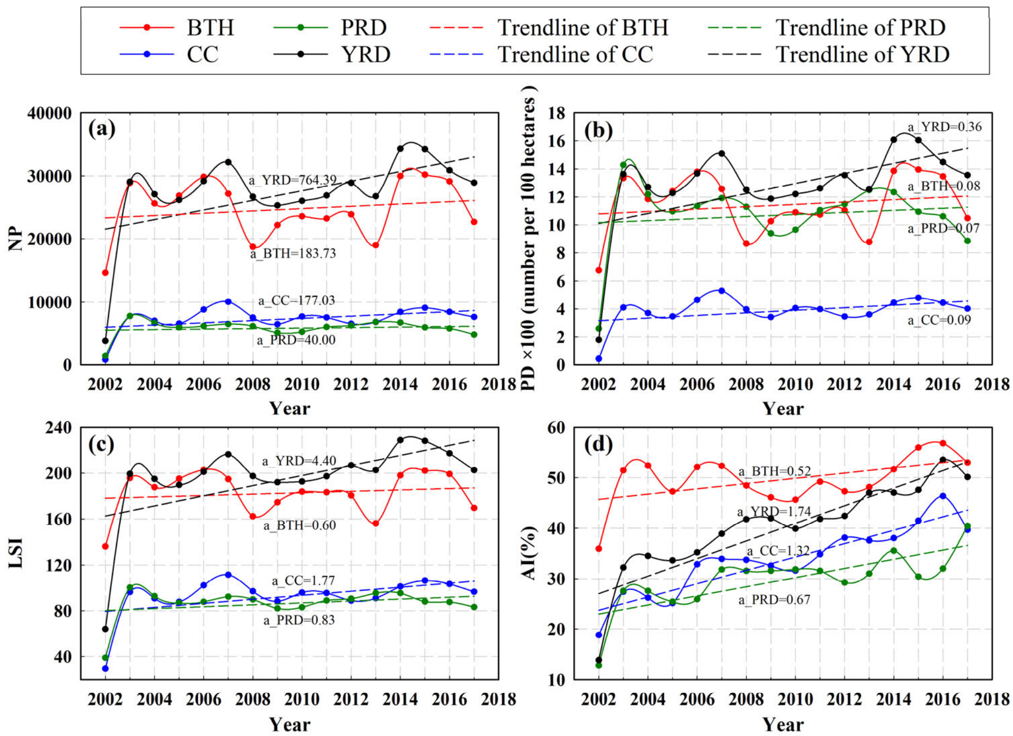

Figure 5. The landscape indices of abandoned patches in the four studied UAs from 2002 to 2017. The landscape indices include (**a**) Number, (**b**) Density, (**c**) Shape Index, and (**d**) Aggregation Index. The coefficient a_BTH refers to the slope of the trendline of BTH, like a_CC, a_PRD and a_YRD.

4.3. The Spatial Characteristics of Farmland Abandonment

Across the past two decades, the spatial distribution characteristics of farmland abandonment in the four studied UAs changed with the development of urbanization (Figure 6). The spatial distribution of farmland abandonment tended to align with population distribution in BTH and secondary industry agglomeration in PRD. For CC and YRD, the distribution of farmland abandonment was gradually approaching the direction of urban expansion.

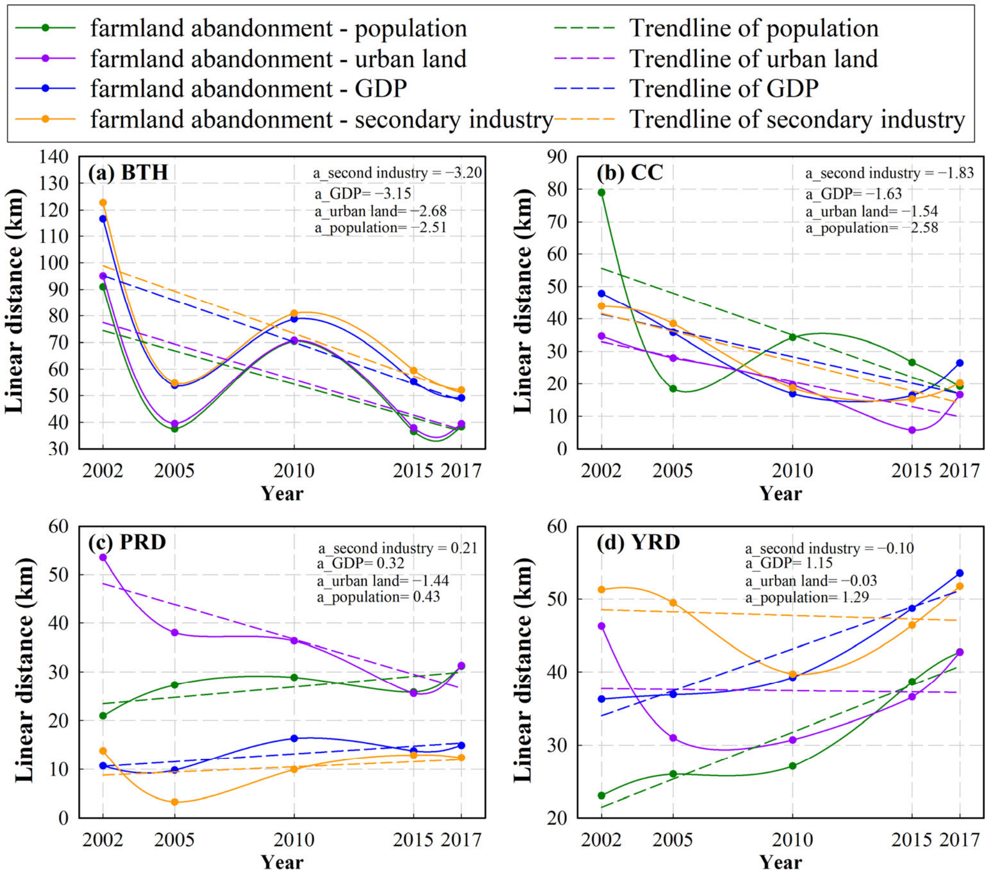

Figure 6. The distance between the gravity center of abandoned farmland and other gravity centers.

In BTH, the gravity center of farmland abandonment became closer to that of the population distribution. In CC, after 2015, the gravity center of farmland abandonment became closer to that of urban expansion. Since 2005, the gravity center of farmland abandonment in PRD has tended to be closer to that of secondary industry development, although the distance increased gradually between them. In YRD, prior to 2015, the gravity center of farmland abandonment had been moving closer to that of the population distribution; however, since 2015, it has been closer to that of urban expansion.

4.4. Driving Factors of Farmland Abandonment

Table 4 demonstrates the driving factors ($q > 0.20$) in the detection results of the four studied UAs. Different types of urbanization have different driving effects on farmland abandonment, due to diverse development strategies and statutes among UAs. Although the impact of the different types of urbanization varied in different UAs, the abandonment experience factor was the most important driving factor in the four studied UAs.

Table 4. Driving factor detection results in the four studied UAs derived from Geodetector.

Year	Serial Number	BTH		CC		PRD		YRD	
		Variable	q-Statistic	Variable	q-Statistic	Variable	q-Statistic	Variable	q-Statistic
2005	1	Ae_fa	0.92	Ae_fa	0.74	Ae_fa	0.92	Ae_fa	0.89
	2	Nc_ai	0.49	Lu_pua	0.47	Nc_pa	0.76	Eu_sp	0.47
	3	Nc_as	0.43	Eu_psd	0.43	Nc_re	0.67	Eu_psd	0.43
	4	Nc_pd	0.42	Eu_sp	0.38			Lu_pua	0.33
	5	Nc_ae	0.40	Pu_pd	0.34			Eu_sd	0.30
	6	Nc_re	0.40					Lu_ua	0.28
	7	Nc_pa	0.38					Pu_crpd	0.26
	8	Nc_lsi	0.28						
	9	Nc_np	0.23						
2010	1	Ae_fa	0.80	Ae_fa	0.74	Ae_fa	0.94	Ae_fa	0.89
	2	Nc_ai	0.72	Eu_psd	0.66	Nc_re	0.68	Eu_psd	0.44
	3	Nc_pa	0.63	Lu_pua	0.62	Pu_crpd	0.59	Lu_pua	0.42
	4	Nc_as	0.57	Eu_sp	0.49	Pu_pd	0.48	Eu_sp	0.41
	5	Nc_pd	0.54	Pu_pd	0.45			Eu_sd	0.26
	6	Nc_ae	0.53	Lu_ua	0.34			Nc_area	0.21
	7	Nc_re	0.48	Nc_area	0.28				
	8	Nc_np	0.48	Pu_crpd	0.23				
	9	Nc_lsi	0.40						
	10	Nc_at	0.33						
2015	1	Ae_fa	0.79	Ae_fa	0.86	Ae_fa	0.95	Ae_fa	0.90
	2	Nc_ai	0.54	Lu_pua	0.66	Pu_crep	0.54	Eu_pGDP	0.43
	3	Nc_pd	0.48	Eu_pGDP	0.65			Nc_ai	0.41
	4	Nc_ae	0.47	Pu_pd	0.61			Pu_crpd	0.40
	5	Nc_as	0.43	Eu_sp	0.41			Eu_sp	0.39
	6	Nc_pa	0.35	Lu_ua	0.33			Pu_crep	0.39
	7	Nc_re	0.32	Pu_crep	0.27			Lu_pua	0.31
	8	Nc_lsi	0.22	Nc_area	0.27			Nc_pa	0.28
	9			Nc_ap	0.24			Pu_ep	0.23
	10			Pu_crpd	0.24			Nc_area	0.21
2017	1	Ae_fa	0.91	Ae_fa	0.92	Ae_fa	0.97	Ae_fa	0.87
	2	Nc_pd	0.56	Lu_pua	0.42			Lu_pua	0.33
	3	Nc_as	0.55	Eu_sp	0.42			Nc_ai	0.32
	4	Nc_ai	0.54	Lu_ua	0.38			Eu_sp	0.30
	5	Nc_ae	0.48	Eu_pGDP	0.33			Eu_pGDP	0.30
	6	Nc_re	0.44	Pu_pd	0.29			Nc_pa	0.26
	7	Nc_pa	0.42	Nc_area	0.25			Eu_GDP	0.24
	8	Nc_lsi	0.31					Pu_ep	0.21
	9	Nc_np	0.25						
	10	Nc_at	0.25						

In BTH, abandonment experience and natural conditions were the main driving factors of farmland abandonment, while urbanization factors did not have a dominant influence. In 2005, the major types of factors affecting farmland abandonment in BTH included abandonment experience and natural conditions, with q values of Ae_fa, Nc_{ai}, and Nc_as of 0.92, 0.49, and 0.43, respectively. The driving factors in other years were similar to those in 2005.

In addition to abandonment experience, land urbanization and economic urbanization were the primary drivers of farmland abandonment in CC. Economic urbanization had a more serious impact on farmland abandonment in 2010, with q values of Eu_psd and Lu_pua of 0.66 and 0.62, respectively; while the impact of land urbanization was greater than that of economic urbanization in 2005, 2015, and 2017.

For PRD, population urbanization was generally one of the driving factors, in addition to that of abandonment experience. In 2010 and 2015, population urbanization became the dominant factor in farmland abandonment, with a q value of Pu_crpd of 0.59 in 2010 and a q value of Pu_crep of 0.54 in 2015.

In YRD, abandonment experience and economic urbanization were mostly the dominant driving factors. Economic urbanization was the continuous leading factor in farmland abandonment before 2017, with a q value of Eu_sp of 0.47 in 2005, a q value of Eu_psd of 0.44 in 2010, and a q value of Eu_pGDP of 0.43 in 2015. Howver, the dominant influence of economic urbanization was replaced by land urbanization in 2017, with a q value of Lu_pua of 0.33 in 2017.

5. Discussion

Among all the factors including natural conditions, land urbanization, population urbanization, and economic urbanization, past experience of abandonment stands out as the most significant influencer of farmland abandonment. Consequently, farmland that has undergone abandonment in the past may face a higher likelihood of abandonment in future agricultural activities. This aspect distinguishes our study from others examining the impact of urbanization on farmland abandonment [27,40]. The underlying reasons for this phenomenon may be attributed to the integrated cultivation conditions resulting from both the inherent resource endowment and the geographical condition of the farmland. This finding suggests that targeted attention should be paid to previously abandoned farmland by systematically integrating monitoring of the distribution of farmland abandonment and assessments of farmland suitability into the farmland policymaking process.

Although past abandonment experiences are the primary driving force behind farmland abandonment in the studied UAs, the mechanisms driving farmland abandonment varied due to differences in the development trajectories of the UAs.

Among the four studied UAs, the development of urbanization did not significantly drive farmland abandonment in BTH, although BTH has the largest area of abandoned farmland and the highest proportion of farmland abandonment in terms of total arable land area. As the political center of China, BTH's farmland is more likely to be subjected to stricter agricultural land policy regulation. Due to its location in northern China, BTH experiences relatively poor natural conditions for cultivation, resulting in a great portion of arable land being utilized by farmers for developing economic crops such as greenhouses. While these farming practices may align with policies aimed at agricultural development, in our study, it is identified as abandonment. This may explain the high levels of farmland abandonment in terms of both area and proportion in this region. To enhance the reclamation of grain crops in this region, it is crucial to develop scientific and technological advancements aimed at improving soil quality, increasing crop yields, and implementing measures to ensure agricultural production, thereby encouraging more farmers to engage in grain production. Alternatively, in accordance with national food demand planning, the region could continue developing economic crops based on land suitability.

While related studies have demonstrated the direct impact of topographical conditions on farmland abandonment within CC [76,77], our research findings indicate that farmland abandonment is also influenced by economic urbanization and land urbanization in the region. CC encompasses Sichuan Province, which is one of the major agricultural provinces in western China. Farmland in this region is primarily concentrated in eastern basins and low hills. Farmland affected by changes in elevation and slope conditions serves as the primary source of abandonment. Existing research on farmland abandonment highlights CC as a hotspot region for such phenomena in China. However, our research confirms that farmland abandonment in this area is relatively low compared to the other three UAs, both in terms of farmland abandonment area and as a proportion of arable land area. Despite being the largest urban agglomeration in western China, nationally, CC has the greatest farmland area and the highest proportion of farmland area. The increasing variance in savings deposits and GDP among counties within CC indicates a widening economic gap, which is a primary factor exacerbating farmland abandonment. This trend was particularly pronounced around 2010. Also, the urbanization of CC is currently in a phase of sustained growth and optimization, with minimal disparities in the degree of land urbanization across its various regions. Consequently, the advancement of land urbanization and economic urbanization will both be significant factors contributing to farmland abandonment in the region. CC continues to be a city cluster undergoing rapid urbanization and development, thus, agricultural land policy formulation in the region needs to comprehensively consider both urbanization and the sustainable development of farmland.

Due to the impact of population urbanization, a large influx of rural laborers to urban areas attracted by the rapid regional industrial transformation and upgrading has contributed to farmland abandonment in PRD. The significant disparities in GDP and population density among different areas in PRD reflect the substantial development disparities within the urban agglomeration. This dynamic results in a considerable number of rural laborers being affected by the urban–rural income gap, prompting them to abandon low-income agricultural work in favor of urban employment, leading to significant population mobility. Since 2017, the impact of population urbanization has diminished, which can potentially be attributed to the advancement of the land-leasing market, coupled with enhancements in urban social insurance systems and increased levels of urban social integration, thereby leading to a deceleration in population density growth within the region. Therefore, to alleviate farmland abandonment in PRD, targeted subsidies can be provided to increase farmers' income, thereby enhancing their productivity and reducing rural labor outflow, thus mitigating the trend of farmland abandonment in the region.

Economic urbanization continues to serve as a sustained driving force on farmland abandonment in YRD. YRD has diverse economic development opportunities, with significant increases in residents' savings balances and regional GDP growth over the past two decades. YRD is located in central China with favorable natural conditions for agriculture. The majority of farmland in this UA is suitable for multiple cropping, making it one of China's primary grain-producing regions. With a significant expanse of farmland, the region also faces a notable issue of farmland abandonment, which should be paid increased attention by the government and relevant administrators. Especially after 2015, the influence of land urbanization in YRD outweighed that of economic urbanization, as during this period, land urbanization outpaced population urbanization [57]. The extensive and inefficient use of construction land resulted in the wastage of a considerable amount of arable land resources. The population density and regional population density differences in this UA are not high compared to other UAs, indicating that population urbanization is not the primary driving factor. YRD can mitigate the trend in farmland abandonment by promoting the revitalization of rural areas in China, narrowing the urban–rural gap, and preventing population urbanization effects from economic urbanization.

6. Conclusions

The findings of this study highlight the role of urbanization in accelerating farmland abandonment, particularly evident in the increasing fragmentation and aggregation of abandoned farmland patches within the four studied UAs over the past two decades. Notably, YRD experienced a greater increase in abandoned farmland compared to the other UAs, indicating a significant extent of farmland abandonment requiring attention. The overall degree of abandoned farmland also exhibited a consistent increase from 2002 to 2017, with each UA reaching a peak degree after 2010. Moreover, the farmland abandonment patches demonstrated a trend of becoming fragmentized and clustered in space in the four UAs over the study period, characterized by smaller sizes and increasing values of NP, PD, and LSI in the four UAs. Further analysis identified abandonment experience as the primary driver of continuous farmland abandonment within the studied UAs across the past two decades, emphasizing the importance of addressing abandoned farmland in land management policies. Additionally, the study revealed diverse driving factors in the politically dominated BTH, resource-dominated CC, population-dominated PRD, and economically dominated YRD at different urbanization stages. Despite BTH having the largest area and the highest proportion of farmland abandonment relative to total arable land, urbanization development did not significantly influence farmland abandonment in this UA. In contrast, economic urbanization and land urbanization were the predominant drivers of farmland abandonment in CC, while population urbanization mainly impacted farmland abandonment in PRD. In the YRD region, the driving factors of farmland abandonment varied with different stages of urbanization development, transitioning from economic urbanization before 2015 to land urbanization after 2015. Despite the range of its findings, the study has some limitations. First, the spatial resolution of farmland abandonment maps was 250 m, which might not adequately capture the effects of varying agriculture patch sizes. Developing methodologies to produce higher-resolution farmland abandonment datasets would be beneficial for more precise analyses. Additionally, slight discrepancies arising from variations in data sources and temporal gaps between years could introduce errors in the driving factor analysis. Due to constraints in accessing statistical and land use data, certain changes and indicators may have been ignored. Moreover, this research solely examined the indirect impacts of land policies, such as GDP, population, and industrial development. Further investigations need to be conducted for accurate assessments of policy impacts. The research findings provide data support and scientific explanation for the formulation of land policies and sustainable development strategies in urban agglomerations under different development strategies.

Author Contributions: Conceptualization, N.Z. and L.L.; methodology, L.L. and L.H.; formal analysis, N.Z., Z.Z., and X.Y.; investigation, Z.Z.; data curation, N.Z. and X.Z.; writing—original draft preparation, N.Z., L.L., and K.Z.; writing—review and editing, L.L. and K.Z.; project administration, L.L.; funding acquisition, L.L. and K.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Project of the National Natural Science Foundation of China (grant No. 41901345, No. 42101417). This research was also supported by the Project of the Science and Technology Foundation of Guangdong Province (grant No. 2023A1515010897, No. 2022A1515010641).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Detection indicators used in this study.

Variables	Abbr.	Description	Calculate or Access
Dependent variable	Y_i	The proportion of abandoned farmland area to arable land area in year *i*	$Y_i = AFA/Nc\_area$ in year i (AFA refers to abandoned farmland area, Nc_area refers to arable land area)
Independent variables		Abandonment experience	
	Ae_fa	The average proportion of abandoned farmland area to arable land area in the past few years	\
		Population urbanization	
	Pu_pop	Total population	Calculate with LandScan in year i
	Pu_pd	Population density	$Pu\_pd = Pu\_pop/AUA$ in year i (AUA refers to the total area of county)

Table A1. *Cont.*

Variables	Abbr.	Description	Calculate or Access
	Pu_crpd	Changing rate of population density	$Pu\_crpd = \frac{[Pu\_pd\ in\ i\ -\ Pu\_pd\ in\ h]}{Pu\_pd\ in\ h}$
	Pu_re	Rural employment	Obtained from the Statistical Yearbook in year i
	Pu_crre	Changing rate of rural employment	$Pu\_crre = \frac{[Pu\_re\ in\ i\ -\ Pu\_re\ in\ h]}{Pu\_re\ in\ h}$
	Pu_ep	Employment in primary industry	$Pu\_ep = pu\_r - pu\_st$ in year i (pu_r refers to registered population in Statistical Yearbook, pu_st refers to people employed in the secondary and tertiary industry in Statistical Yearbook)
	Pu_crep	Changing rate of employment in primary industry	$Pu\_crep = \frac{[Pu\_ep\ in\ i - Pu\_ep\ in\ h]}{Pu\_ep\ in\ h}$
	Economic urbanization		
	Eu_GDP	GDP	Obtained from the Statistical Yearbook in year i
	Eu_pGDP	Per capita GDP	$Eu\_pGDP = Eu\_GDP/Pu\_pop$ in year i
	Eu_sd	Savings deposits of residents	Obtained from the Statistical Yearbook
	Eu_psd	Per capita saving deposits of residents	$Eu\_psd = Eu\_sd/Pu\_pop$ in year i
	Eu_p	Increase in value of primary industry	Obtained from the Statistical Yearbook in year i
	Eu_sp	The ratio of secondary industry increase value to primary industry increase value	$Eu\_sp = eu\_s/Eu\_p$ in year i (eu_s refers to increase value of the secondary industry in Statistical Yearbook)
	Land urbanization		
	Lu_ua	Area of urban land	Calculate with CNLUCC in year i
	Lu_pua	The proportion of urban area in total area	$Lu\_pua = Lu\_ua/AUA$ in year i
	Lu_crpua	Changing rate of urban area proportion	$Lu\_crpua = \frac{[Lu\_pua\ in\ i - Lu\_pua\ in\ h]}{Lu\_pua\ in\ h}$
	Natural topographic conditions		
	Nc_ae	Average elevation	Calculate with DEMs
	Nc_re	Range of elevation	
	Nc_as	Average slope	
	Natural climate conditions		
	Nc_ap	Average annual precipitation in past years	Calculate with monthly temperature and precipitation dataset
	Nc_at	Average annual temperature in past years	
	Patch characteristics of arable land		
	Nc_area	Area of arable land	Calculate with CNLUCC in year i

Table A1. *Cont.*

Variables	Abbr.	Description	Calculate or Access
	Nc_pa	Proportion of arable land area in total area	$Nc\_pa = Nc\_area/AUA$ in year i
	Nc_np	Number of arable land patches	Calculate with CNLUCC in year i
	Nc_pd	Patch density of arable land patches	
	Nc_lsi	Landscape shape index of arable land patches	
	Nc_ai	Aggregation index of arable land patches	

Note: When i = 2005, 2010, 2015, 2017, h = 2002, 2005, 2010, 2015, respectively.

Table A2. Interaction detection mode in Geodetector.

Criterion	Interaction
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear enhancement
$q(X1 \cap X2) = q(X1) + q(X2)$	Mutual independence
$q(X1 \cap X2) > Max(q(X1), q(X2))$	Bilinear enhancement
$Min(q(X1), q(X2)) < q(X1 \cap X2) < Max(q(X1), q(X2))$	Single-factor nonlinear weakening
$q(X1 \cap X2) < Min(q(X1), q(X2))$	Nonlinear weakening

Appendix B Interactive Detection Results of Farmland Abandonment

Across the past 20 years, the experience of farmland abandonment, urbanization processes, and the combined influence of natural conditions have mainly led to a gradually intensifying trend in farmland abandonment in the four studied UAs (Figure A1).

The interaction between farmland abandonment experience and natural conditions in BTH intensified the phenomenon of farmland abandonment from 2002 to 2005 and 2010 to 2015, while it contributed to a partial alleviation of farmland abandonment occurrences from 2005 to 2010 and 2015 to 2017. The interaction between farmland abandonment experience and economic urbanization and the interaction between farmland abandonment experience and land urbanization, respectively, promoted the aggravation of farmland abandonment in CC from 2002 to 2010 and 2010 to 2015. Fortunately, the interaction of farmland abandonment experience and economic urbanization gave relief from farmland abandonment after 2015.

In PRD, the interaction between farmland abandonment experience and natural conditions aggravated farmland abandonment from 2002 to 2005, and, from 2005 to 2015, the interaction between farmland abandonment experience and population urbanization greatly promoted the continuance of abandonment. The single factor of farmland abandonment experience promoted the intensification of farmland abandonment from 2015 to 2017. The interaction between farmland abandonment experience and economic urbanization accelerated the occurrence of farmland abandonment in YRD before 2015. However, the interaction of farmland abandonment experience and natural conditions slowed down the occurrence of abandonment from 2015 to 2017.

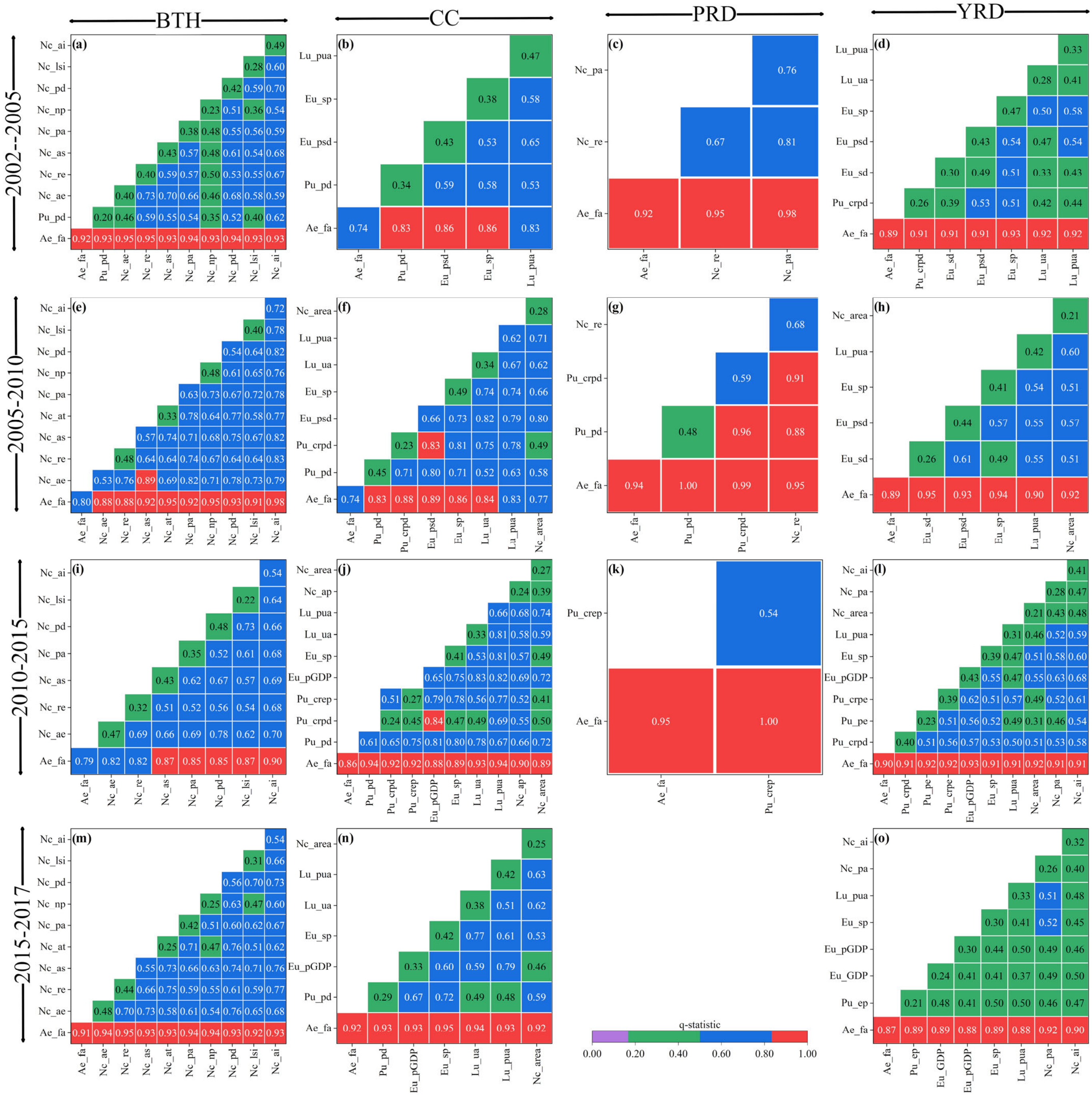

Figure A1. Interaction detection results of drivers of farmland abandonment in the four studied UAs from 2002 to 2017. ((**a**,**e**,**i**,**m**) depict the interactive detection results of dominant driving factors of BTH during 2002–2005, 2005–2010, 2010–2015, 2015–2017, respectively. (**b**,**f**,**j**,**n**) illustrate the interactive detection results of dominant driving factors of CC during 2002–2005, 2005–2010, 2010–2015, 2015–2017, respectively. (**c**,**g**,**k**) show the interactive detection results of dominant driving factors of PRD during2002–2005, 2005–2010, 2010–2015, 2015–2017, respectively. (**d**,**h**,**l**,**o**) exhibit the interactive detection results of dominant driving factors of YRD during 2002–2005, 2005–2010, 2010–2015, 2015–2017, respectively).

References

1. Zheng, Q.; Ha, T.; Prishchepov, A.V.; Zeng, Y.; Yin, H.; Koh, L.P. The neglected role of abandoned cropland in supporting both food security and climate change mitigation. *Nat. Commun.* **2023**, *14*, 6083. [CrossRef]
2. Ghose, B. Food security and food self-sufficiency in China: From past to 2050. *Food Energy Secur.* **2014**, *3*, 86–95. [CrossRef]

3. Zhou, T.; Koomen, E.; Ke, X. Determinants of Farmland Abandonment on the Urban–Rural Fringe. *Environ. Manag.* **2020**, *65*, 369–384. [CrossRef]
4. Zhu, X.; Xiao, G.; Zhang, D.; Guo, L. Mapping abandoned farmland in China using time series MODIS NDVI. *Sci. Total Environ.* **2021**, *755*, 142651. [CrossRef] [PubMed]
5. He, C.; Liu, Z.; Xu, M.; Ma, Q.; Dou, Y. Urban expansion brought stress to food security in China: Evidence from decreased cropland net primary productivity. *Sci. Total Environ.* **2017**, *576*, 660–670. [CrossRef]
6. Khanal, U. Why are farmers keeping cultivatable lands fallow even though there is food scarcity in Nepal? *Food Secur.* **2018**, *10*, 603–614. [CrossRef]
7. Katayama, N.; Mashiko, M.; Koshida, C.; Yamaura, Y. Effects of rice-field abandonment rates on bird communities in mixed farmland–woodland landscapes in Japan. *Agric. Ecosyst. Environ.* **2021**, *319*, 107539. [CrossRef]
8. Lark, T.J.; Spawn, S.A.; Bougie, M.; Gibbs, H.K. Cropland expansion in the United States produces marginal yields at high costs to wildlife. *Nat. Commun.* **2020**, *11*, 4295. [CrossRef]
9. Grădinaru, S.R.; Kienast, F.; Psomas, A. Using multi-seasonal Landsat imagery for rapid identification of abandoned land in areas affected by urban sprawl. *Ecol. Indic.* **2017**, *96*, 79–86. [CrossRef]
10. Qiu, B.; Yang, X.; Tang, Z.; Chen, C.; Li, H.; Berry, J. Urban expansion or poor productivity: Explaining regional differences in cropland abandonment in China during the early 21st century. *Land Degrad. Dev.* **2020**, *31*, 2540–2551. [CrossRef]
11. Zhou, B.B.; Aggarwal, R.; Wu, J.; Lv, L. Urbanization-associated farmland loss: A macro-micro comparative study in China. *Land Use Policy* **2021**, *101*, 105228. [CrossRef]
12. Liu, X.; Xu, Y.; Engel, B.A.; Sun, S.; Wang, Y. The impact of urbanization and aging on food security in developing countries: The view from Northwest China. *J. Clean. Prod.* **2021**, *292*, 126067. [CrossRef]
13. Soma, K.; Hennen, W.; Berkum, S.v. Can Domestic Food Production Provide Future Urban Populations with Food and Nutrition Security?—Insights from Bangladesh, Kenya and Uganda. *Sustainability* **2023**, *15*, 9005. [CrossRef]
14. Wang, S.; Bai, X.; Zhang, X.; Reis, S.; Chen, D.; Xu, J.; Gu, B. Urbanization can benefit agricultural production with large-scale farming in China. *Nat. Food* **2021**, *2*, 183–191. [CrossRef] [PubMed]
15. Vasylieva, N.; James, H. The Effect of Urbanization on Food Security and Agricultural Sustainability. *Econ. Sociol.* **2021**, *14*, 76–88. [CrossRef]
16. Fang, C. Important progress and future direction of studies on China's urban agglomerations. *J. Geogr. Sci.* **2015**, *25*, 1003–1024. [CrossRef]
17. Fang, C.; Yu, D. Urban agglomeration: An evolving concept of an emerging phenomenon. *Landsc. Urban Plan.* **2017**, *162*, 126–136. [CrossRef]
18. Li, L.; Ma, S.; Zheng, Y.; Xiao, X. Integrated regional development: Comparison of urban agglomeration policies in China. *Land Use Policy* **2022**, *114*, 105939. [CrossRef]
19. Wang, Y.; Niu, Y.; Li, M.; Yu, Q.; Chen, W. Spatial structure and carbon emission of urban agglomerations: Spatiotemporal characteristics and driving forces. *Sustain. Cities Soc.* **2022**, *78*, 103600. [CrossRef]
20. Hu, S.; Tong, L.; Frazier, A.E.; Liu, Y. Urban boundary extraction and sprawl analysis using Landsat images: A case study in Wuhan, China. *Habitat Int.* **2015**, *47*, 183–195. [CrossRef]
21. Scott, A.J.; Storper, M. The Nature of Cities: The Scope and Limits of Urban Theory. *Int. J. Urban Reg. Res.* **2014**, *39*, 1–15. [CrossRef]
22. Hu, T.; Dong, J.; Hu, Y.n.; Qiu, S.; Yang, Z.; Zhao, Y.; Cheng, X.; Peng, J. Stage response of vegetation dynamics to urbanization in megacities: A case study of Changsha City, China. *Sci. Total Environ.* **2023**, *858*, 159659. [CrossRef]
23. Wu, J.; Chen, B.; Mao, J.; Feng, Z. Spatiotemporal evolution of carbon sequestration vulnerability and its relationship with urbanization in China's coastal zone. *Sci. Total Environ.* **2018**, *645*, 692–701. [CrossRef] [PubMed]
24. Zanden, V.D.; Emma, H.; Verburg; Peter, H.; Schulp; Catharina, J.E.; Verkerk; Johannes, P. Trade-offs of European agricultural abandonment. *Land Use Policy* **2017**, *62*, 290–301. [CrossRef]
25. Xingrong, Z.; Shuai, S.; Xi, Z. Decoupling CO_2 emissions and industrial growth in China over 1993–2013: The role of investment. *Energy Econ.* **2016**, *60*, 275–292.
26. Zhou, C.; Wang, S.; Wang, J. Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Sci. Total Environ.* **2019**, *675*, 472–482. [CrossRef]
27. Sroka, W.; Pölling, B.; Wojewodzic, T.; Strus, M.; Stolarczyk, P.; Podlinska, O. Determinants of Farmland Abandonment in Selected Metropolitan Areas of Poland: A Spatial Analysis on the Basis of Regression Trees and Interviews with Experts. *Sustainability* **2019**, *11*, 3071. [CrossRef]
28. Chen, J.; Wang, L.; Li, Y. Research on the impact of multi-dimensional urbanization on China's carbon emissions under the background of COP21. *J. Environ. Manag.* **2020**, *273*, 111123. [CrossRef] [PubMed]
29. Shi, T.; Li, X.; Xin, L.; Xu, X. The spatial distribution of farmland abandonment and its influential factors at the township level: A case study in the mountainous area of China. *Land Use Policy* **2018**, *70*, 510–520. [CrossRef]
30. Deng, X.; Huang, J.; Rozelle, S.; Zhang, J.; Li, Z. Impact of urbanization on cultivated land changes in China. *Land Use Policy* **2015**, *45*, 1–7. [CrossRef]
31. Zhang, Q.; Song, C.; Chen, X. Effects of China's payment for ecosystem services programs on cropland abandonment: A case study in Tiantangzhai Township, Anhui, China. *Land Use Policy* **2018**, *73*, 239–248. [CrossRef]

32. Wang, Y.; Li, X.; Xin, L.; Tan, M. Farmland marginalization and its drivers in mountainous areas of China. *Sci. Total Environ.* **2020**, *719*, 135132. [CrossRef] [PubMed]
33. Quintas-Soriano, C.; Buerkert, A.; Plieninger, T. Effects of land abandonment on nature contributions to people and good quality of life components in the Mediterranean region: A review. *Land Use Policy* **2022**, *116*, 106053. [CrossRef]
34. Kuemmerle, T.; Hostert, P.; Radeloff, V.C.; Linden, S.V.D.; Perzanowski, K.; Kruhlov, I. Cross-border Comparison of Post-socialist Farmland Abandonment in the Carpathians. *Ecosystems* **2008**, *11*, 614–628. [CrossRef]
35. Alcantara, C.; Kuemmerle, T.; Prishchepov, A.V.; Radeloff, V.C. Mapping abandoned agriculture with multi-temporal MODIS satellite data. *Remote Sens. Environ.* **2012**, *124*, 334–347. [CrossRef]
36. Li, L.; Pan, Y.; Zheng, R.; Liu, X. Understanding the spatiotemporal patterns of seasonal, annual, and consecutive farmland abandonment in China with time-series MODIS images during the period 2005–2019. *Land Degrad. Dev.* **2022**, *33*, 1608–1625. [CrossRef]
37. Deng, J.; Guo, Y.; Chen, X.; Liu, L.; Liu, W. Abandoned Farmland Extraction and Feature Analysis Based on Multi-Sensor Fused Normalized Difference Vegetation Index Time Series-A Case Study in Western Mianchi County. *Appl. Sci.* **2024**, *14*, 2102. [CrossRef]
38. Chaudhary, S.; Wang, Y.; Dixit, A.M.; Khanal, N.R.; Xu, P.; Fu, B.; Yan, K.; Liu, Q.; Lu, Y.; Li, M. A Synopsis of Farmland Abandonment and Its Driving Factors in Nepal. *Land* **2020**, *9*, 84. [CrossRef]
39. Xie, H.; Wang, P.; Yao, G. Exploring the Dynamic Mechanisms of Farmland Abandonment Based on a Spatially Explicit Economic Model for Environmental Sustainability: A Case Study in Jiangxi Province, China. *Sustainability* **2014**, *6*, 1260–1282. [CrossRef]
40. Hou, D.; Meng, F.; Prishchepov, A.V. How is urbanization shaping agricultural land-use? Unraveling the nexus between farmland abandonment and urbanization in China. *Landsc. Urban Plan.* **2021**, *214*, 104170. [CrossRef]
41. Liu, B.; Tian, C.; Li, Y.; Song, H.; Ma, Z. Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. *J. Clean. Prod.* **2018**, *197*, 1374–1381. [CrossRef]
42. Pazur, R.; Lieskovsky, J.; Buergi, M.; Mueller, D.; Lieskovsky, T.; Zhang, Z.; Prischchepov, A.V. Abandonment and Recultivation of Agricultural Lands in Slovakia-Patterns and Determinants from the Past to the Future. *Land* **2020**, *9*, 316. [CrossRef]
43. Corbelle-Rico, E.; Crecente-Maseda, R.; Sante-Riveira, I. Multi-scale assessment and spatial modelling of agricultural land abandonment in a European peripheral region: Galicia (Spain), 1956–2004. *Land Use Policy* **2012**, *29*, 493–501. [CrossRef]
44. Subedi, Y.R.; Kristiansen, P.; Cacho, O.; Ojha, R.B. Agricultural Land Abandonment in the Hill Agro-ecological Region of Nepal: Analysis of Extent, Drivers and Impact of Change. *Environ. Manag.* **2021**, *67*, 1100–1118. [CrossRef] [PubMed]
45. Mueller, D.; Leitao, P.J.; Sikor, T. Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. *Agric. Syst.* **2013**, *117*, 66–77. [CrossRef]
46. Zhou, Y.; Chen, T.; Feng, Z.; Wu, K. Identifying the contradiction between the cultivated land fragmentation and the construction land expansion from the perspective of urban-rural differences. *Ecol. Inform.* **2022**, *71*, 101826. [CrossRef]
47. Jose Ruiz-Lendinez, J. Abandoned Farmland Location in Areas Affected by Rapid Urbanization Using Textural Characterization of High Resolution Aerial Imagery. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 191. [CrossRef]
48. Chen, H.P.; Shen, Q.L.; Zang, D.G.; Li, H.J.; Sow, Y. Study on the impact of environmental pollution on farmland abandonment. *Environ. Sci. Pollut. Res.* **2022**, *29*, 1458–1469. [CrossRef]
49. Mameno, K.; Kubo, T. Socio-economic drivers of irrigated paddy land abandonment and agro-ecosystem degradation: Evidence from Japanese agricultural census data. *PLoS ONE* **2022**, *17*, e0266997. [CrossRef]
50. Levers, C.; Mueller, D.; Erb, K.; Haberl, H.; Jepsen, M.R.; Metzger, M.J.; Meyfroidt, P.; Plieninger, T.; Plutzar, C.; Sturck, J.; et al. Archetypical patterns and trajectories of land systems in Europe. *Reg. Environ. Change* **2018**, *18*, 715–732. [CrossRef]
51. Ustaoglu, E.; Collier, M.J. Farmland abandonment in Europe: An overview of drivers, consequences, and assessment of the sustainability implications. *Environ. Rev.* **2018**, *26*, 396–416. [CrossRef]
52. Tang, L.; Li, K. A comparative analysis on energy-saving and emissions-reduction performance of three urban agglomerations in China. *J. Clean. Prod.* **2019**, *220*, 953–964. [CrossRef]
53. Zhang, L.; Zhao, N.; Zhang, W.; Wilson, J.P. Changes in Long-Term PM2.5 Pollution in the Urban and Suburban Areas of China's Three Largest Urban Agglomerations from 2000 to 2020. *Remote Sens.* **2022**, *14*, 1716. [CrossRef]
54. Li, S.; Xiao, J.; Lei, X.; Wang, Y. Farmland abandonment in the mountainous areas from an ecological restoration perspective: A case study of Chongqing, China. *Ecol. Indic.* **2023**, *153*, 110412. [CrossRef]
55. Wang, Y.; Peng, P.; Li, Q.; Chen, Z.; Tang, W. Spatial Heterogeneity of Farmland Abandonment in the Sichuan Province, China. *Sustainability* **2020**, *12*, 3356. [CrossRef]
56. Ding, R.; Fu, J.; Zhang, Y.L.; Zhang, T.; Yin, J.; Du, Y.M.; Zhou, T.; Du, L.Y. Research on the Evolution of the Economic Spatial Pattern of Urban Agglomeration and Its Influencing Factors, Evidence from the Chengdu-Chongqing Urban Agglomeration of China. *Sustainability* **2022**, *14*, 10969. [CrossRef]
57. National Development and Reform Commission. Development Planning of Chengdu Chongqing Urban Agglomeration. 2016. Available online: https://www.ndrc.gov.cn/ (accessed on 1 June 2022).
58. Bright, E.; Coleman, P.; King, A. LandScan Global 2005. 2006. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).
59. Bright, E.; Coleman, P.; Rose, A.; Urban, M. LandScan Global 2010. 2011. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).

60. Bright, E.; Rose, A.; Urban, M. LandScan Global 2015. 2016. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).
61. Bright, E.; Coleman, P. LandScan Global 2002. 2003. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).
62. Rose, A.; McKee, J.; Urban, M.; Bright, E. LandScan Global 2017. 2018. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).
63. Chen, J.; Xu, C.; Li, K.; Song, M. A gravity model and exploratory spatial data analysis of prefecture-scale pollutant and CO_2 emissions in China. *Ecol. Indic.* **2018**, *90*, 554–563. [CrossRef]
64. Peng, S.; Ding, Y.; Liu, W.; Li, Z. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017. *Earth Syst. Sci. Data* **2019**, *11*, 1931–1946. [CrossRef]
65. National Bureau of Statistics of China. *China County Statistical Yearbook*; NBS: Beijing, China, 2003.
66. National Bureau of Statistics of China. *China County Statistical Yearbook*; NBS: Beijing, China, 2006.
67. National Bureau of Statistics of China. *China County Statistical Yearbook*; NBS: Beijing, China, 2011.
68. National Bureau of Statistics of China. *China County Statistical Yearbook*; NBS: Beijing, China, 2016.
69. National Bureau of Statistics of China. *China County Statistical Yearbook*; NBS: Beijing, China, 2018.
70. Gilbert, R.O. *Statistical Methods for Environmental Pollution Monitoring*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 1987.
71. Zhao, Y.; Zou, X.; Gao, J.; Xu, X.; Wang, C.; Tang, D.; Wang, T.; Wu, X. Quantifying the anthropogenic and climatic contributions to changes in water discharge and sediment load into the sea: A case study of the Yangtze River, China. *Sci. Total Environ.* **2015**, *536*, 803–812. [CrossRef]
72. Ariken, M.; Zhang, F.; Liu, K.; Fang, C.; Kung, H.-T. Coupling coordination analysis of urbanization and eco-environment in Yanqi Basin based on multi-source remote sensing data. *Ecol. Indic.* **2020**, *114*, 106331. [CrossRef]
73. Wang, J.F.; Li, X.H.; Christakos, G.; Liao, Y.L.; Zhang, T.; Gu, X.; Zheng, X.Y. Geographical Detectors-Based Health Risk Assessment and its Application in the Neural Tube Defects Study of the Heshun Region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127. [CrossRef]
74. Zhou, Y.; Li, X.; Liu, Y. Land use change and driving factors in rural China during the period 1995–2015. *Land Use Policy* **2020**, *99*, 105048. [CrossRef]
75. Yan, H.; Zhu, D.Z.; Loewen, M.R.; Zhang, W.; Liang, S.; Ahmed, S.; van Duin, B.; Mahmood, K.; Zhao, S. Impact of rainfall characteristics on urban stormwater quality using data mining framework. *Sci. Total Environ.* **2023**, *862*, 160689. [CrossRef] [PubMed]
76. Liang, X.; Li, Y.; Zhou, Y. Study on the abandonment of sloping farmland in Fengjie County, Three Gorges Reservoir Area, a mountainous area in China. *Land Use Policy* **2020**, *97*, 104760. [CrossRef]
77. Zhang, Y.; Li, X.; Song, W. Determinants of cropland abandonment at the parcel, household and village levels in mountain areas of China: A multi-level analysis. *Land Use Policy* **2014**, *41*, 186–192. [CrossRef]