

## Article

# Structural Transformation or Crisis? The Dynamics of Cultivated Land Abandonment and Reuse in China's Rural Development, 1992–2022

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## Abstract

The study investigates whether cultivated land abandonment (CLA) reflects structural transformation or an intensifying crisis. CLA is defined as land that has remained uncultivated for a minimum of two consecutive years, with the exclusion of land that is subject to deliberate programs such as the “Grain-for-Green” initiative. Utilizing the China Land Cover Dataset and a moving-window approach, we conducted a comprehensive analysis of spatiotemporal patterns across 2847 Chinese counties from 1992 to 2022. The research employed OLS, Tobit, high-dimensional fixed effects and instrumental variable regressions. The findings of the present study indicate an annual average abandonment rate of 2.3995%, with 12.3649% of cropland abandoned at least once and 9.2028% reclaimed, suggesting a fragile equilibrium. The Huang-Huai-Hai region and Northeast China's plains emerged as low-abandonment clusters. Cropland fragmentation was found to trigger abandonment, while a higher ecological land ratio significantly exacerbates CLA. Rural labor migration and urbanization drive cumulative abandonment, worsened by the COVID-19 pandemic. Effective governance requires context-specific interventions that address key constraints and integrate land reuse into sustainable rural development frameworks. The research methods and theoretical mechanisms presented offer a reference for balancing food security, rural revitalization, and ecological sustainability worldwide.

**Keywords:** cultivated land abandonment; structural transformation; driving mechanisms; reuse; China

Academic Editor: Wei Song

Received: 24 May 2026

Revised: 6 July 2026

Accepted: 8 July 2026

Published: 10 July 2026

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## 1. Introduction

Global land scarcity is intensifying, and land use has become central to achieving the Sustainable Development Goals (SDGs) [1,2]. Concurrently, cultivated land abandonment (CLA) has emerged as a widespread form of global land-cover change [3]. As a significant food producer with a large population, China has historically prioritized food production

and security, considering cropland as a fundamental resource in these efforts. However, China's cultivated land area has declined annually due to conversion to construction land, agricultural restructuring, and natural disasters. CLA [4] and agricultural marginalization are becoming increasingly prevalent, particularly in mountainous regions [5,6]. As rural economies transition toward non-agricultural sectors and urban areas absorb rural populations [7,8], dependence on cultivated land has gradually diminished. To combat CLA, the Chinese government has implemented a comprehensive and stringent cropland protection system. The Land Administration Law explicitly prohibits land vacancy and CLA. A compensation system imposes penalties on non-agricultural projects occupying cropland for more than two years. The Regulations on Basic Cropland Protection stipulate that management contracts must be terminated if land is abandoned for two years, with subsidies withdrawn and land reclaimed. China's land consolidation initiatives have yielded significant results, evolving into large-scale regional projects [9]. However, such consolidation programs [10] typically require years to complete, and restoring abandoned land to cultivation is often protracted [11]. The longstanding Grain-for-Green program and ongoing agricultural reforms continue to shape land use patterns. This study focuses on land left uncultivated for extended periods that has naturally transitioned to grassland, shrubland, or forest, distinct from Grain-for-Green land actively afforested for ecological purposes. China also employs crop rotation and fallow systems, with fallow periods ranging from one season to two years.

CLA exhibits dual effects—both detrimental and beneficial. Numerous studies have explored its diverse impacts on food security, climate [12], and environmental processes, including water, carbon [13,14], and nitrogen [15] cycles. Abandoned cultivated land can transform into habitats, improving landscape connectivity and promoting biodiversity, habitat restoration, and rewilding [16–18]. Conversely, CLA can generate negative externalities, such as increased weeds, pests, and pathogens in adjacent fields, leading to higher pest infestations. A critical analytical step involves distinguishing between long-term and short-term CLA, which is driven by various factors including economic pressures, natural disasters, and policy shifts. Long-term monitoring is essential to assess intervention effectiveness. This phenomenon is influenced by rural revitalization efforts [19,20], such as e-commerce growth [21] and increasing rural capital inflows [22]. Remote sensing is the primary method for quantifying CLA. Remote sensing technology [23–25] plays a vital role in detecting abandoned agricultural land across diverse contexts but faces significant challenges. While micro-scale field surveys and questionnaires are common, studies at large spatial scales and over extended timeframes remain limited. CLA distribution varies considerably, influenced by socioeconomic development, land infrastructure, landscape patterns [26], and natural environments changes. Studies span national [27], regional [28,29], and household scales [30]. Researchers aim to identify the drivers of CLA within complex systems and elucidate underlying mechanisms. Beyond spatial analysis [31], machine learning [32], enabled by artificial intelligence, is increasingly employed for remote sensing interpretation and causal inference. Structurally, transformation refers to the dynamic, growth-driven shift of land use from agriculture to ecological and urban functions. Driven by labor migration, GDP growth, and infrastructure expansion, this process can be reversed through land consolidation and targeted compensation. In contrast, a structural crisis involves a self-reinforcing cycle of abandonment and labor loss—initiated when cropland fragmentation exceeds a critical threshold and exacerbated by urbanization and external shocks—which undermines resilience and exposes governance deficiencies.

Academic definitions of CLA vary considerably, with previous studies often framing it within the context of cropland marginalization [33,34]. CLA is a multifaceted phenom-

enon that has been characterized in diverse ways and classified according to different typologies. These range from short-term seasonal abandonment to long-term abandonment lasting five years or more. Furthermore, they encompass active versus passive as well as explicit versus implicit forms. This study addresses the following research questions: (1) What are the spatiotemporal patterns and key drivers of long-term CLA in China? (2) How do cultivated land fragmentation and ecological constraints influence CLA, and what mechanisms underpin these relationships? (3) How do CLA and land reclamation (LR) vary spatially and temporally, and what factors affect their dynamics? (4) Which governance processes shape these land-use transitions, and do these transitions reflect structural transformation or structural crisis? The objective of this research is to provide policy insights and support institutional innovations for sustainable land management by addressing the aforementioned questions.

## 2. Materials and Methods

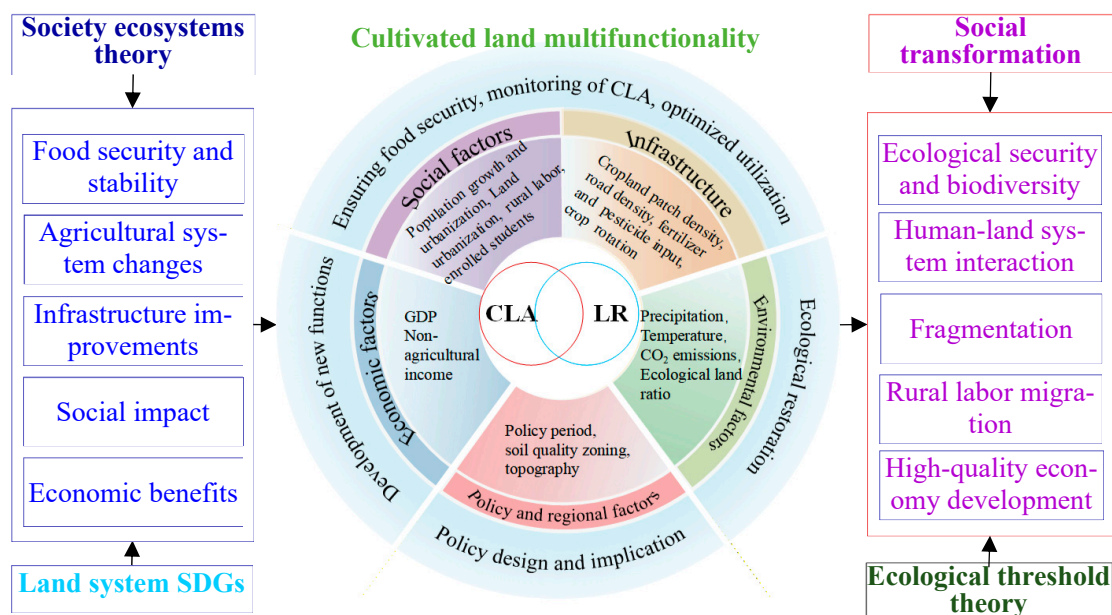
### 2.1. Theoretical Framework

The core premise of society-ecosystem theory [35,36] posits that CLA reflects imbalances within the social-ecological system [37,38]. Grounded in multiple factors such as resource utilization, policy interventions, and cultural traditions, this theoretical framework conceptualizes CLA not as stochastic but as an inevitable outcome of social transformation and development. Ecological threshold theory [16,39] further posits a nonlinear relationship between CLA and ecosystem services, with an optimal ecological range. Moderate abandonment can facilitate ecological recovery, whereas excessive abandonment may trigger ecosystem degradation. The analytical framework of this study integrates biophysical factors (e.g., topography, climate, fragmentation), socioeconomic variables (e.g., rural labor [40], share of secondary and tertiary industries), and spatial characteristics (Figure 1), all aligned with the Sustainable Development Goals for land systems. First, it accommodates simultaneous spatial and temporal dynamics. Second, analogous to studies on transitional land-use change, it explores strategies for addressing recurrent abandonment, including improved cropland infrastructure, policy development, and responses to socioeconomic-environmental impacts. Third, it promotes multifunctional land use—encompassing cropland patterns, structures, and infrastructure—to better forecast recultivation, ecological restoration, and emerging land-use trajectories. Application of ecological threshold theory also necessitates measures to prevent cyclical abandonment of agricultural resources, utilize abandoned land to enhance ecological conditions, and promote integrated development.

Drawing on current research trends—including the definition, dynamics, drivers, and management of CLA—this study aims to elucidate the spatiotemporal patterns and mechanisms underlying its recurrent occurrence. Furthermore, the study examines the impact of cropland fragmentation and ecological constraints on CLA. For comparative analysis, in addition to land reclamation (LR), the model assesses broadly defined CLA, operationalized as any farmland remaining abandoned for two years being counted as one abandonment event.

During the study period, CLA exhibits both temporal fluctuations and spatial heterogeneity. The determinants of CLA and reclamation are multifaceted and can be categorized into the following groups: (1) economic factors, including GDP and the contributions of secondary and tertiary industries; (2) social factors, comprising population growth rate, urbanization rates of population and land, rural labor force, and student enrollment; (3) agricultural infrastructure and inputs, such as road density, fertilizer and pesticide application, crop rotation systems, and cropland patch density (PD); (4) ecological and environmental variables, including precipitation, temperature, CO<sub>2</sub> emissions, and ecological

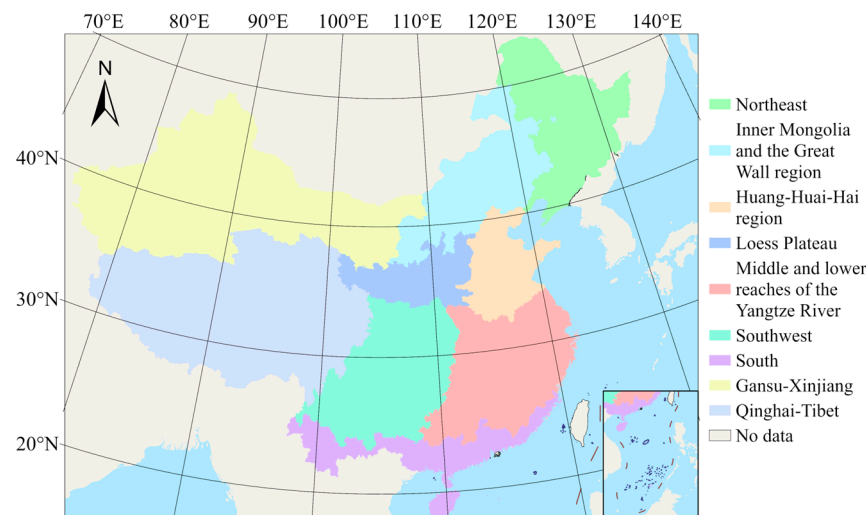
land ratio (ELR); and (5) policy regimes and spatial characteristics, such as provincial boundaries, cropland quality zones, and topographical divisions.



**Figure 1.** Theoretical framework. CLA refers to cultivated land abandonment, while LR denotes land reclamation. The innermost circle illustrates the relationship between CLA and LR. Moving from the outermost layer to the innermost, the diagram considers the following elements: the multifunctionality of the land use system, the categorization of influencing factors, and the specific factors that directly influence these processes.

## 2.2. Study Area and Data

Since the initiation of reform and opening-up policies, China has undergone rapid socioeconomic development, accompanied by substantial shifts in economic and demographic structures. CLA represents a highly probable phase in this economic transformation. As a populous nation, China faces challenges analogous to those encountered by other countries. CLA threatens national food security and stable supplies of key agricultural products, while also causing ecological degradation such as soil deterioration and erosion. China has implemented a rigorous cropland protection system, encompassing land consolidation programs and basic cropland preservation policies. The topography of China is characterized by elevated land in the western regions and comparatively lower elevations in the eastern regions. The landscape is characterized by a series of terraces, with only 33% of the total land area comprising flat terrain. Cropland distribution is concentrated in the plains, basins, and gently rolling hills of the eastern monsoon region. The current grain distribution pattern exhibits a north-to-south flow. China conducts regular cropland quality monitoring and grading through the Ministry of Agriculture and Rural Affairs, which has initiated a comprehensive nationwide survey and evaluation program utilizing standardized protocols for cropland quality assessment. The evaluation framework delineates cropland into nine distinct regions: (1) Northeast China, (2) Inner Mongolia and the Great Wall Region, (3) Huang-Huai-Hai Region, (4) Loess Plateau, (5) Middle and Lower Yangtze River Region, (6) Southwest China, (7) South China, (8) Gansu-Xinjiang Region, and (9) Qinghai-Tibet Region (Figure 2). This study encompasses 2847 counties across China, with detailed county-level data for each region provided in Supplementary Table S1.



**Figure 2.** Location and zoning of the study area.

Land use data spanning from 1990 to 2024 were utilized in this study. To ensure temporal continuity, a 30-m annual land cover dataset for China [41], updated to 2024, was selected as the primary land use and land cover source. This comprehensive and continuous dataset was also employed to calculate the ELR. The spatiotemporal distribution of CLA in China from 1992 to 2022 was derived using a moving-window approach. Concurrently, thematic cropland data were integrated with a 30-m annual cropland dataset covering 1986 to 2021, which exhibited a mean overall accuracy of  $0.93 \pm 0.01$  and a change detection accuracy of 0.84. This integrated dataset was used to calculate cropland patch density (PD). All socioeconomic data were obtained from official statistical yearbooks. Road length and road density were calculated based on historical OpenStreetMap data. Detailed information regarding data sources is provided in Supplementary Table S2. Spatial data processing was conducted using ArcGIS Pro 3.0.2, while statistical analyses were performed using Stata MP 17. Data analysis and visualization were carried out using Python 3.9 and 3.14.

## 2.3. Methodology

### 2.3.1. Moving-Window Approach

The window method is a robust technique [42,43] for assessing CLA using spatial-temporal data from 1990 to 2024, implemented with the rasterio Python package. A 4-year window was employed as the primary configuration, with a 3-year window used for comparison. CLA was operationalized as two consecutive years of non-cultivation, confirmed only when at least two independent detections occurred across different windows. This criterion distinguishes persistent abandonment from temporary fallow or short-term crop rotation, reduces misclassification, enables earlier detection, and supports dynamic monitoring. The additional detection threshold further enhances accuracy and minimizes false positives. While the 4-year window provides robustness, the 3-year window balances sensitivity and specificity. In the context of China's fallow-rotation policy, two consecutive years of fallow are often implemented in ecologically fragile or resource-constrained regions, such as areas affected by heavy-metal contamination or groundwater depletion, thereby revealing CLA dynamics and policy effectiveness.

Grid cells satisfying the abandonment criteria were labeled as CLA in the first year following conversion from cultivated land to other land uses. Each grid cell was assigned a binary value: 0 indicates potential continued cultivation, land consolidation, conversion to construction land, afforestation, or temporary fallow; 1 indicates CLA. Similarly, for the 3-year window, if the first monitored year was non-cultivated land and the subsequent

year was cultivated land, a threshold of one detection was applied, and the year of successful conversion to cultivated land was recorded LR. Although LR monitoring could be based on a 2-year window, for consistency with CLA detection, the window size was not reduced; results remained unchanged regardless of window duration. Application of the moving-window method yielded annual CLA and LR maps for the period 1992–2022. Annual CLA and LR counts were aggregated to determine abandonment and reclamation frequency throughout the study period. Implementation steps are provided in Supplementary Figure S1.

### 2.3.2. Identification of Determinants of CLA

To analyze the theoretical mechanisms of county-level CLA, China's county-level vector data were utilized to calculate CLA and LR areas at the county scale. Given the variability in county sizes, comparability was maintained by defining the dependent variable CAR as the ratio of CLA area to cultivated land area, and LRR as the ratio of LR area to cultivated land area. The expression is as follows.

$$CAR_i = CLA_i / C_i \times 100 \quad (1)$$

$$LRR_i = LR_i / C_i \times 100 \quad (2)$$

where CAR denotes the annual rate of CLA for county  $i$ . The LRR represents the annual rate of LR. Both CAR and LRR values range from 0 to 100 and are expressed as percentages. The term  $C$  denotes the total cultivated land area, measured in square kilometers.

To identify influential factors within the theoretical framework and ensure robustness of average effect estimation, multiple regression approaches were employed, including the Tobit model, ordinary least squares (OLS) regression, and instrumental variable (IV) estimation. A High-dimensional Fixed Effects (HDFFE) model was applied to examine the determinants of CLA. The model is constructed as follows.

$$CAR_{it} = \alpha_0 + \alpha_i X_i + \mu_i + \beta_t + \delta_{ct} + \varepsilon_{it} \quad (3)$$

This model is particularly well-suited to address endogeneity concerns inherent in panel data, as it effectively accounts for individual fixed effects ( $\mu_i$ )—that is, unobservable time-invariant factors influencing county-level CLA. Time fixed effects ( $\beta_t$ ) are included to control for annual macro-level shocks, such as changes in national agricultural policies or climate conditions, uniformly across all observations. Furthermore, city-year interaction fixed effects ( $\delta_{ct}$ ) are incorporated to capture unobservable time-varying factors at the city level.

### 2.3.3. Variable Selection and Descriptive Statistics

CLA is influenced by multiple factors. The social–ecological systems theory is structured as a three-tiered nested subsystem: micro-system, meso-system, and macro-system. These systems exert continuous influence through dynamic feedback relationships across levels, forming a framework for explaining interactive mechanisms between individuals and their environments. Based on social–ecological systems theory and ecological threshold theory, potential factors affecting CLA were categorized into five major groups: economic factors, social factors, cropland infrastructure, environmental impacts, and regional policy. Due to variations in statistical coverage across data sources, the final analysis period was 1992–2022, encompassing 2847 counties within 341 cities. Table 1 provides comprehensive definitions and descriptive statistics for these variables.

**Table 1.** Definition and descriptive statistics for variables.

| Dimension                 | Variable          | Definition                                                                                                                                   | Mean  | S. D. |
|---------------------------|-------------------|----------------------------------------------------------------------------------------------------------------------------------------------|-------|-------|
| Dependent variable        | CAR               | Cultivated land abandonment rate (%)                                                                                                         | 1.60  | 3.77  |
|                           | LRR               | Land reclamation rate (%)                                                                                                                    | 2.92  | 12.67 |
| Economic factors          | lnGDP_capita      | GDP per capita (ln, ten thousand yuan)                                                                                                       | 0.29  | 1.20  |
|                           | S&T               | Share of secondary and tertiary industries in GDP (%)                                                                                        | 0.73  | 0.22  |
| Social factors            | lnRL              | Rural laborers (ln, ten thousand people)                                                                                                     | 2.75  | 0.91  |
|                           | lnPOP             | Total population (ln, ten thousand people)                                                                                                   | 12.73 | 0.95  |
|                           | lnSTU             | Enrolled students (ln, ten thousand people)                                                                                                  | 10.11 | 1.41  |
|                           | PGR               | Population growth rate (PGR, %)                                                                                                              | 0.01  | 0.15  |
|                           | PUR               | Population Urbanization Ratio (PUR, %)                                                                                                       | 0.32  | 0.26  |
| Infrastructure            | lnPD              | Cropland patch density (ln, patches/km <sup>2</sup> )                                                                                        | 2.83  | 1.22  |
|                           | lnRD              | Road density (RD) within the county (ln, km/km <sup>2</sup> )                                                                                | 0.38  | 1.67  |
|                           | lnGP              | Grain production (ln, t)                                                                                                                     | 11.64 | 1.63  |
|                           | Fertilizer        | Quantity of chemical fertilizer (ten thousand t)                                                                                             | 2.27  | 2.54  |
|                           | Rotation          | Multiple cropping index                                                                                                                      | 1.06  | 0.89  |
|                           | ELR               | Ecological land rate (%)                                                                                                                     | 0.49  | 0.34  |
|                           | Tem               | The mean temperature of each county (°C) [44]                                                                                                | 12.95 | 6.14  |
| Environmental Im-<br>pact | Precipitation     | The mean precipitation of each county (m) [44]                                                                                               | 1.12  | 0.60  |
|                           | lnCO <sub>2</sub> | The mean CO <sub>2</sub> emissions (ln, Mt) [45]                                                                                             | 13.63 | 1.44  |
|                           | Terrain           | 1 = Plain; 2 = Hilly; 3 = Mountainous county                                                                                                 | 1.81  | 0.88  |
| Control variables         |                   | 1 = Before the second revision of the Land Management Law (1992–2003); 2 =                                                                   |       |       |
|                           | Policy period     | Three agricultural subsidies period (2004–2014); 3 = period for land rights confir-<br>mation (2015–2020); 4 = post-pandemic era (2021–2022) |       |       |

Note: Given that crops planted in 2019 were harvested in 2020, the CAR in 2020 is expected to be lower; therefore, 1992–2020 was treated as a relatively stable period, 2021–2022 as the post-pandemic period, with major pandemic-era impacts excluded from the baseline analysis.

The Chinese Yuan (CNY) is the official currency of China, with an exchange rate of 1 USD = 6.98 CNY as of January 2026. The population urbanization ratio was defined as the proportion of urban population relative to total population. Prior to empirical analysis, the variance inflation factor (VIF) was employed to assess potential multicollinearity among explanatory variables. As presented in Table 1, a comprehensive multicollinearity diagnostic was performed. Results indicate that precipitation exhibited the highest VIF value of 2.79, which remains below the threshold of 3, while the mean VIF was 1.74, suggesting no severe multicollinearity.

China's "Three Subsidies" refer to a set of agricultural subsidy policies implemented between 2004 and May 2016, comprising direct grain subsidies, subsidies for high-quality seeds, and comprehensive subsidies for agricultural inputs. Due to insufficient data availability, pesticide application information was excluded from subsequent analyses.

PD is a key landscape metric used to characterize the spatial distribution of landscape patches and to quantify landscape fragmentation and spatial heterogeneity. Its formula is as follows:

$$PD_i = N_i/C_i \quad (4)$$

where PD denotes cropland patch density, N represents the total number of cultivated land patches within the county, and *i* signifies the county area. PD was calculated using Fragstats 4.0 software. Higher PD values indicate more patches per unit area, reflecting greater landscape fragmentation and complexity, as well as more frequent interactions between patches and ecological processes.

Road density (RD) was defined as the total road length within a county, measured in kilometers per km<sup>2</sup>. The formula is as follows:

$$RD_i = L_i/A_i \quad (5)$$

where RD denotes road density, L represents the total road length within the county (km), and A signifies the total area of the county (km<sup>2</sup>).

Ecological land refers to land use types primarily designated for the provision of ecosystem services, including ecological product production, environmental regulation, and biodiversity conservation. Mountains, waters, forests, croplands, lakes, grasslands, and deserts collectively constitute an interconnected life community. The ELR is a critical factor influencing CLA. The calculation formula for ELR is as follows:

$$ELR_i = E_i/A_i \quad (6)$$

where ELR is defined as the ratio of total ecological land area (E) to total county area (A), ranging from 0 to 1. Ecological land in this study encompasses forests, shrublands, grasslands, wetlands, water bodies, and barren land.

### 3. Results

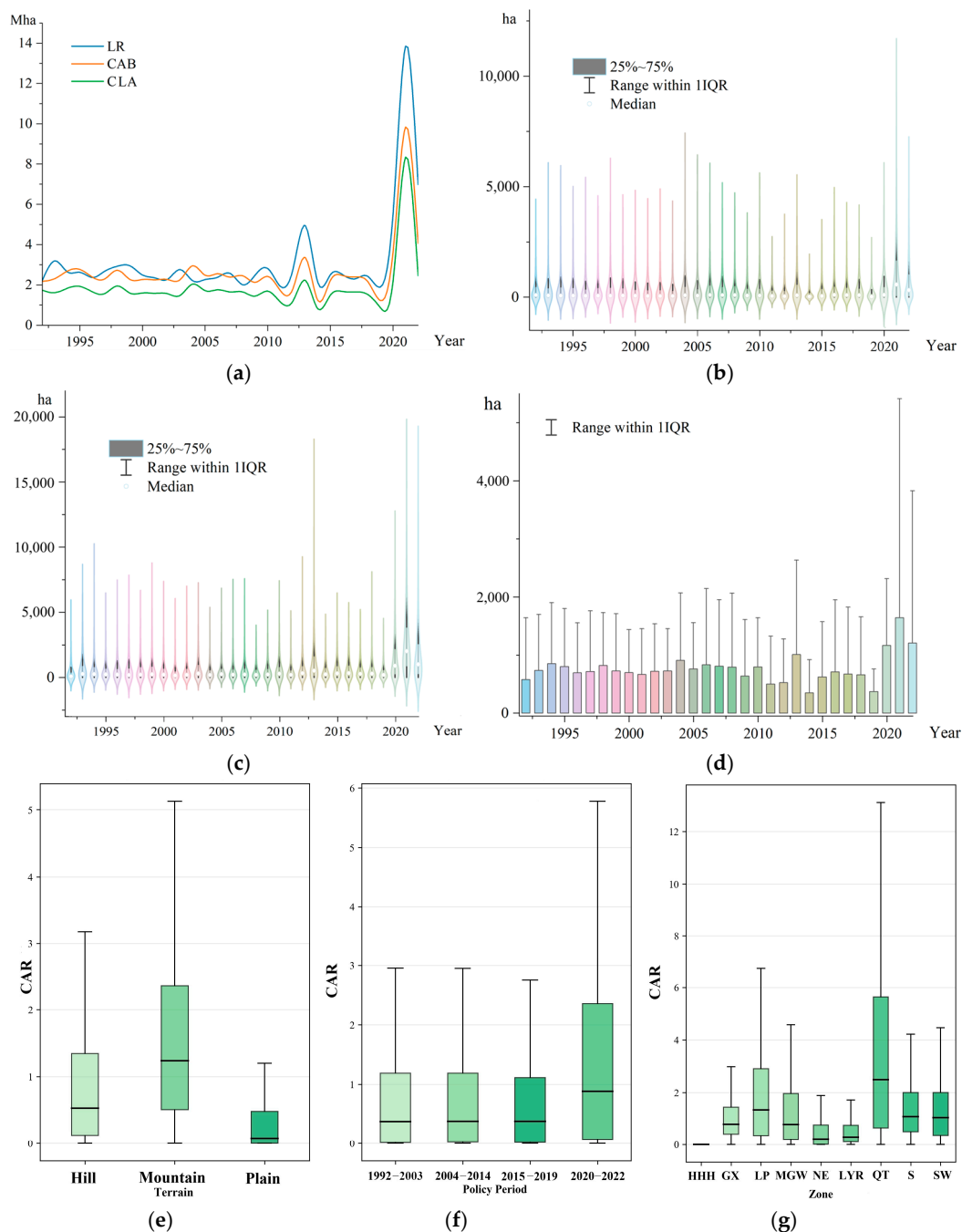
#### 3.1. Spatiotemporal Variations in CA and LR Areas

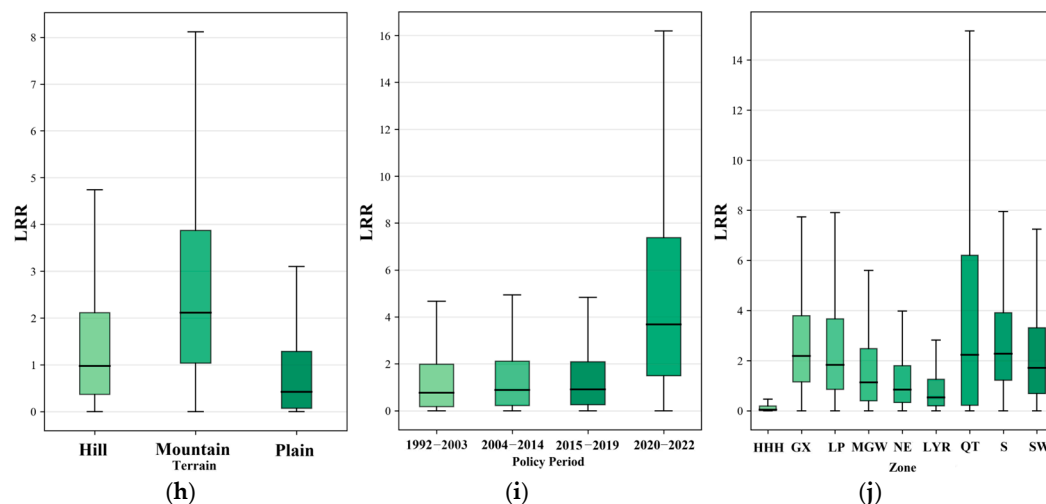
A stratified random sampling design was employed based on CLA category and year to validate against an independent Annual Cropland Dataset of China (CADC) [46] time-series reference. Following quality control, 4617 valid samples were retained from 5075 total samples to ensure representativeness and prevent data leakage. The resulting map exhibited an overall accuracy of 64.6%, precision of 75.3%, recall of 93.9%, and an F1-score of 83.6%, demonstrating high efficacy in detecting true abandonment with minimal omission. Notably, the map demonstrated high sensitivity in identifying abandoned cultivated land but limited ability to distinguish non-abandoned areas. Consequently, this product is more suitable for preliminary identification of abandonment hotspots rather than serving as a direct basis for precise area estimation.

Compared to 1990, approximately 21.5676% of China's cultivated land has experienced abandonment, with 3.281% undergoing long-term abandonment on two or more occasions. The area of CLA fluctuated temporally, averaging  $1.5985 \pm 0.7252$  million hectares (Mha) from 1992 to 2019. The minimum recorded area occurred in 2019 and a maximum of 2.23 Mha in 2013. The abandoned areas from 2020 to 2022 were 2.1959, 8.3485, and 2.4603 Mha, respectively. Concurrently, annual LR efforts averaged 1.6894 times the area of CLA. The annual average CAR was 2.3995%, peaking at 8.4619% in 2021. The LRR averaged 2.8202%, surging to 16.9144% in 2021, resulting in an exceptionally high cultivated land area in 2022. From 1992 to 2008, the CAR and LRR exhibited inverse fluctuations, nearly equaling each other between 2009 and 2011, and thereafter followed similar patterns, with LR efforts occurring concurrently with CLA. Over the entire study period (1992–2022), 9.2028% of CLA was reclaimed, although 12.3649% remained abandoned at least once, with 2.5150% abandoned two or more times, closely reflecting the annual average CAR. Among reclaimed lands, 10.4534% had been abandoned one or more times, and 3.8988% underwent reclamation two or more times. The CAR values in mountainous areas were notably high with significant fluctuation (see Figure 3a–j).

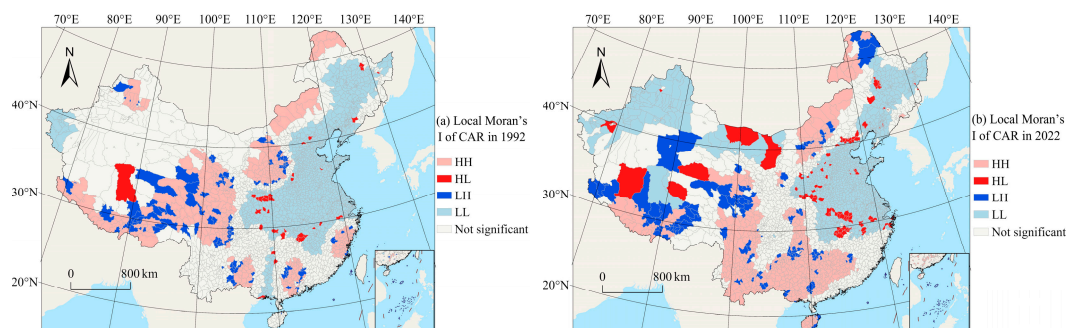
Pronounced spatial variations were observed. The global Moran's I index for CLA and LR ranged between 0.1084 and 0.2658 annually, with z-scores exceeding 31.1777 ( $p < 0.01$ ), indicating statistically significant spatial clustering. An abrupt surge to 0.7438 was recorded in 2021, with CLA demonstrating intensified clustering. LR exhibited the highest clustering intensity in 2021 and 2022. Local autocorrelation results for 1992 and 2022 are presented in Figure 4, with complete annual data provided in Supplementary Figures S2

and S3. The Huang-Huai-Hai region and Northeast China plains were identified as consistent low-CAR clusters, with the Loess Plateau and Sichuan Basin emerging as additional low-value clusters in 2021. Perennial high-value clusters were evident in Southwest China's mountainous regions, with notable expansion into Inner Mongolia's agricultural areas since 2020, subsequently spreading toward Southwest China and Xinjiang. Accelerated CLA in Xinjiang was progressively mitigated during this period. Low-value clusters for LR were identified in the Huang-Huai-Hai plains, Inner Mongolia, Northeast China, Hunan, and Sichuan Basin. High-value LR areas initially occurred sporadically in counties surrounding the Sichuan Basin, subsequently expanding toward southeastern coastal regions and concentrating in Inner Mongolia's agricultural zones, reflecting spatial shifts in cultivated land restoration efforts.





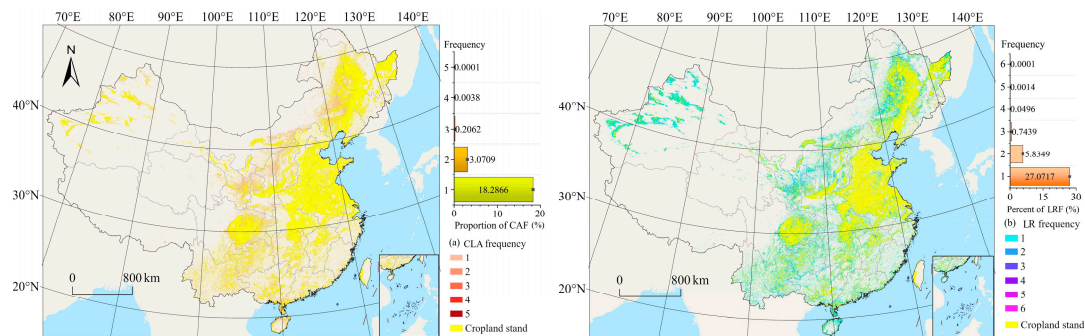
**Figure 3.** Time and category variations in the CLA and LR areas. (a) The annual variations of the areas of CLA and LR. (b) Violin plot of annual changes of CLA area. (c) Violin plot of annual changes of LR area. (d) Box plot of annual changes of broadly CLA area. (e) CAR box plot by terrain. (f) CAR box plot by period. (g) CAR box plot by region. (h) LRR box plot by terrain. (i) LRR box plot by period; (j) LRR box plot by region. Cultivated land abandonment (CLA), the central concept of this study, is shown in (a,b,d). The phenomenon of CLA, as measured using a moving window of three (CAB) is illustrated in (a). The purpose is to enable a comparison of changes in the different meanings of CLA in its area. It is noteworthy that all subsequent CLAs exclusively concern themselves with explanatory variables, eschewing any consideration of CAB. Land reclamation (LR) area is shown in (a,c,e–j), representing the cultivated land abandonment rate (CAR) and land reclamation rate (LRR), respectively. The abbreviations for Zone are listed in Supplementary Table S1.



**Figure 4.** Local Moran's I of CAR in 1992 and 2022. (a) Local Moran's I of CAR in 1992. (b) Local Moran's I of CAR in 2022. High–High cluster (HH): a high-CAR county surrounded by other high-CAR counties; Low–Low cluster (LL): a low-CAR county surrounded by other low-CAR counties; High–Low cluster (HL): a high-CAR county surrounded by low-CAR counties; Low–High cluster (LH): a low-CAR county surrounded by high-CAR counties.

Spatially, the average CLA frequency was lowest in plain counties (0.0846) and highest in hill counties (0.1584), exceeding that of mountainous areas (Figure 5). LR trends across landforms mirrored CLA patterns, with hill counties recording the highest average frequency (0.2007). Cultivated land without abandonment or reclamation was primarily distributed in the Huang-Huai-Hai, Northeast, and Jiangnan plains, while LR occurred with high frequency in Xinjiang's designated basins. Spatial heterogeneity of CLA and LR areas exhibited scale effects: the interannual average CLA area was highest in Inner Mongolia Province, followed by Xinjiang, with similar patterns observed for LR. At the county level, Xinjiang recorded an average CAR of 3.3513%, while the Huang-Huai-Hai Plain demonstrated the lowest rate (0.1340%). The middle and lower reaches of the Yangtze

River followed with 0.796%, and the northeast region with 1.0053%. The spatial variation among zones demonstrated strong alignment with annual spatial differentiation patterns (Supplementary Figure S4).



**Figure 5.** Spatial Distribution of the cumulative difference between LR and CLA frequency from 1992 to 2022. (a) CLA frequency; (b) LR frequency.

### 3.2. Exploring the Driving Mechanism of CLA

#### 3.2.1. Tobit and OLS Regression Analyses

A baseline OLS regression with individual fixed effects was first estimated using panel data, with the CAR and the area of CLA as dependent variables (Supplementary Table S3). Multivariate stepwise random-effects Tobit regression results are presented in Table 2, and the full regression results can be found in Supplementary Table S4. OLS analysis indicated that the drivers of CAR were more readily identifiable than those of LRR. The CAR model demonstrated greater explanatory power ( $R^2 = 0.2557$ ) than the CLA area model. Cropland fragmentation, road density, and non-agricultural GDP influenced both CAR and CLA area ( $p < 0.01$ ). Cropland fragmentation exhibited a positive association with CAR, with considerable variability in both CLA and LRR observed in highly fragmented regions. Infrastructure development substantially mitigated CLA and stabilized cultivated land use, whereas economic restructuring—marked by declining agricultural reliance—reduced CLA. The relationship between per capita grain yield and CAR was complex: higher yields were associated with lower CAR, potentially driven by economies of scale. Labor availability was inversely associated with both CAR and LRR while increasing reclaimed land area; however, regions with labor surpluses paradoxically exhibited elevated CLA and LR levels. Population growth rate was negatively correlated with CAR. Conversely, higher ELR was robustly associated with CLA expansion, underscoring the inherent instability of cultivated land in ecologically fragile areas where natural succession encroaches upon arable fields.

**Table 2.** Random-effects Tobit Regression Results.

|              | Tobit 1                 | Tobit 2                | Tobit 3 <sup>1</sup>    |
|--------------|-------------------------|------------------------|-------------------------|
| lnGDP_capita | −0.0898 ***<br>(0.0328) | −0.0689 **<br>(0.0320) | −0.1417 ***<br>(0.0234) |
| S&T          | −0.1753 *<br>(0.1049)   | −0.1629<br>(0.1040)    | 0.0570<br>(0.0912)      |
| PGR          | −0.0124<br>(0.1267)     | −0.0046<br>(0.1267)    | 0.0602<br>(0.0974)      |
| PUR          | 0.7801 ***<br>(0.2251)  | 1.0139 ***<br>(0.2269) | 0.5379 ***<br>(0.1430)  |
| lnRL         | 0.3171 ***<br>(0.1064)  | 0.3218 ***<br>(0.1073) | 0.0432<br>(0.0627)      |

|                          |                         |                         |                             |
|--------------------------|-------------------------|-------------------------|-----------------------------|
| lnSTU                    | 0.0017<br>(0.0213)      | −0.0021<br>(0.0212)     | 0.0130<br>(0.0152)          |
| lnGP                     | −0.1349 ***<br>(0.0431) | −0.1791 ***<br>(0.0437) |                             |
| lnRD                     | −0.1601 ***<br>(0.0309) | −0.1919 ***<br>(0.0308) |                             |
| Fertilizer               | 0.0065<br>(0.0121)      | −0.0270 **<br>(0.0124)  |                             |
| Rotation                 | 0.0009 ***<br>(0.0001)  | 0.0009 ***<br>(0.0001)  |                             |
| Precipitation            | −0.0988<br>(0.0688)     |                         |                             |
| Temperature              | −0.0785 ***<br>(0.0191) |                         |                             |
| lnPD                     | 0.0010 **<br>(0.0004)   |                         |                             |
| lnCO <sub>2</sub>        | 0.0671 **<br>(0.0292)   |                         |                             |
| ELR                      | 3.8804 ***<br>(0.2573)  |                         |                             |
| Observations             | 38,440                  | 38,750                  | 80,972                      |
| Region control variables | Yes                     | Yes                     | Yes                         |
| City × year FE           | Yes                     | Yes                     | Yes                         |
| LR                       | −79,815.44 ***          | −80,583.91 ***          | −1.88 × 10 <sup>5</sup> *** |
| Rho (ρ)                  | 0.1506                  | 0.1769                  | 0.2132                      |
| Wald χ <sup>2</sup>      | 5358.15                 | 4804.24                 | 6887.41                     |

<sup>1</sup> Note: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. Coefficients in the table below have identical meanings.

To account for the censored nature of the dependent variable and unobserved heterogeneity, a Tobit model with provincial random effects was employed. Higher economic development, proxied by logarithm of per capita GDP (coefficients ranging from −0.0689 to −0.1417), is associated with a lower CAR, likely due to improved non-agricultural employment opportunities. The share of secondary and tertiary industries in GDP demonstrated negative coefficients (−0.1753 to −0.1629), though statistical significance was marginal in one specification ( $p < 0.10$ ), suggesting that industrial upgrading may not be a robust driver for rural transformation or CLA alleviation. Significant positive coefficients for the logarithm of rural labor (0.2436 to 0.3218) and urbanization rate (0.5379 to 1.0139) indicated that labor surpluses and rural–urban migration were associated with agricultural stagnation and heightened CLA. Regarding agricultural conditions, cropland PD exhibited a positive correlation with CAR, highlighting the detrimental impact of land fragmentation on management efficiency and costs. Conversely, improved road density substantially reduced CAR (−0.1601 to −0.2125) by enhancing market accessibility. Fertilizer input effects were ambiguous; moderate application may reduce CLA, whereas a high cropping index (0.0009) suggests that cultivated land overuse increased CLA risks. Environmental factors are also critical. Temperature shows a negative association with CAR (−0.0785). ELR exhibited consistently positive coefficients (3.88–4.12), indicating that higher ecological land proportion intensified CLA through spatial competition. Regional and temporal heterogeneity was evident: cultivation incentives during the Three Subsidies Period were ineffective, while the COVID-19 pandemic significantly exacerbated CLA (coefficients: 2.5552–2.6667), presumably through disruptions in labor mobility and

supply chains. Topographic disadvantages in hilly and mountainous areas further contributed to CLA (coefficients: 0.9476–1.9132). The estimated provincial random effects (best linear unbiased predictions) indicate that economically developed provinces exhibited lower CAR, whereas fragile ecological zones faced higher risks.

### 3.2.2. Quantile Regression and Marginal Effects

Quantile regression analysis (Q10 to Q95) revealed varying impacts of independent variables on CAR across its distribution (Table 3; Supplementary Table S5). The influence of most factors escalated with higher CAR levels. Per capita GDP (lnGDP\_percap) consistently demonstrated negative effects, with coefficients ranging from −0.0187 at Q10 to −0.2582 at Q95. The share of secondary and tertiary industries exhibited minimal effects at lower quantiles but became significantly negative beyond the median (−0.1723 at Q75). The urbanization rate displayed a J-shaped pattern, with a marked positive coefficient of 1.3566 at Q95, whereas rural labor (lnRL) maintained steady negative correlation. PD emerged as a strong positive driver, with coefficients increasing from 0.0243 at Q10 to 1.7518 at Q95. Road density (lnRD) was negatively correlated, while fertilizer usage was positively associated with CAR. These patterns suggest that protective factors (e.g., infrastructure) provide greater benefits in regions with severe abandonment, whereas risk factors amplify abandonment risks at high quantiles, creating potentially vicious cycles in heavily affected areas.

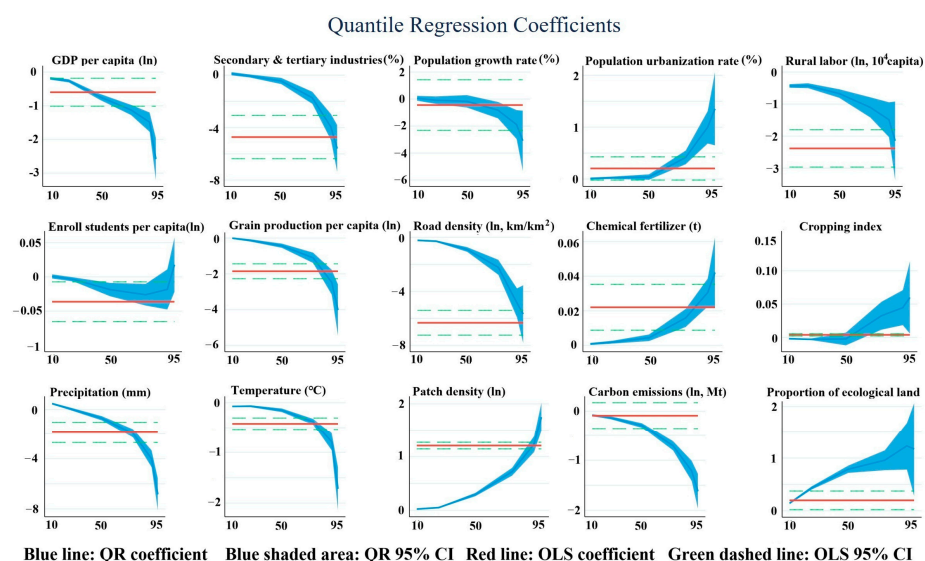
**Table 3.** Quantile regression results.

| CAR               | Q10                     | Q25                     | Q50                     | Q75                     | Q90                     | Q95                     |
|-------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| lnGDP_capita      | −0.0187 ***<br>(0.0020) | −0.0259 ***<br>(0.0024) | −0.0735 ***<br>(0.0046) | −0.1123 ***<br>(0.0078) | −0.1488 ***<br>(0.0147) | −0.2582 ***<br>(0.0319) |
| S&T               | 0.0113 *<br>(0.0064)    | −0.0060<br>(0.0061)     | −0.0439 ***<br>(0.0123) | −0.1723 ***<br>(0.0237) | −0.3957 ***<br>(0.0510) | −0.5595 ***<br>(0.0916) |
| lnPOP             | 0.0061<br>(0.0093)      | −0.0079<br>(0.0144)     | −0.0164<br>(0.0236)     | −0.0819 ***<br>(0.0311) | −0.1886 ***<br>(0.0549) | −0.3085 ***<br>(0.1138) |
| PUR               | 0.0101<br>(0.0094)      | 0.0248 **<br>(0.0117)   | 0.0383<br>(0.0271)      | 0.4178 ***<br>(0.0678)  | 0.9982 ***<br>(0.1601)  | 1.3566 ***<br>(0.3606)  |
| lnRL              | −0.0434 ***<br>(0.0029) | −0.0425 ***<br>(0.0040) | −0.0669 ***<br>(0.0069) | −0.1102 ***<br>(0.0162) | −0.1487 ***<br>(0.0279) | −0.2146 ***<br>(0.0626) |
| lnSTU_percap      | 0.0006<br>(0.0016)      | −0.0038 **<br>(0.0016)  | −0.0185 ***<br>(0.0050) | −0.0261 ***<br>(0.0081) | −0.0183<br>(0.0150)     | 0.0178<br>(0.0203)      |
| lnGP_capita       | −0.0006<br>(0.0022)     | −0.0135 ***<br>(0.0034) | −0.0429 ***<br>(0.0062) | −0.1103 ***<br>(0.0149) | −0.2472 ***<br>(0.0357) | −0.4025 ***<br>(0.0733) |
| lnRD              | −0.0218 ***<br>(0.0027) | −0.0280 ***<br>(0.0031) | −0.0897 ***<br>(0.0090) | −0.2214 ***<br>(0.0286) | −0.4852 ***<br>(0.0551) | −0.5681 ***<br>(0.1091) |
| Fertilizer        | 0.0008 ***<br>(0.0003)  | 0.0019 ***<br>(0.0004)  | 0.0044 ***<br>(0.0010)  | 0.0159 ***<br>(0.0027)  | 0.0305 ***<br>(0.0041)  | 0.0422 ***<br>(0.0104)  |
| Rotation          | −0.0002 ***<br>(0.0000) | −0.0003 ***<br>(0.0000) | −0.0002<br>(0.0005)     | 0.0032 ***<br>(0.0011)  | 0.0045 ***<br>(0.0013)  | 0.0060 **<br>(0.0028)   |
| Pre               | 0.0480 ***<br>(0.0036)  | 0.0050<br>(0.0055)      | −0.0701 ***<br>(0.0088) | −0.1940 ***<br>(0.0180) | −0.4010 ***<br>(0.0345) | −0.6841 ***<br>(0.0650) |
| Tem               | −0.0073 ***<br>(0.0006) | −0.0069 ***<br>(0.0010) | −0.0151 ***<br>(0.0019) | −0.0381 ***<br>(0.0030) | −0.0791 ***<br>(0.0088) | −0.1719 ***<br>(0.0216) |
| lnPD              | 0.0243 ***<br>(0.0055)  | 0.0519 ***<br>(0.0066)  | 0.2949 ***<br>(0.0161)  | 0.7181 ***<br>(0.0376)  | 1.2329 ***<br>(0.0765)  | 1.7518 ***<br>(0.1375)  |
| lnCO <sub>2</sub> | −0.0078 ***<br>(0.0011) | −0.0130 ***<br>(0.0015) | −0.0287 ***<br>(0.0024) | −0.0709 ***<br>(0.0048) | −0.1211 ***<br>(0.0104) | −0.1618 ***<br>(0.0178) |
| ELR               | 0.1430 ***              | 0.4317 ***              | 0.7872 ***              | 0.9587 ***              | 1.2311 ***              | 1.1722 **               |

|                |            |            |            |            |            |            |
|----------------|------------|------------|------------|------------|------------|------------|
|                | (0.0087)   | (0.0154)   | (0.0358)   | (0.0968)   | (0.2301)   | (0.4554)   |
| Policy_period  | 0.0399 *** | 0.0508 *** | 0.1190 *** | 0.2214 *** | 0.4026 *** | 0.6753 *** |
|                | (0.0024)   | (0.0029)   | (0.0056)   | (0.0113)   | (0.0278)   | (0.0579)   |
| Zone           | 0.0248 *** | 0.0196 *** | 0.0281 *** | 0.0830 *** | 0.2205 *** | 0.5070 *** |
|                | (0.0013)   | (0.0021)   | (0.0041)   | (0.0090)   | (0.0237)   | (0.0707)   |
| _cons          | 0.0624 *** | 0.1220 *** | 0.0603 *   | 0.2882 *** | 0.6052 *** | 1.1892 *** |
|                | (0.0176)   | (0.0215)   | (0.0358)   | (0.0631)   | (0.1206)   | (0.2096)   |
| Observations   | 56,865     | 36,691     | 36,691     | 36,691     | 36,691     | 36,691     |
| R <sup>2</sup> | 0.7050     | 0.7370     | 0.7477     | 0.7467     | 0.7556     | 0.7646     |

Note: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Quantile regression analysis revealed distinct nonlinearities in driver-CAR relationships (Figure 6). The GDP share of secondary and tertiary industries exhibited promotional effects during low-abandonment periods, followed by significant suppression beyond CAR = 0.0208%. Rural labor growth (lnRL) demonstrated slope changes at CAR = 0.0318%, with suppressive effects intensifying substantially beyond CAR = 0.5245% (coefficient transition: −0.0669 to stronger suppression). The cropping index showed slight inhibition during low-abandonment periods but promoted growth during high-abandonment periods (CAR threshold: 0.5916%). Population growth (lnPOP) demonstrated slight promotion at extremely low-abandonment periods, followed by suppression beyond CAR = 0.0139%. Road density (lnRD) exhibited mild inhibitory impacts at lower CAR levels, transitioning to strong inhibition at elevated CAR levels. Cropland fragmentation (lnPD) revealed significant positive association with CAR, with a notable threshold at CAR = 0.5245%, where effects transitioned from moderate promotion (coefficient < 0.0519) to strong promotion (coefficient > 0.2949). An inverted U-shaped relationship was identified between ELR and CAR, initially intensifying to a peak (marginal coefficient: 1.2311 at CAR ≈ 3.77%) before diminishing slightly at extreme levels, suggesting a saturation threshold for ecological pressures. The effect elasticity was most pronounced in low-CAR areas and diminished in high-CAR regions. Carbon dioxide (CO<sub>2</sub>) emissions demonstrated inhibitory effects in low-emission zones; conversely, they promote CLA in high-emission zones, although this effect is not particularly pronounced. Precipitation exhibited contrasting effects: in low-abandonment regions, increased precipitation may trigger flooding and subsequent abandonment; conversely, in high-abandonment areas, higher precipitation inhibited further abandonment.



**Figure 6.** Quantile regression coefficients and OLS estimated coefficients Results. The horizontal axis of the graph represents quantile values. To capture factors influencing higher cultivated land abandonment rates ( $CAR > 6.25\%$ , percentile = 95), the quantile yielding values of 0.1, 0.25, 0.5, 0.75, 0.9, and 0.95 must be taken into consideration.

### 3.2.3. Analysis of High-Dimensional Fixed Effects Model Results

The High-dimensional Fixed Effects (HDFE) model analysis was conducted to elucidate the mechanisms underlying CLA through progressive model specification evolution. The analysis progressed from a baseline model incorporating provincial fixed effects and basic control variables to an extended model with comprehensive controls, culminating in a stringent interaction fixed effects specification incorporating region-topography-year interactions. Cropland patch density ( $\ln PD$ ) demonstrated substantial positive effects, peaking at 1.5095 and achieving significance at the 1% level in the most rigorous specification (1992–2022), thereby affirming its critical role in driving CAR independent of regional, topographical, and temporal interactions. This coefficient magnitude falls between the 90th and 95th percentiles in quantile regression analysis and remains comparable across alternative specifications. Notably, exclusion of the post-pandemic period (2021–2022) would yield larger coefficients, potentially reaching 1.9750, suggesting that pandemic-related disruptions partially attenuated the fragmentation effect. Other variables, including student ratio ( $\ln STU$ ), maintained consistent negative effects ( $p < 0.05$ ), indicating that increased educational attainment was associated with reduced CAR. This relationship likely reflects enhanced human capital and improved agricultural management practices. Temporal analysis revealed that inclusion of post-pandemic years did not substantially alter core structural mechanisms, suggesting that COVID-19 functioned as an external demand shock rather than fundamentally restructuring underlying drivers. The pandemic's impact increased CAR by an average of 2.6–2.7 percentage points, constituting an additive shock independent of structural factors. This analysis underscores the long-term stability of critical mechanisms (e.g., land fragmentation and ecological constraints) while highlighting the necessity of considering external shocks in CLA dynamics.

Across the majority of extended specifications, ELR maintained consistently significant positive coefficients, ranging from 0.99 to 8.07 across different estimators, confirming its role as a core structural driver of CAR alongside  $\ln PD$ . However, the magnitude of ELR's effect demonstrated moderate sensitivity to geographic controls and dynamic specifications, suggesting localized rather than universally homogeneous influence. This nested framework indicates that structural factors form the foundation, moderated by economic conditions and influenced by external disturbances, thereby delineating clear policy boundaries for addressing CLA challenges.

Results from six progressively stricter fixed-effects models (Supplementary Table S6), analyzing data from 1992 to 2022 and excluding pandemic years respectively, revealed robust hard constraint mechanisms driving CAR. Two core factors consistently demonstrated strong positive effects: land fragmentation significantly increased transaction costs and management challenges, while ELR (coefficients: 0.9937–8.0772) emphasized the fundamental conflict between ecological conservation and agricultural production. Road density ( $\ln RD$ ) consistently suppressed CLA, although its protective effectiveness diminished when accounting for region-topography-year interactions, suggesting that infrastructure benefits were intertwined with inherent regional characteristics. Per capita grain yield generally exhibited negative correlation with CAR, indicating that increased agricultural productivity could mitigate CLA; however, its significance fluctuated and was often overshadowed by structural factors. Rural labor ( $\ln RL$ ) exhibited considerable coefficient variability across models, ranging from  $-0.1311$  to  $0.3592$ , even reversing sign when controlling for individual time trends. This pattern aligns with instrumental variable (IV)

regression conclusions demonstrating severe bidirectional causality between labor and CAR—an interaction ordinary panel models cannot adequately capture. Consequently, rural labor functions simultaneously as both an endogenous outcome variable and a transmission channel, necessitating specialized econometric treatment. Climate factors, CO<sub>2</sub> emissions, and cropping intensity index demonstrated unstable significance across specifications, indicating their impacts on CAR were context-dependent rather than universally robust. The pandemic served as a stress test, revealing that core variables related to land fragmentation and ecological land use remained structurally unchanged, suggesting that COVID-19 exposed system vulnerabilities without altering fundamental drivers. Model HDFE3, incorporating individual and urban time trends, achieved the highest R<sup>2</sup> (0.6706), indicating significant individual-level trends in CAR. More strictly controlled specifications exhibited reduced explanatory power, reflecting trade-offs between controlling for confounding and capturing true causal effects. The complete reports can be found in Supplementary Table S7.

### 3.2.4. Instrumental Variable Regression

Table 4 presents a series of models designed to elucidate the roles of core drivers of CLA, specifically PD and the ELR. Endogeneity tests indicate that lnPD and ELR possess intrinsic characteristics that correlate with other determinants, such as agricultural productivity. To mitigate potential reverse causality and omitted-variable bias, Two-Stage Least Squares (IV-2SLS) and Difference Generalized Method of Moments (Diff-GMM) estimators were employed. Both approaches affirm significant positive effects: IV estimates yield coefficients of 1.290 for lnPD and 1.657 for ELR. The Diff-GMM results interpreted only as exploratory or sensitivity evidence. When comparing these results with the HDFE findings, particularly the instrumental variable (IV) regression and quantile regression analyses, notable consistencies and discrepancies emerge.

The comparative model analysis highlights the importance of accounting for dynamic persistence and HDFE (Table 4). When only the second-order CLA lag is included with interactive city–year or zone–topography–year fixed effects (HDFE1 and HDFE2), the lnPD coefficient remains high, at approximately 1.06 and 0.91, respectively. However, adding the first-order CLA lag (HDFE3 and HDFE4) reduces the lnPD coefficient to about 0.25 while preserving statistical significance. This suggests that prior abandonment dynamics absorb much of the apparent contemporaneous effect of fragmentation. The coefficient further declines from 0.253 in HDFE3 to 0.223 in HDFE4, indicating that finer geographic controls better capture topography- and region-specific confounders. Nevertheless, the fact that ELR’s significance sharpens notably under stricter geographic controls suggests that this persistence is spatially localized and mediated through dynamic land-use feedbacks, rather than originating from broad city-level macroeconomic shocks.

Once historical abandonment inertia (lagged CAR) is controlled for, the immediate impact of lnPD substantially weakens. In contrast, ELR maintains a significant cumulative effect in the long-run dynamic specifications, underscoring its persistent temporal influence. Rural labor effects differ markedly between the IV and HDFE approaches, likely due to their different treatments of endogeneity and heterogeneity. The dual heterogeneity identified through quantile regression—reflecting variation by CLA severity and spatial-temporal context—provided additional support for HDFE results. Collectively, these findings elucidated the complex interactions shaping CAR and underscored the necessity for targeted policies accounting for both structural and contextual dynamics.

**Table 4.** Instrumental variable regression results.

|                    | IV-2SLS                | HDFE1                  | HDFE2                  | HDFE3                  | HDFE4                  |
|--------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| InPD               | 1.2903 ***<br>(0.1368) | 1.0643 ***<br>(0.0703) | 0.9064 ***<br>(0.0774) | 0.2534 ***<br>(0.0238) | 0.2233 ***<br>(0.0305) |
| ELR                | 1.6566 ***<br>(0.3278) | 0.0935<br>(0.1302)     | 0.9147 ***<br>(0.2044) | 1.0103 ***<br>(0.0850) | 1.5088 ***<br>(0.1462) |
| CAR_lag2           | 0.2300 ***<br>(0.0192) | 0.2923 ***<br>(0.0198) | 0.3071 ***<br>(0.0205) | 0.1852 ***<br>(0.0181) | 0.2100 ***<br>(0.0193) |
| CAR_lag1           |                        |                        |                        | 0.2411 ***<br>(0.0177) | 0.2323 ***<br>(0.0346) |
| City × year        | YES                    | YES                    |                        | YES                    |                        |
| Zone × topo × year |                        |                        | YES                    |                        | YES                    |
| Other variables    | YES                    | YES                    | YES                    | YES                    | YES                    |
| Observations       | 62,806                 | 63,922                 | 64,232                 | 78,341                 | 78,594                 |
| F                  | 290.9129               |                        |                        |                        |                        |
| R <sup>2</sup>     | 0.2224                 | 0.6667                 | 0.4668                 | 0.6339                 | 0.4534                 |

Note: \*\*\* denote significance at the 1% levels.

## 4. Discussion

### 4.1. The Phenomenological Essence of CLA and Action Pathways for Reuse

CLA in China should not be interpreted solely as agricultural decline. Rather, it reflects a dynamic land-use process shaped by structural constraints, socioeconomic transition, ecological governance, and external shocks. Examination of abandoned land areas and CAR across our studies reveals that approximately 9.20% of abandoned land was reclaimed during 1990–2024. In contrast, 12.36% of cultivated land experienced abandonment at least once, with 2.52% abandoned multiple times, closely aligning with this study's average annual CAR (2.40%). Among the abandoned lands, 10.45% had been abandoned once or multiple times, while 3.90% were reclaimed twice or more, yielding an annual LRR of 2.82%. Other studies have reported annual CLA areas ranging from 2.34 to 12.60 Mha [47], accounting for 1.33% to 7.16% of the cultivated land.

The empirical results suggest that CLA is driven primarily by two structural constraints: cropland fragmentation and increase in ecological land. Cropland fragmentation increases management costs, weakens economies of scale, and reduces the economic viability of continued cultivation. Increase in ecological land also reflects the spatial tension between agricultural production and ecological conservation. These findings indicate that CLA is not only a behavioral response of individual farmers but also a manifestation of accumulated structural imbalances in rural land systems [48]. Socioeconomic transformation further modifies these structural effects. Urbanization, rural labor migration [49], industrial upgrading, infrastructure conditions, and agricultural productivity all influence CLA, but their effects vary across regions and abandonment intensities [22,30]. In high-abandonment areas, the effects of fragmentation, ecological constraints [3,16,17], and urbanization become stronger, suggesting that abandonment may become self-reinforcing once structural constraints exceed certain thresholds. The COVID-19 pandemic acted as an external shock that amplified abandonment risks, but it did not fundamentally change the underlying mechanisms. In regions with strong agricultural infrastructure and relatively consolidated cultivated land, abandonment may reflect an adaptive reallocation of land and labor. In ecologically fragile, fragmented, or labor-depleted regions, however, CLA may indicate weakening rural land-use resilience. The pathway for reuse should therefore not be limited to restoring all abandoned land to cultivation [15]. Instead, reuse

strategies should distinguish between land suitable for agricultural recovery, land requiring consolidation and infrastructure improvement, and land more appropriate for managed ecological restoration.

#### 4.2. Policy Implications

Findings warrant a fundamental shift in CLA governance from uniform subsidies and reactive reclamation toward differentiated structural interventions. Since cropland fragmentation constitutes a core CLA driver, land consolidation, parcel restructuring, cooperative farming arrangements, and flexible land transfer mechanisms should be prioritized in regions where abandoned cultivated land remains agriculturally viable. Concurrent improvements in rural road networks, irrigation infrastructure, and agricultural service systems can further reduce cultivation costs and support sustainable land reuse.

Simultaneously, ecological constraints require more differentiated governance. Not all abandoned cultivated land warrants reclamation for intensive cultivation, particularly in ecologically fragile regions. Where ecological restoration provides long-term public benefits, policy should support managed restoration through tiered ecological compensation, livelihood alternatives, and clear benefit-sharing mechanisms. Land reuse should be embedded within broader rural revitalization objectives, leveraging long-term leasing arrangements, cooperative management models, agricultural socialized services, and participation by new agricultural operators to reconnect abandoned land with productive use while safeguarding the rights of original landholders.

Finally, Policy design should incorporate explicit regional differentiation [50]. Major grain-producing plains warrant emphasis on cropland protection, productivity enhancement, and stable reuse systems. Mountainous and fragmented regions require prioritization of land consolidation, specialty agriculture development, and infrastructure modernization. Ecologically fragile zones necessitate focus on moderate land utilization, ecological compensation mechanisms, and restoration-oriented governance frameworks. Such differentiated strategies can facilitate transformation of CLA from a potential structural crisis into a manageable process of rural land-use transition aligned with sustainability objectives.

This study faces several noteworthy limitations. First, distinguishing CLA from ecological restoration relies upon the CLCD classification system, which exhibits imperfect categorical delineation and risks misclassification and potential underestimation of abandonment, particularly in areas experiencing rapid natural recovery. The classification methodology demonstrates relatively elevated commission error rates (user accuracy of 75.3%) and suboptimal recognition capabilities for non-fallow field categories. Second, we use proxy variables for governance but lack direct measures, limiting our ability to confirm whether processes lead to sustainable transformation or systemic crisis. Third, spatial confounding was controlled through fixed effects specifications; however, comprehensive spatial panel models were not employed, which could enhance causal inference robustness. Future research should use higher-resolution data, direct governance metrics, and spatial models to better understand these dynamics and the conditions for sustainable outcomes.

## 5. Conclusions

Between 1992 and 2022, China's CLA exhibited characteristics of both structural transformation and systemic crisis. The national average CAR of 2.3995%, coupled with a reclamation rate of only 9.2028%, reflects a system struggling to achieve equilibrium; yet persistent low-abandonment clusters, such as the Huang-Huai-Hai Plain and Northeast China Plain, show that regional contexts can buffer transition pressures. The key drivers—

including fragmentation, competition for ecological land, and feedback from labor migration—are not incidental but embody deep contradictions between labor mobility and land use, ecological conservation, and agricultural viability, and short-term responses versus long-term institutional reform. The trajectory is not predetermined; whether abandonment results in transformation or crisis depends critically on governance capacity—the ability to manage transition situations, address core constraints, and embed land reuse within a broader framework of sustainable rural development. China’s experience offers important lessons for other rapidly transforming economies, emphasizing that effective governance requires foresight and institutional adaptability.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071244/s1>, Figure S1: Schematic diagram of moving window method for detecting cropland abandonment; Figure S2: Local spatial autocorrelation of cropland abandonment rate and terrain of counties from 1992 to 2022; Figure S3: Local spatial autocorrelation of land reclamation rate and terrain of counties from 1992 to 2022; Figure S4: Spatial distribution of the cumulative difference between LR and CA frequency from 1992 to 2022; Table S1: Zone of the area classified by cultivated land quality grade; Table S2: Data sources of variables; Table S3: OLS regression on the panel data using the CAR, CA area, LRR, and LR area; Table S4: Random-effects Tobit regression results (Full); Table S5: Percentile and centile of CAR; Table S6: High-dimensional Fixed Effects model results; Table S7: Instrumental variable regression and High-dimensional Fixed Effects model.

**Author Contributions:** Conceptualization, B.G.; writing—original draft preparation, B.G.; writing—review and editing, B.G. and Y.F.; visualization, X.Z.; supervision, Y.C.; project administration, S.Y. and Y.Z.; funding acquisition, B.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the National Natural Science Foundation of China (Grant No. 42271272, 42171238) and the Natural Science Foundation of Anhui Province of China (2208085MD92).

**Data Availability Statement:** Data are unavailable due to privacy or ethical restrictions.

**Acknowledgments:** Expressions of gratitude are extended to those who furnished the data and those who provided assistance.

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

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