Original Research Article

Spatiotemporal patterns and driving mechanisms of agricultural land crimes in Jiangsu Province, China

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Abstract: Early warning and targeted crackdown on agricultural land crimes are crucial to China's food security and ecological civilization strategies. Revealing the spatial patterns and driving factors of such crimes is essential for governance decisions. Using judicial data from 2015 to 2024 on China Judgments Online for Jiangsu Province, this study employed spatial autocorrelation analysis and the GeoDetector model to explore these patterns and factors. The results indicated that: (1) crimes in Jiangsu exhibited significant spatial agglomeration, with hotspots in the northwestern and southwestern regions and low-risk areas in the central and eastern parts; (2) slope was the primary driving factor, followed by socioeconomic activities and landscape characteristics of farmland and built-up land; and (3) interactions among driving factors showed synergistic enhancement effects. Consequently, prevention measures should account for natural conditions, human activities, and landscape patterns to mitigate these effects and improve governance efficiency.

Keywords: agricultural land crimes; GeoDetector; spatial analysis

1. Introduction

Existing land management studies have supported territorial spatial planning to maintain stable quantity and quality of agricultural land resources (Liu et al., 2019; Ye et al., 2024). However, agricultural land crimes—Such as illegal land-use conversion and large-scale destruction constituting criminal offenses—Are initially handled through administrative supervision by natural resources authorities in China (Jiang et al., 2021; Su et al., 2026). Criminal justice intervenes only when damage reaches the threshold for case filing. Yet, weak interdepartmental coordination typically causes delayed detection and slow response, allowing destruction to escalate and seriously impeding resource protection. Therefore, criminological research and improved protection strategies are essential to safeguard high-quality agricultural land resources (Paukku, 2024).

To develop such strategies, a critical challenge in crime geography is how to effectively allocate limited policing resources across extensive agricultural land (Braga et al., 2014; Deng et al., 2023). Early studies used historical crime data and statistical methods to identify hotspots, establishing the core approach for early warning. However, merely describing crime frequency cannot reveal the spatial structure of regional risk. Drawing on spatial autocorrelation theory, researchers have used Local Indicators of Spatial Association (LISA) to identify hotspots and coldspots by integrating frequency and spatial structure. Yet, revealing spatiotemporal patterns without exploring driving mechanisms is insufficient for effective prevention (Cowan et al., 2020; Jiang et al., 2021). Recently, environmental criminology theory has demonstrated how natural conditions, resource endowments, and human activities drive resource-based crimes (de Oliveira et al., 2023; Wo, 2019). With increasing open-source spatiotemporal data, national-scale studies have emerged (Su et al., 2026). These studies indicate that land use and landscape patterns, in addition to natural and human activity characteristics, also act as significant drivers of resource-based

crimes.

In terms of methodology, studies on crime driving mechanisms fall into three approaches. The first involves multi-factor models represented by risk maps, which rely on weighted overlay of risk factors but cannot adequately capture spatial heterogeneity and nonlinear interactions (Cowan et al., 2020). The second involves regression-based analyses (Chen et al., 2024). Given spatial variation of risk factors, Geographically Weighted Regression (GWR) models have been widely applied in this field (Ha et al., 2024). The third utilizes ensemble machine learning algorithms, which effectively capture nonlinear relationships and predict regional crime risks with high accuracy (Deng et al., 2023; Wheeler & Steenbeek, 2017). However, their applicability at large spatial scales requires further examination. Recently, the GeoDetector model has demonstrated distinct advantages in quantitatively assessing explanatory power of individual factors and accurately identifying driving factors (Wang et al., 2016). Moreover, this model performs well with small sample sizes and can detect interaction types among multiple factors, offering an effective alternative for investigating the driving mechanisms of agricultural land crimes.

To investigate spatiotemporal patterns and driving factors of agricultural land crimes in Jiangsu Province, China, this study employed LISA and the GeoDetector model to: (1) identify the spatial hotspot patterns of agricultural land crimes in Jiangsu Province; (2) reveal the differential driving effects of natural environmental conditions, resource endowments, socioeconomic factors, and landscape patterns on such crimes; and (3) detect the interactions among driving factors and their impacts on crime risk. The results are expected to provide decision support for the development of prevention strategies for agricultural land crimes.

2. Data sources

To ensure the reliability of the research results, all data used in this study were obtained from official sources or publicly available datasets. Detailed information on data sources is provided in **Table 1**.

Table 1. Detailed information of the research data.

Category	Dataset	Description
Criminal Data (https://wenshu.court.gov.cn/)	China Judgments Online dataset	Historical data on agricultural land crimes in Jiangsu from 2015 to 2024. For each case, information on the crime location and the damaged area was extracted.
Natural Environment (https://www.resdc.cn/)	Digital Elevation Model (DEM)	Raster dataset with a 1-km resolution. Each grid cell contains a land surface evaluation value. Slope data was derived from this dataset.
Land Use (https://www.resdc.cn/)	Land Use Structure	Raster dataset with a 1-km resolution. Each grid cell represents a land-use type. Landscape indices were subsequently calculated from this dataset.
Socioeconomic Condition (https://www.resdc.cn/)	Nighttime Light	Raster dataset with a 1-km resolution. Higher values indicate greater human activity intensity.
Socioeconomic Condition (www.openstreetmap.org/)	Road Network	This vector data was acquired from Open Street Map.

3. Methodology

To explore spatial patterns and driving factors of agricultural land crimes, this study first converted location descriptions from case texts on China Judgments Online into coordinates using the Gaode

Geocoding API. Using damaged area in each case as the weight, we then applied weighted kernel density estimation to generate a continuous crime risk surface for the entire province. Based on county-level boundaries, we performed zonal statistics to calculate mean kernel density for each county, which served as the county-level crime risk indicator. Finally, with this indicator as the dependent variable and natural environmental conditions, socioeconomic factors, land use, and landscape patterns as explanatory variables, we applied the GeoDetector model to identify dominant driving factors.

3.1. Local indicators of spatial association

The core idea of LISA is to identify statistically significant local spatial clusters or outliers. In crime geography, LISA considers both crime frequency and spatial structure, effectively distinguishing hotspots (high-value clusters), coldspots (low-value clusters), and spatial outliers (high values surrounded by low values or vice versa). This allows detailed description of spatial variation in regional crime risk.

3.2. Landscape indices

Landscape indices quantitatively describe how human activities shape natural environments. This study included four indices—Shape, connectivity, division, and aggregation—As explanatory variables to represent driving effects of landscape patterns on agricultural land crimes. The FRAGSTATS platform was used for calculation.

3.3. GeoDetector

The core assumption of GeoDetector is that if an independent variable significantly affects the dependent variable, their spatial distributions should be similar (Wang et al., 2016). This study employed the factor and interaction detectors. The factor detector computes the q-value to quantify explanatory power of each driving factor on spatial variation of agricultural land crimes, with larger values indicating stronger power.

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

q: The explanatory power of driving factor X on Y, with a value range of [0, 1]. h: The number of strata of factor X; this study used the natural breaks method to divide the data into three strata. N_h: The number of county units in strata h. N: The total number of counties in Jiangsu Province. σ_h^2: The variance of Y within strata h. σ^2: The overall variance of Y for the entire province.

In addition, this study used the interaction detector to identify the interaction types between factors (such as two-factor enhancement and nonlinear enhancement) by comparing the q-value under the interaction of two factors with the q-values of each factor acting alone. The specific criteria for identification are shown in **Table 2**.

Table 2. Criteria for interpreting interaction detector results.

Interaction	Description
Nonlinear weaken	$q(X_1 \cap X_2) < Min[q(X_1), q(X_2)]$
Univariate weaken	$Min[q(X_1), q(X_2)] < q(X_1 \cap X_2) < Max[q(X_1), q(X_2)]$
Bivariate enhance	$q(X_1 \cap X_2) > Max[q(X_1), q(X_2)]$
Independent	$q(X_1 \cap X_2) = q(X_1)+q(X_2)$
Nonlinear enhance	$q(X_1 \cap X_2) > [q(X_1)+q(X_2)]$

3.4. Potential factors underlying crime mechanisms

Based on open-source datasets and existing research findings, this study selected candidate explanatory variables across four dimensions: Natural environmental conditions, socioeconomic factors, land use, and landscape patterns. The definitions of these variables are provided in **Table 3**.

Table 3. Driving factors used as explanatory variables in the GeoDetector model.

Index	Description
Elevation (DEM)	This indicator is used to measure the effect of elevation on agricultural land crimes.
Slope	This indicator is used to measure the effect of surface relief on agricultural land crimes.
Nighttime light	It measures the effect of socioeconomic and human activity intensity on agricultural land crimes.
Road density	This raster layer is based on kernel density analysis of road network data, used to measure the effect of regional infrastructure development on crime.
Land use structure	The area of different land use types in each county is used to measure the effect of regional resource conditions on crime.
Landscape shape index(LSI)	It measure the complexity and irregularity of landscape patches, with higher values indicating more fragmented and irregular agricultural land parcels.
Connectivity	It measures the spatial connectedness of landscape patches, with higher values indicating more physically connected and contiguous agricultural land.
Division	It measures the degree to which landscape patches are separated or fragmented, with higher values indicating more isolated and dispersed agricultural land parcels.
Aggregation index(AI)	It measures the degree to which landscape patches are clustered together, with higher values indicating more compact and contiguous agricultural land configurations.

4. Results and discussion

4.1. Spatial patterns of agricultural land crimes in Jiangsu Province

Agricultural land crimes in Jiangsu Province exhibited a distinct spatial pattern (**Figure 1**): Higher in the north, south, and west, and lower in the central and eastern regions. Global Moran's I was 0.92, indicating strong spatial clustering. This confirms that criminal behavior is not spatially random, but driven by combined effects of incidents, individuals, and environmental characteristics (Su et al., 2026).

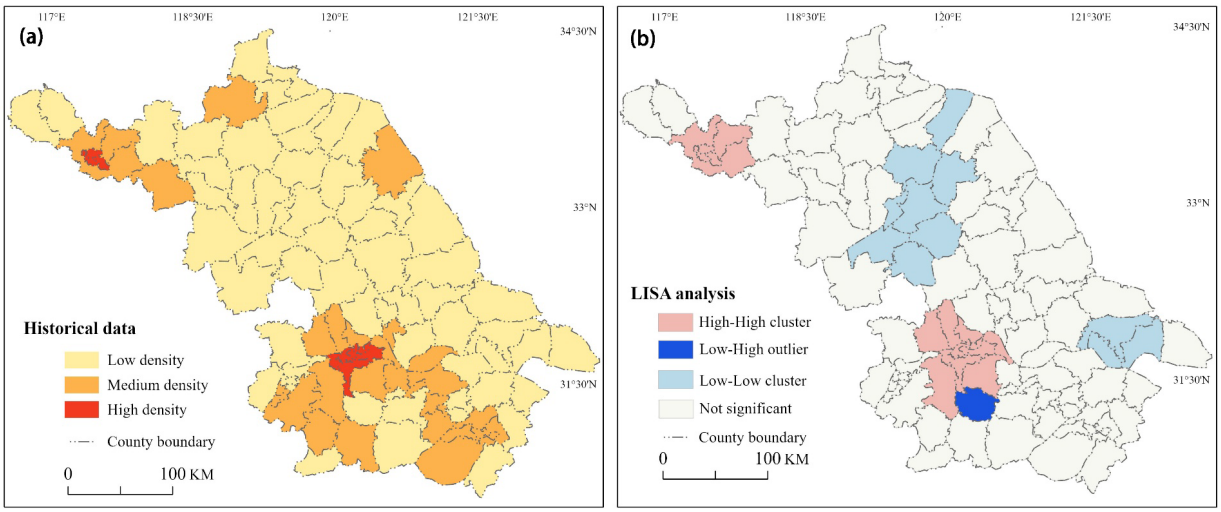


Figure 1. Spatial patterns of agricultural land crimes in Jiangsu Province based on (a) historical data; (b) LISA analysis.

LISA results indicated significant spatial clustering of agricultural land crimes in Jiangsu Province, forming two major hotspots (**Figure 1**). The northwestern hotspot is entirely within Xuzhou City, while the southwestern encompasses Zhenjiang City and southern Yangzhou City. Both hotspots share similar natural environments dominated by flat terrain with gentle slopes, but differ in socioeconomic characteristics. The northwestern hotspot centers on Xuzhou, a regional economic center in northern Jiangsu. In contrast, the southwestern hotspot lies within the southern Jiangsu urban agglomeration but avoids the most urbanized or economically intensive areas. These spatial differences indicate complex driving mechanisms of

agricultural land crimes.

4.2. Agricultural land crime mechanisms in Jiangsu Province

4.2.1. Natural environment and human activities form the dominant driving factors

The GeoDetector model showed that agricultural land crimes in Jiangsu Province are driven by multiple interacting factors (**Table 4**). Regarding the independent explanatory power of each factor, slope exhibited the strongest driving effect, with the highest q-value. Land use structure, which represents the outcome of human-land interactions, ranked second. The nighttime light index, reflecting the intensity of socioeconomic activities, followed. These results indicate that the combined effect of natural environmental conditions and human activities dominates the spatial pattern of crime risk, consistent with existing findings (de Oliveira et al., 2023; Wo 2019).

Table 4. Results of the GeoDetector model analysis.

Variables	q-value	p-value
Elevation	0.12	<0.01
Slope	0.28	<0.01
Nighttime light	0.15	<0.01
Road density	0.10	0.01
Farmland area	0.17	<0.01
Built-up land area	0.15	<0.01
$Division_{(farmland)}$	0.08	0.03
$AI_{(farmland)}$	0.11	<0.01
$AI_{(forest)}$	0.07	0.05
$LSI_{(built\text{-}up\ land)}$	0.09	0.02
$Connectivity_{(built\text{-}up\ land)}$	0.08	0.05
$Division_{(built\text{-}up\ land)}$	0.11	<0.01

Note: Only variables that passed the significance test (p-value≤0.05) are shown.

4.2.2. Landscape pattern dynamics indicate the risk of agricultural land crime

Although landscape pattern indices have lower q-values than natural and socioeconomic indicators such as slope and land use, farmland and built-up land patterns still significantly affect crime risk (Ha et al., 2024). As shown in **Table 4**, fragmented farmland is more vulnerable to criminal activities, while forest land aggregation effectively indicates crime risk. Built-up land patterns—Dominated by human activities—Exhibit stronger indicative power than natural resource patterns. The continuous spread and complex edges from uncontrolled expansion have become important landscape markers of agricultural land crimes.

Given that landscape patterns are subject to institutional constraints from territorial spatial planning, guiding built-up land configuration can support prevention system construction under the integrated administrative–criminal justice framework. Moreover, increasing availability of high-resolution land-use monitoring products enables early detection of abnormal landscape trends and timely preventive measures.

4.3. Interaction between crime driving factors

Using the interaction detector, this study further revealed the interactions among driving factors. As shown in **Table 5**, 50% of the factor combinations exhibited bivariate enhancement (combined effect of two factors far exceeds a simple linear sum). This indicates that agricultural land crimes arise from the nonlinear synergy of multiple factors. Moreover, the combinations of built-up land and socioeconomic factors showed extremely strong driving effects. Specifically, the landscape indices of built-up land (LSI and Division) paired with socioeconomic factors (nighttime light and road density) all produced high interaction q-values. Therefore, crime prevention measures should not consider individual factors in isolation; instead, a comprehensive assessment from a holistic perspective is required (Chen et al., 2021).

Table 5. Results of the interaction detector analysis.

Variables	q-value	Variables	q-value
$Division_{(farmland)}$ & $Connectivity_{(built\text{-}up\ land)}$	0.15*	$Division_{(farmland)}$ & $AI_{(farmland)}$	0.21-
$Division_{(farmland)}$ &$Division_{(built\text{-}up\ land)}$	0.17*	$Division_{(farmland)}$ & $AI_{(forest)}$	0.20-
$Division_{(farmland)}$ &Farmland area	0.22*	$Division_{(farmland)}$ & $LSI_{(built\text{-}up\ land)}$	0.24-
$AI_{(farmland)}$ & $LSI_{(built\text{-}up\ land)}$	0.20*	$Division_{(farmland)}$ & Built-up land area	0.30-
$AI_{(farmland)}$ & $Division_{(built\text{-}up\ land)}$	0.20*	$Division_{(farmland)}$ & Elevation	0.35-
$AI_{(farmland)}$ & Farmland area	0.21*	$Division_{(farmland)}$ & Road density	0.23-
$AI_{(farmland)}$ & Elevation	0.22*	$Division_{(farmland)}$ & Slope	0.37-
$AI_{(farmland)}$ & Road density	0.20*	$Division_{(farmland)}$ & Nighttime light	0.26-
$AI_{(farmland)}$ & Slope	0.30*	$AI_{(farmland)}$ & $AI_{(forest)}$	0.20-
$AI_{(farmland)}$ & Nighttime light	0.23*	$AI_{(farmland)}$ & $Connectivity_{(built\text{-}up\ land)}$	0.18-
$AI_{(forest)}$ & $Connectivity_{(built\text{-}up\ land)}$	0.14*	$AI_{(farmland)}$ & Built-up land area	0.28-
$AI_{(forest)}$ & $Division_{(built\text{-}up\ land)}$	0.17*	$AI_{(forest)}$ & $LSI_{(built\text{-}up\ land)}$	0.21-
$AI_{(forest)}$ & Farmland area	0.23*	$AI_{(forest)}$ & Built-up land area	0.26-
$AI_{(forest)}$ & Slope	0.30*	$AI_{(forest)}$ & Elevation	0.19-
$LSI_{(built\text{-}up\ land)}$ & $Division_{(built\text{-}up\ land)}$	0.16*	$AI_{(forest)}$ & Road density	0.26-
$LSI_{(built\text{-}up\ land)}$ & Farmland area	0.18*	$AI_{(forest)}$ & Nighttime light	0.22-
$LSI_{(built\text{-}up\ land)}$ & Built-up land area	0.19*	$LSI_{(built\text{-}up\ land)}$ & $Connectivity_{(built\text{-}up\ land)}$	0.18-
$LSI_{(built\text{-}up\ land)}$ & Slope	0.34*	$LSI_{(built\text{-}up\ land)}$ & Elevation	0.29-
$LSI_{(built\text{-}up\ land)}$ & Nighttime light	0.16*	$LSI_{(built\text{-}up\ land)}$ & Road density	0.29-
$Connectivity_{(built\text{-}up\ land)}$ & $Division_{(built\text{-}up\ land)}$	0.18*	$Connectivity_{(built\text{-}up\ land)}$ & Built-up land area	0.23-
$Connectivity_{(built\text{-}up\ land)}$ & Farmland area	0.22*	$Connectivity_{(built\text{-}up\ land)}$ & Elevation	0.27-
$Connectivity_{(built\text{-}up\ land)}$ & Slope	0.33*	$Connectivity_{(built\text{-}up\ land)}$ & Road density	0.18-
$Division_{(built\text{-}up\ land)}$ & Farmland area	0.17*	$Connectivity_{(built\text{-}up\ land)}$ & Nighttime light	0.22-
$Division_{(built\text{-}up\ land)}$ & Slope	0.35*	$Division_{(built\text{-}up\ land)}$ & Built-up land area	0.35-
$Division_{(built\text{-}up\ land)}$ & Nighttime light	0.16*	$Division_{(built\text{-}up\ land)}$ & Elevation	0.29-
Farmland area & Built-up land area	0.24*	$Division_{(built\text{-}up\ land)}$ & Road density	0.23-
Farmland area & Slope	0.35*	Farmland area & Elevation	0.32-
Farmland area & Nighttime light	0.20*	Farmland area & Road density	0.27-
Built-up land area & Slope	0.40*	Built-up land area & Elevation	0.37-
Built-up land area & Nighttime light	0.25*	Built-up land area & Road density	0.30-
Elevation & Slope	0.29*	Elevation & Road density	0.32-
Road density & Slope	0.38*	Elevation & Nighttime light	0.36-
Slope & Nighttime light	0.36*	Road density & Nighttime light	0.33-

Note: * indicates the bivariate_enhance of variables, - indicates the nonlinear_enhance.

5. Conclusions

This study integrated historical crime data from China Judgments Online with open-source spatiotemporal datasets to investigate spatiotemporal characteristics and dominant driving factors of agricultural land crimes in Jiangsu Province from 2015 to 2024. The main conclusions are:

(1) Agricultural land crimes exhibited significant spatial autocorrelation. Hotspots concentrated in Xuzhou (northern Jiangsu) and Zhenjiang and Yangzhou (southern Jiangsu), with no distinct patterns in central and eastern regions.

(2) Natural environmental constraints and human activity intensity were dominant driving factors shaping overall crime risk patterns. Landscape patterns of farmland and built-up land further served as important indicators.

(3) Driving factors exhibited a coupled amplification mechanism. Combinations of built-up land and socioeconomic factors showed particularly strong effects, indicating severe conflict between human activities and resource protection.

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