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Reducing cropland fragmentation may not be universally beneficial at increasing land use efficiency: Evidence from multiscale spatial analysis of Huang-Huai-Hai region, China

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ABSTRACT

Cropland fragmentation, a global issue affecting agricultural efficiency, poses management challenges while offering opportunities to optimize production and mitigate risks. In this study, we investigated the impact of cropland fragmentation on cropland use intensity in the Huang-Huai-Hai region using data from China's Second National Land Survey (2010). By analysing spatial patterns of fragmentation—focusing on mean plot size, cropland density, and the area-weighted mean shape index—this research applies advanced methods, including empirical orthogonal function (EOF) analysis of the leaf area index (LAI) and sliding window local regression, to capture spatiotemporal variations and localized relationships. The findings reveal substantial spatial variability in fragmentation and cropland use intensity. In plains regions such as the Huang-Huai Plain, the cropland density has reached over 0.7, with the mean plot size exceeding 2.1 ha. In contrast, mountainous areas exhibit lower cropland density (below 0.37) and mean plot sizes often less than 1.3 ha. EOF analysis explained 70.6 % of the spatiotemporal variance in the leaf area index, reflecting clear seasonal patterns of agricultural activity. The relationship between fragmentation and cropland use intensity is complex and context-dependent: while fragmentation may reduce productivity in highly mechanized systems, small-scale farms can adapt fragmented cropland for food production through strategies such as crop diversification. These results suggest that uniform land consolidation policies may be inefficient, and highlight the need for region-specific strategies. For plains regions, consolidation could enhance efficiency, whereas in fragmented mountainous areas, infrastructure improvements and resilient land management practices are more critical. Evidence from the Huang–Huai–Hai region, derived from a multiscale spatial framework, underpins differentiated land governance strategies with empirical and methodological insights.

1. Introduction

Cropland fragmentation (CLF) refers to the division of agricultural land into numerous, irregular, and often spatially scattered plots (Abubakari et al., 2016; Tan et al., 2006; Ye et al., 2024a). As a spatial structural attribute of land systems, CLF reflects the physical configuration of cropland and is commonly quantified by indicators such as mean plot size (MPS), cropland density (CLD), and area-weighted mean shape index (AWMSI), which represent the scale, distribution, and geometric complexity of land parcels (Liang et al., 2022; Pang et al., 2023; Ye et al., 2024a). These characteristics significantly influence land management efficiency, transaction costs, and the feasibility of mechanized operations (Xu et al., 2025; Zang et al., 2024; Zhang et al., 2019). A high degree of CLF is often associated with reduced agricultural

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efficiency and operational difficulties (Deininger et al., 2012; Lotfi et al., 2023; Sklenicka, 2016), although some studies report potential benefits such as increased crop diversification or enhanced ecological resilience under certain conditions (Ciaian et al., 2018; Yu et al., 2022).

Beyond its spatial and institutional dimensions, the significance of CLF lies in its potential to influence overall land system performance, particularly functional intensity and efficiency, through changes in the spatial configuration of parcels (Xiang et al., 2019; Zheng et al., 2023). This calls for an integrated structure–function perspective that can explain the effects of plot configurations on agricultural outcomes under varying ecological and institutional settings. Cropland use intensity (CLUI) offers a critical entry point for such analysis, as it captures how actively and productively land is being used (Yu et al., 2021). CLUI is commonly used as a proxy for land-use efficiency and is conceptually related to agricultural intensification, though the two are not equivalent: the former reflects realized output per unit of land, while the latter emphasizes the process of increasing inputs and outputs. Clarifying the relationship between CLF and CLUI is thus essential to assess whether—and under what conditions—fragmented land structures may hinder or enhance land-use performance.

CLUI is commonly assessed through indicators such as crop yields, multiple cropping indices, or remote-sensing proxies like the Leaf Area Index (LAI), and reflects the combined effects of human inputs, management practices, and ecological productivity (Kuemmerle et al., 2013; Li et al., 2023b; Yu et al., 2021). The structural configuration of land parcels may influence CLUI through at least three pathways: (1) operational efficiency constraints due to scattered or irregular fields (Colombo and Perujo Villanueva, 2017; Valtiala et al., 2023); (2) institutional transaction costs related to tenure and coordination (Lin et al., 2026); and (3) ecological interactions with terrain or microclimate conditions (Mayer et al., 2016). Increased fragmentation can raise operational complexity, reduce contiguous field area, and constrain mechanization, thereby lowering input efficiency and cropping frequency (Deininger, 2003; Latruffe and Piet, 2014; Xie and Lu, 2017). Conversely, in heterogeneous or subsistence-oriented landscapes, fragmentation may allow for diversified planting strategies, risk mitigation, or better alignment with local micro-conditions (Ntihinyurwa et al., 2019; Tanrıvermiş et al., 2024; Tittonell et al., 2010). These heterogeneous effects suggest that the CLF–CLUI relationship is nonlinear, spatially variable, and conditional upon multiple contextual factors including topography, infrastructure access, labor availability, cropping systems, and policy regimes (Deng et al., 2024; Jürgenson, 2016). Yet, few studies have empirically identified the conditions under which fragmentation suppresses or facilitates land use intensity, especially at regional scales (Aslam and Fazal, 2025; Ndip et al., 2023; Ye et al., 2022).

Given these complexities, governments across Asia and Central-Eastern Europe have promoted land consolidation to mitigate the presumed inefficiencies of CLF (Hartvigsen, 2015; Jiang et al., 2022; Jürgenson, 2016). In China, where fragmented land tenure remains widespread, land-use policy increasingly emphasizes intensification and ecological protection (Duan et al., 2021; Li et al., 2023a; Ntihinyurwa and de Vries, 2020). However, most empirical studies remain descriptive or rely on household-level data, often neglecting spatial heterogeneity and masking localized structure–function interactions (Hao et al., 2023; Wang and Li, 2021; Ye et al., 2022). Moreover, prior studies tend to adopt global regression models such as OLS or SAR, which assume spatial stationarity and thus fail to capture local variations in the CLF–CLUI relationship (Fotheringham et al., 2017; LeSage and Pace, 2009). This methodological limitation makes it difficult to draw context-specific policy implications, especially in ecologically and socially diverse agricultural regions.

This study is guided by two research questions: (1) how does the spatial configuration of fragmented cropland influence land-use intensity at the landscape scale? and (2) under what spatial conditions do these effects become more positive or negative? We focus on the Huang-Huai-Hai region of China, a representative agricultural heartland characterized by intensive land use, fine-grained parcel structures, and increasing consolidation pressures. To capture structural and functional dynamics, we integrate parcel-level indicators from China's Second National Land Survey with CLUI metrics derived from remote-sensing LAI time series. Empirical orthogonal function (EOF) analysis, commonly applied in climatology and oceanography, is adapted here to an agricultural land system context, enabling the extraction of dominant spatiotemporal modes of CLUI variation. Building on this, we develop a sliding-window local linear regression framework tailored for this study, which relaxes the spatial stationarity assumption of global models and allows parameters to vary across both location and scale. This integrated approach reveals conditional, scale-sensitive, and spatially heterogeneous effects of cropland fragmentation on land-use intensity that conventional methods often overlook, thereby providing a more robust empirical basis for context-specific land consolidation and governance strategies.

2. Materials and methods

2.1. Study area

The Huang-Huai-Hai region, encompassing Beijing, Tianjin, Hebei, Shandong, and most of Henan Province (Fig. d), is one of China's core agricultural production bases, dominated by wheat–maize rotation systems that support national food security. However, cropland fragmentation has become increasingly prominent due to the combined effects of historical land redistribution, rapid socioeconomic transformation, and complex natural constraints, leading to inefficient and scattered land-use patterns.

This fragmentation is shaped by topographical, soil, and spatial heterogeneity across the region (Fig. 1 a–d). While the central North China Plain supports large, contiguous farmland, the surrounding Yin Mountain zone, Shandong Hills, and Henan Earth-rock Mountains impose physical constraints on land consolidation. The region's soils—classified into seven major types, including dark soils (chernozems), yellow soils, sandy and saline soils, calcareous chestnut soils, among others—exhibit notable spatial differentiation in fertility and water retention. These classifications are based on the 1:1 million "Soil Map of the People's Republic of China" provided by Resource and Environment Data Cloud Platform. Fertile plains are associated with continuous land blocks, while marginal areas with sandy or less productive soils tend to maintain fragmented cropland structures. Cropland distribution patterns (Fig. c) reflect this contrast, with dense cultivation in the Hebei–Henan–Shandong plains and higher fragmentation in hilly, riverine, and peri-urban zones.

To account for such spatial complexity, this study adopts the agricultural resources and environmental zoning framework proposed by Xu (2021), which divides the region into functional subzones—such as the North China Plain Zone, Huang-Huai Plain Zone, Shandong Hill Zone, and Henan Hill Zone—based on topography, soil, and land-use suitability. This classification offers a systematic lens for analyzing cropland fragmentation and provides a spatially explicit foundation for designing differentiated governance strategies.

2.2. Data sources

The CLF and extent of cropland were calculated via data from the Second National Land Use Survey of China (NLUS II) released in 2010. This dataset remains one of the most comprehensive and reliable sources for large-scale land use analysis, as it integrates detailed field survey data with high spatial accuracy (Chen et al., 2022). Despite the temporal

Table 1
Detailed dataset information to estimate cropland fragmentation, the CLUI, and their interactions.

Indicators			Definition of Indicators	Dataset
Cropland Fragmentation and Spatial Extent		Mean Plot Size	The average size of each cropland patch	Database of the Second National Land Use Survey of China, 2010 (Ye et al., 2024a)
		Cropland Density	The ratio of the area of a given cropland patch to the area per square kilometre.	
		Area-Weighted Mean Shape Index	The sum of the perimeter-to-area ratios of individual patches in a given cropland patch multiplied by their respective area weights	
Cropland Use Intensity		Leaf Area Index	The one-sided green leaf area per unit ground area in broadleaf canopies and half the total needle surface area per unit ground area in coniferous canopies	MODIS Leaf Area Index/FPAR, 2010 (Myneni et al., 2015)
Control Variables	Climate	Temperature	Annual average temperature	1-km monthly mean temperature dataset for China 1901–2022 (Peng et al., 2019)
		Precipitation	Annual average precipitation	1-km monthly precipitation dataset for China 1901–2022 (Peng et al., 2019)
	Topography	Elevation	Elevation of cropland	ASTER GDEM V3 dataset (Abrams et al., 2020)
		Field Slope	Slope or degree of incline of cropland	
	Soil	Soil Organic Matter Content (0–5 cm depth)	Content of carbon-containing organic compounds present in various forms within the top 5 cm of soil depth	High-resolution National Soil Information Grids of China 2010–2018 (Liu et al., 2022b)
	Socio-economic	GDP Density	County-level GDP data is scaled down to kilometre-grid units, in 1995, 2000, 2005, 2010, 2015 and 2019	(Xu, 2017a) (http://www.resdc.cn/)
		Population Density	County-level demographic data is scaled down to kilometre-grid units, in 1995, 2000, 2005, 2010, 2015 and 2019	(Xu, 2017b) (http://www.resdc.cn/)
		Farming Distance	Euclidean distance from the plot to the nearest rural settlement (excluding roads)	A peer-reviewed 30-metre resolution global land cover dataset in 30-metre spatial resolution (Chen et al., 2015)

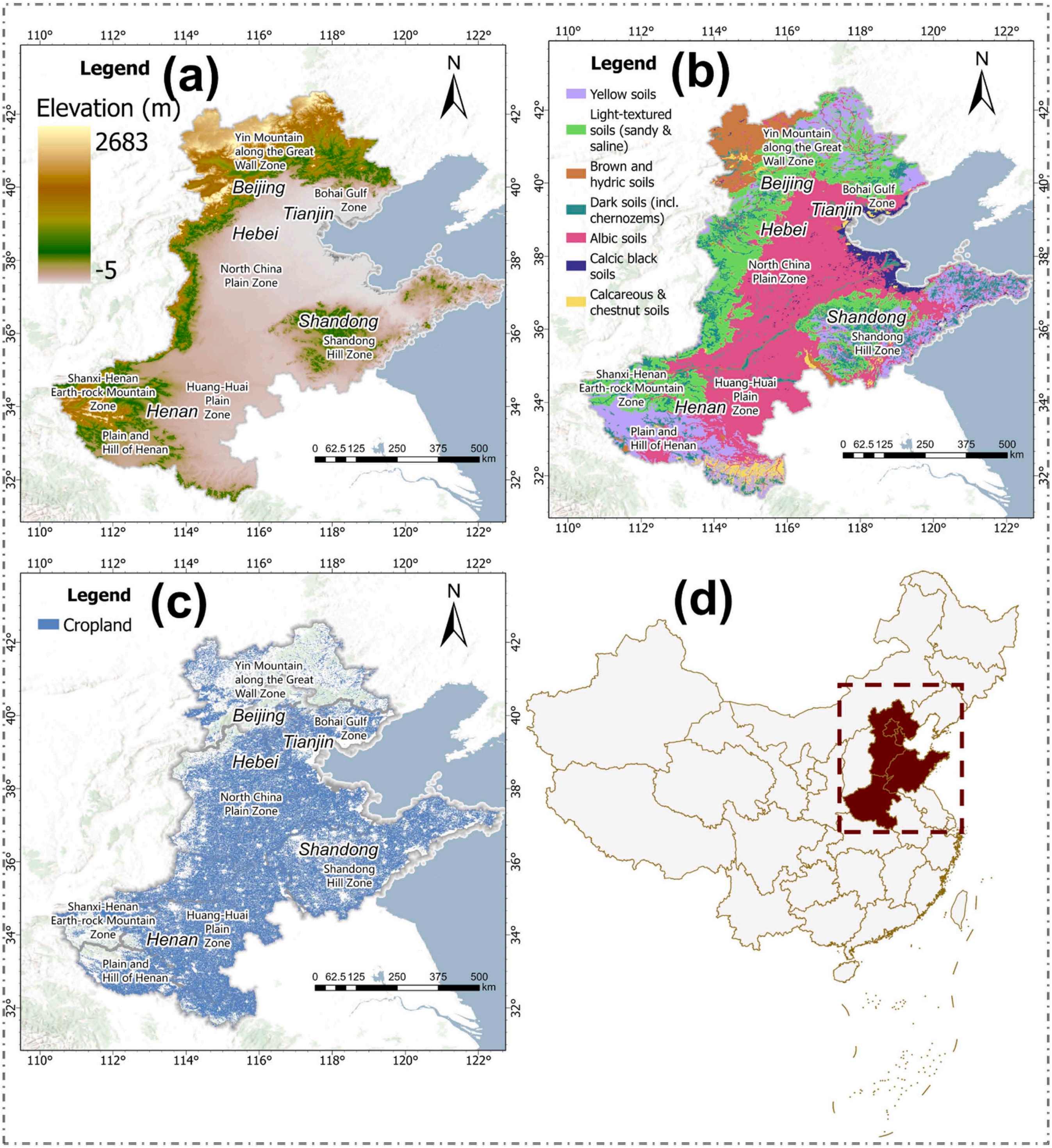

Fig. 1. Geographic characteristics of the Huang-Huai-Hai region: (a) Elevation, (b) Soil types, (c) Cropland distribution, and (d) Location within China.

gap, the NLUSII remains the most comprehensive and authoritative land-use dataset in China. It integrates high-resolution field survey data, cadastral boundary information, and land tenure records, offering not only detailed physical representations of cropland parcels but also ownership-related attributes critical for capturing institutional dimensions of fragmentation. Given the relatively stable nature of cropland spatial structures, which evolve slowly under long-term policy, topographic, and institutional constraints, the 2010 data are considered valid for analyzing structural-functional relationships at landscape scales.

While this study primarily quantifies cropland fragmentation through spatial indicators such as mean plot size, cropland density, and shape complexity, we acknowledge that fragmentation is a multidimensional phenomenon encompassing both physical and institutional aspects. In particular, tenure fragmentation—the dispersion of land rights among multiple small plots—plays a critical role in shaping land-use behavior and outcomes. Although this form of fragmentation is typically assessed through household-level data (e.g., number of plots per household, inter-parcel distances), such information is difficult to obtain and integrate at regional scales. Therefore, this study adopts a spatial-structural approach based on land survey data, which, while emphasizing physical configuration, also implicitly captures elements of tenure fragmentation due to its basis in parcel-level ownership records.

The cropland use intensity (CLUI) was quantified using the empirical orthogonal functions (EOF) method applied to the MODIS Leaf Area Index (LAI) product (MOD15A2H, 500 m resolution, 8-day composites) for the year 2010, obtained from the NASA EOSDIS Land Processes DAAC (Myneni et al., 2015). Cropland fragmentation indicators—including mean plot size, cropland density, and the area-weighted mean shape index—were derived from the Second National Land Use Survey of China (NLUS II, 2010), which integrates detailed field survey and cadastral boundary data and remains the most authoritative source for parcel-level spatial structure in China (Chen et al., 2022). To control for environmental and socio-economic heterogeneity, ten covariates were assembled: annual temperature and precipitation from the 1-km gridded climate dataset for China (Peng et al., 2019); elevation and slope from the ASTER GDEM V3 dataset (Abrams et al., 2020); soil organic matter (0–5 cm depth) from the high-resolution National Soil Information Grids of China (Liu et al., 2022b); county-level GDP density and population density downscaled to 1-km grids (Xu, 2017a; 2017b); and farming distance from a 30-m resolution global land cover dataset (Chen et al., 2015). To ensure temporal consistency, all datasets—including LAI, cropland fragmentation metrics, and control variables such as GDP and population density—were strictly limited to the year 2010. More detailed dataset descriptions are provided in Table 1.

2.3. Analytical framework

To systematically explore how cropland fragmentation influences cropland use intensity, this study constructs a multi-layered analytical framework integrating spatial structural measurement, functional proxy extraction, and multiscale interaction models. Specifically, cropland fragmentation was quantified using geometric and density-based indicators derived from 1-km grid-based land survey data, while CLUI was estimated via empirical orthogonal function decomposition of MODIS-based LAI time series. A sliding window local regression model was then applied to quantify spatially heterogeneous relationships between fragmentation indicators and CLUI, controlling for climatic, topographic, soil, and socioeconomic covariates. This framework enables a spatially explicit assessment of the structure–function linkage across varying scales and contexts, providing robust insights into the differential effects of fragmentation across the Huang-Huai-Hai region. In particular, it establishes a theoretical linkage between the structural configuration of cropland parcels and their functional performance in land-use efficiency, highlighting the importance of spatially explicit and scale-sensitive analysis.

2.3.1. Generating 1-KM grid-based cropland fragmentation maps using China land survey data

High-resolution maps of cropland fragmentation were generated to analyze spatial patterns and inform subsequent modeling efforts. By

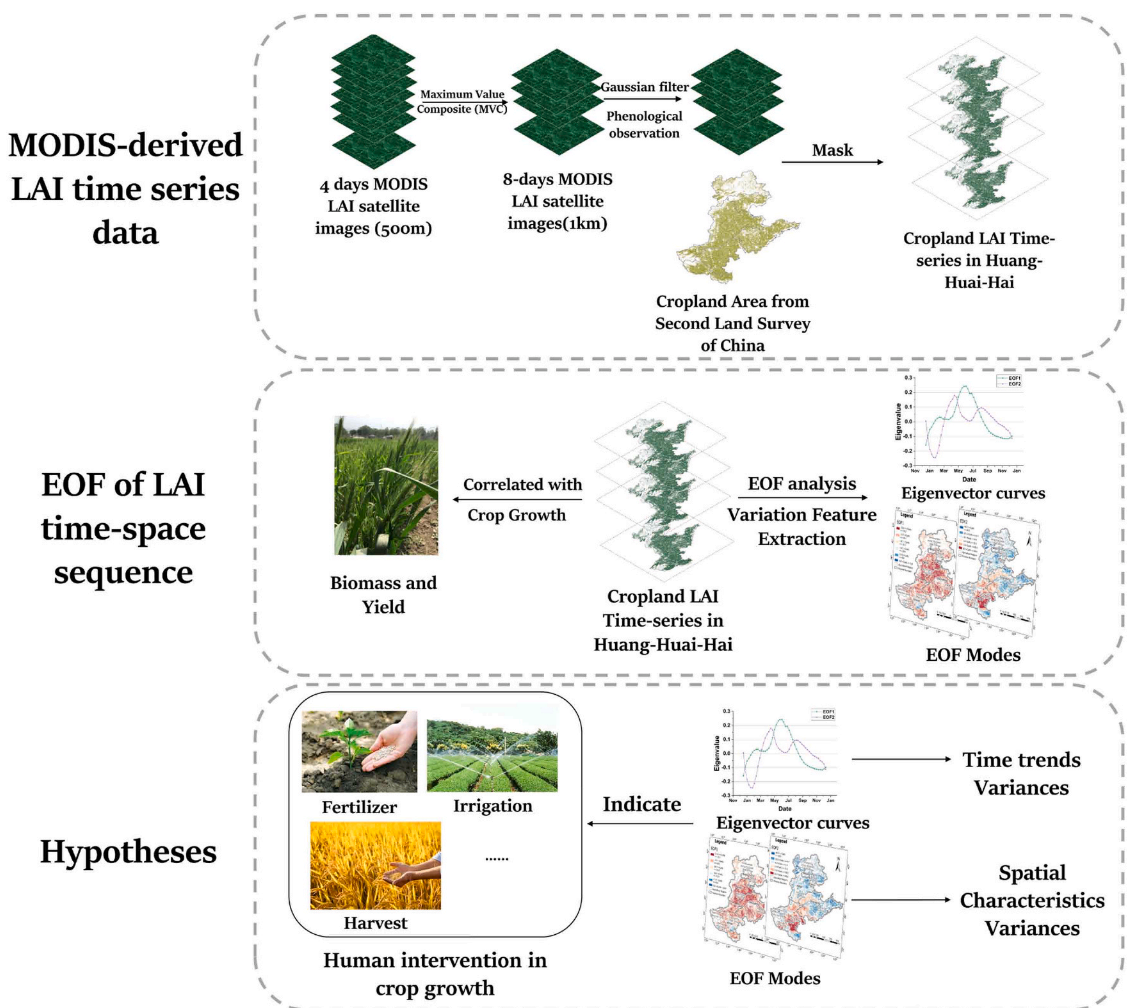

Fig. 2. Conceptual model integrating empirical orthogonal function (EOF) analysis with MODIS leaf area index (LAI) time series to quantify cropland use intensity (CLUI) in the Huang-Huai-Hai region.

utilizing the Second National Land Use Survey of China data, the approach integrates geometric indicators such as mean plot size (MPS), area-weighted mean shape index (AWMSI), and cropland density (CLD) to assess fragmentation characteristics at a fine spatial scale. When initial cropland plot data are organized at the county level, each county serves as an independent spatial data file. Following Ye et al., 2024a approach, the method employs a 1 km^2 grid and calculates the mean plot size, area-weighted mean shape index, and cropland density for each grid. The subsequent steps involve generating CLF maps based on 1 km grids, which can be executed simultaneously across multiple grids.

Step 1: County-level cropland plot vector data were converted from Gauss 3-degree projection to Albers equal-area conic projection.

Step 2: A 1 km^2 grid was generated using the Albers projection method based on the boundaries of mainland China.

Step 3: Intersecting cropland plots within each grid were organized without altering their original shapes.

Step 4: MPS were extracted and calculated for each grid using Eq. (1), outputting an MPS map based on 1-km grids. Eq. (2) was used to generate the AWMSI map. The vector data files were clipped according to the grid boundaries. CLD within each grid was calculated as the proportion of land area to the total grid area (1 km^2).

$$MPS = A/N \tag{1}$$

$$AWMSI = \sum_{i=1}^{N} \frac{0.25 \times P_i}{\sqrt{a_i}} \times \frac{a_i}{A} \tag{2}$$

MPS was calculated using Eq. (1) and the results were assigned to the grid, resulting in a 1-km grid-based *MPS* map. *A* represents the total cropland area of a specific vector data file (i.e., grid); *N* represents the number of cropland plots. Similarly, a 1-km grid-based *AWMSI* map was generated using Eq. (2). For specific plot *i*, its perimeter, and area are represented as P_i and a_i, respectively. Lastly, the corresponding vector data file of each grid has been clipped using the bounding box of the grid. The CLD of each grid is then calculated as the proportion of plot area to the total area of the grid (i.e., 1 km^2).

2.3.2. Combining leaf area index data and empirical orthogonal function measure of cropland use intensity

Empirical Orthogonal Functions (EOF) were initially introduced in meteorology during the late 1940s as a means of addressing dynamic, high-dimensional, and spatiotemporal feature problems (Hannachi et al., 2007). The objective of EOF analysis is to reduce the dimensionality of the original dataset. This is accomplished by identifying uncorrelated variables within each group, which are more readily comprehensible and manipulable for subsequent analysis. EOF is a non-model-driven tool that is employed for the exploration of spatiotemporal field data. This enables the separate visualization of time and space, including the display of spatial patterns and temporal indices. They have gained considerable traction in many scientific disciplines, including meteorology, geology, geography, and economics (Hao Quang et al., 2023; Lu et al., 2024; Tatli and Türkeş, 2011). In practice, the objective of EOF analysis techniques is to identify a new set of variables that collectively account for the majority of the observed variance in the data. This is accomplished through a linear combination of the original variables. It should be noted that any subjective evaluations have been excluded from this analysis.

The spatiotemporal field data can be represented as follows. Suppose there are *m* observation points in space in the study area, each with n-time observations. Then, the observation data can be written in matrix form as:

$$X = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)^T = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{3}$$

where X is a spatiotemporal field composed of the spatiotemporal field $X(t, s)$, which represents the value of the *X* field at time *t* and spatial location s. Under $i = 1, \ldots, n$ and $j = 1, \ldots m$, the values of the discrete-time *ti* and grid point *sj* are represented as *xij*. Through EOF, Eq. (1) is decomposed into the sum of the orthogonal spatial matrix (V) and orthogonal time matrix (T) products:

$$\mathrm{X} = \mathrm{VT} \tag{4}$$

$$x_{ij} = \sum_{k=1}^{m} v_{ik} t_{kj} = v_{i1} t_{1j} + v_{i2} t_{2j} + \cdots + v_{im} t_{mj} \tag{5}$$

The spatial matrix can be derived from the eigenvectors of $\mathrm{X}\,\mathrm{X}^{\mathrm{T}}$:

$$C = XX^{\mathrm{T}} = VTT^{\mathrm{T}}V^{\mathrm{T}} \tag{6}$$

Since matrix C is a real symmetric matrix, it is certain that:

$$C = V\Lambda V^{\mathrm{T}} \tag{7}$$

where the columns of matrix V are the eigenvectors of C, and Λ is a diagonal matrix composed of the eigenvalues of C. Once V is obtained, the time matrix can be derived as:

$$T = V^{\mathrm{T}} X \tag{8}$$

The leaf area index (LAI) is defined as the green leaf area per unit ground area (or half area) on one side of a leaf and is a key factor in crop growth processes such as canopy interception, transpiration, and total photosynthesis (Viña et al., 2011). The LAI is widely used in crop yield estimation because it effectively indicates changes in crop growth (Liu et al., 2012). The analysis focused primarily on the wheat- and corn-producing areas of the Huang-Huai-Hai Plain, using 2010 MODIS LAI data with a 4-day temporal resolution and 500 m spatial resolution. To reduce noise, a maximum value composite was generated for every two consecutive observations. This preprocessing procedure enables the extraction of intra-annual vegetation dynamics during the 2010 cropping season, which reflect seasonal variations in land use intensity. The processed time series was then subjected to EOF decomposition. The application of EOF involved the following specific steps.

(1) Data standardization. Standardize the data to eliminate the influence of scale differences.

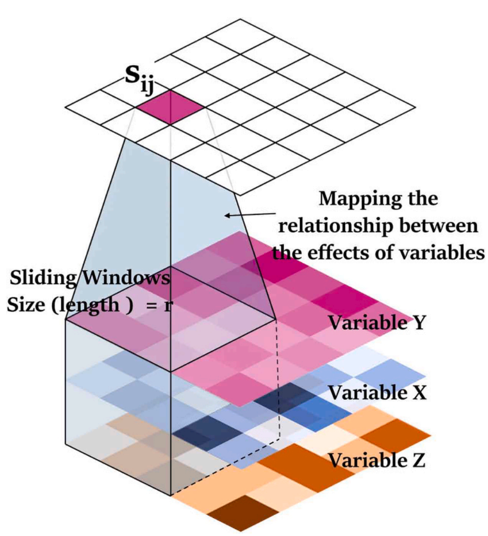

Fig. 3. Sliding window-based local multiple linear regression (MLR) approaches for high-dimensional gridded geographical data. This depicts the computation of a sliding window in which the dependent variable Y, the independent variable X, and the control variable Z perform a multiple linear regression and map their results to a point S_{ij} at the centre of the window.

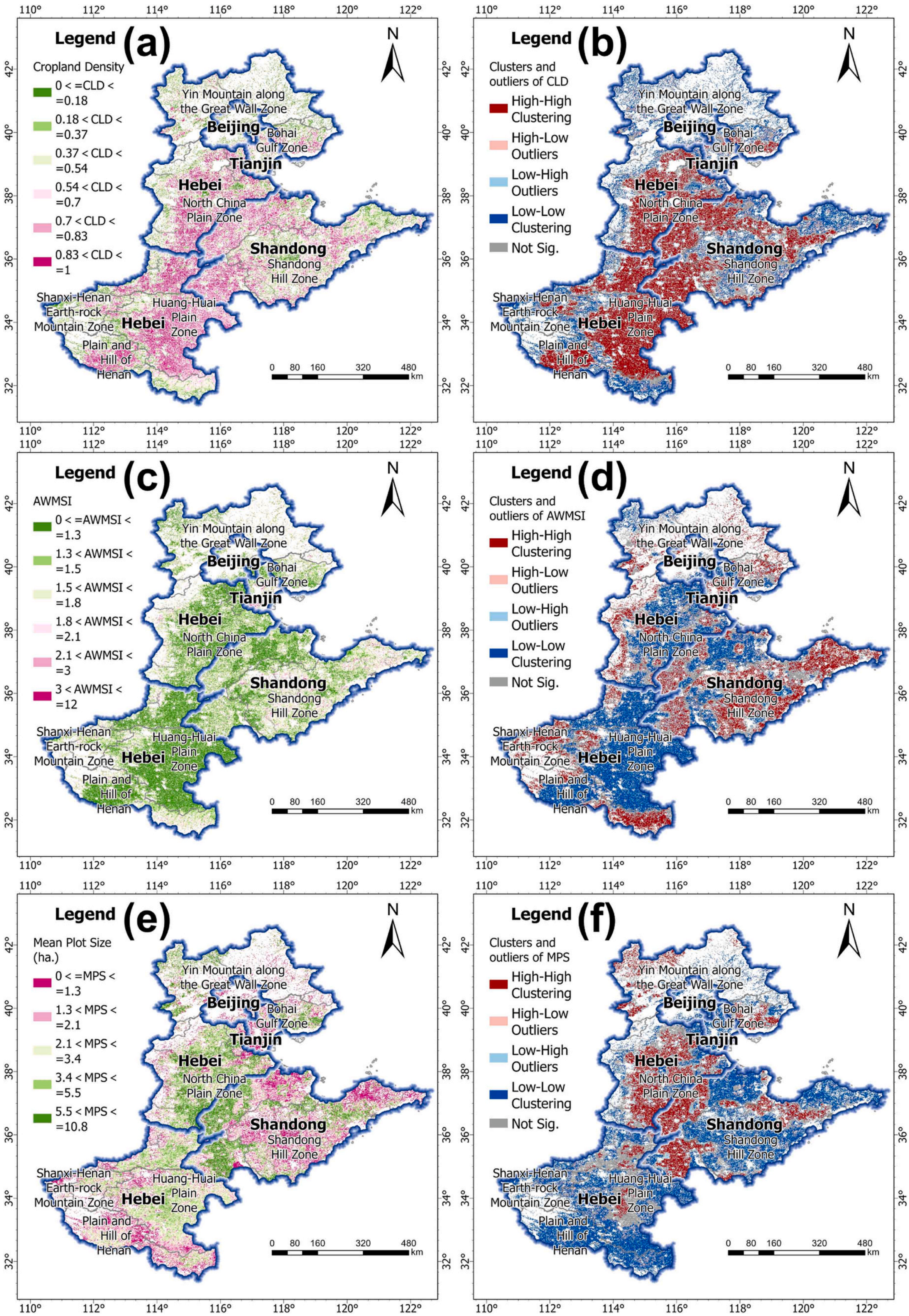

Fig. 4. Spatial distribution and autocorrelation analysis of cropland fragmentation in the Huang-Huai-Hai region. (a) and (b): Cropland density: spatial distribution and local spatial autocorrelation, Moran's I = 0.42, P < 0.001, Z = 2522. (c) and (d): AWMSI, Moran's I = 0.38, P < 0.001, Z = 2383. (e) and (f) Mean plot size, Moran's I = 0.31, P < 0.001, Z = 2020.

(2) Calculation of the spatial covariance matrix. Calculate the covariance matrix $C = XX^{\mathrm{T}}$ of the spatial-temporal matrix.
(3) Eigenvalue decomposition is performed. Eigenvalue decomposition is performed on the covariance matrix C to obtain eigenvalues $\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_m$ and a series of eigenvectors.
(4) Calculation of the variance contribution rate of each eigenvector $\rho_k = \lambda_k / \sum_{i=1}^{m} \lambda_i, k = 1, 2, \cdots, p (p < m)$ and the cumulative variance contribution rate$P = \sum_{i=1}^{p} \lambda_i / \sum_{i=1}^{m} \lambda_i, (p < m)$.
(5) Selection of the principal modes. The principal EOF mode is selected based on the size of the eigenvalues.
(6) Calculation of EOF the time coefficients. The selected main mode is used to calculate the EOF time coefficients for each time step to represent the temporal variation in each mode.

Fig. 2 illustrates the conceptual model that combines the empirical orthogonal function (EOF) method with a time series leaf area index (LAI) to measure the CLUI. The model is divided into three sections. The LAI satellite images obtained from MODIS, with 4-day composites at 500 m resolution and 8-day composites at 1 km resolution, are processed via a Gaussian filter and phenological observations and then masked with cropland area data from the Second Land Survey of China. This produced the LAI time series for croplands in the Huang-Huai-Hai region.

To correlate the cropland LAI time series with crop growth (biomass and yield), EOF analysis is conducted to extract variation features, resulting in eigenvector curves and EOF modes and identifying temporal and spatial patterns in the LAI time series within the Huang-Huai-Hai region.

We aimed to identify and quantify the contribution of human interventions to the spatial and temporal dynamics of crop growth through EOF analyses. It was hypothesized that when EOF analysis is applied to decompose spatiotemporal LAI data, specific modes can reveal the

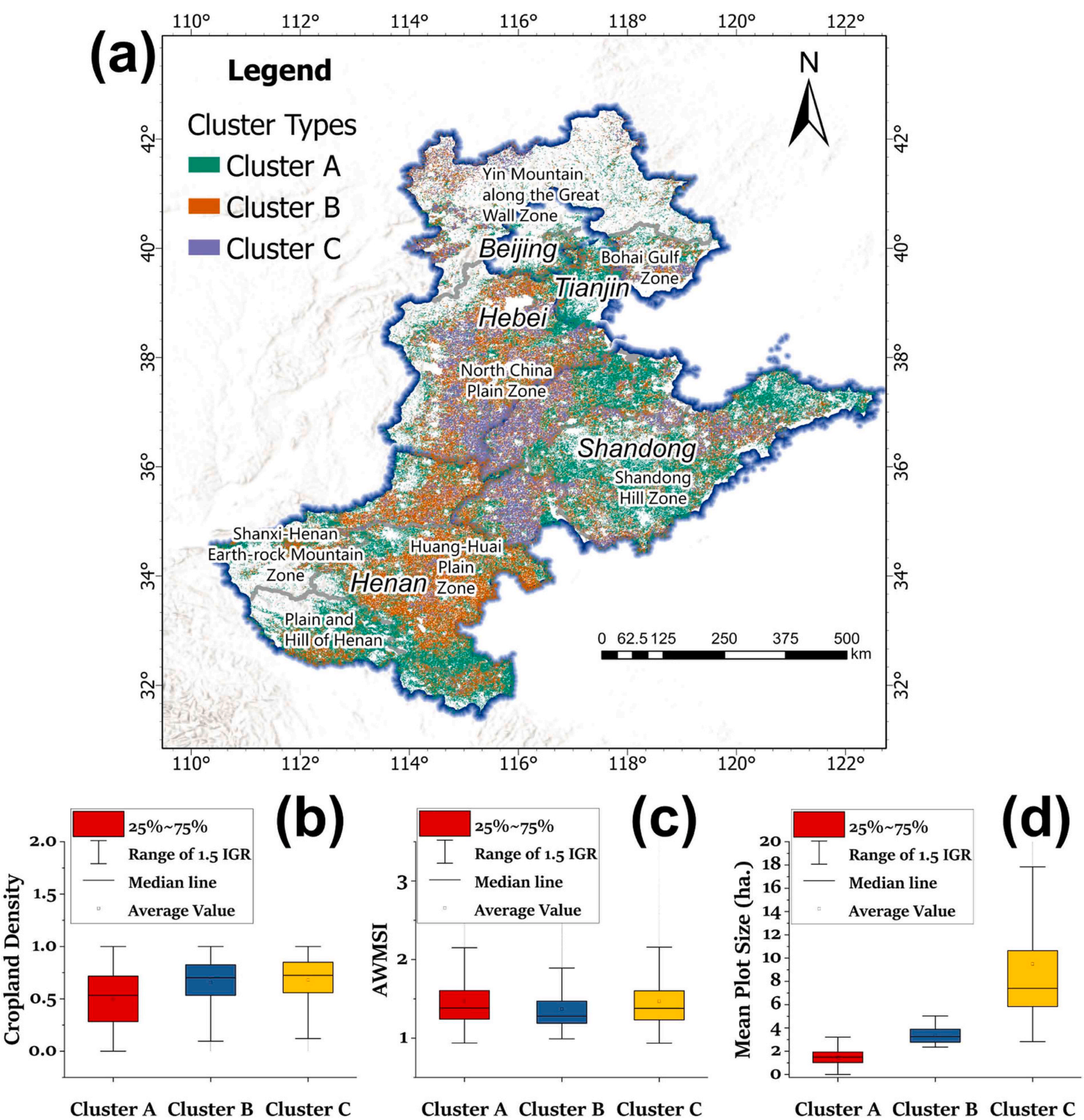

Fig. 5. Shows the clustering of cropland fragmentation indicators in Huang-Huai-Hai via iterative self-organizing (ISO) cluster unsupervised classification. (a) Shows the clustering map. (b), (c), and (d) Show the distribution of cropland density, Area-Weighted Mean Shape Index, and mean plot size under Clusters A, B, and C, respectively.

disturbance effect of the integrated human input-output process on the spatiotemporal variation in the LAI. Specifically, we hypothesize that certain EOF modes can effectively reflect the effects of agricultural management practices (e.g., irrigation, fertilization, harvesting, etc.) on the LAI. These modes are indicative of anthropogenic disturbances and impacts on the intensity of cropland utilization, thus revealing the spatial and temporal characteristics of cropland management and utilization variability.

2.3.3. Local linear regression based on sliding windows

To investigate the spatial heterogeneity of relationships between cropland fragmentation and cropland use intensity, a sliding window-based local linear regression approach was applied. This method reveals localized interaction patterns and scale-dependent effects, enhancing the interpretability of how fragmentation impacts agricultural intensity across varying geographical contexts. For high-dimensional raster-formatted geographical variables, we propose a method based on sliding window local least squares regression (Fig. 3). This method utilizes a window that is moved spatially and performs least squares regression within each window. By varying the window radius, changes in spatial patterns of correlation between variables can be observed, revealing interaction laws at different scales. Local regression coefficients are calculated for each set of data points within a window, quantifying the weights of the independent variables on the dependent variable in that area. This method produces results that are easy to interpret, as it clarifies the relationships between variables in different regions within the spatial extent.

The sliding window local least squares regression method involved the following steps:

(1) Defining the scale range of the sliding window, taking into account spatial correlation and data variation. Smaller windows capture local details, while larger windows capture broader spatial patterns.
(2) Window Sliding, or perform local regression on each window's data points by moving the window across the geographical space. Within each window, data truncation, filtering, and preprocessing were required.
(3) Fitting a linear regression model using weighted least squares for each set of data points within a window. There were no additional assumptions about data distribution within a specific spatial window, ensuring that all points within the window had equal influence on estimation or prediction.
(4) The model fit within the local window range was evaluated, estimating regression coefficients, R^2, and significance *t*-tests.

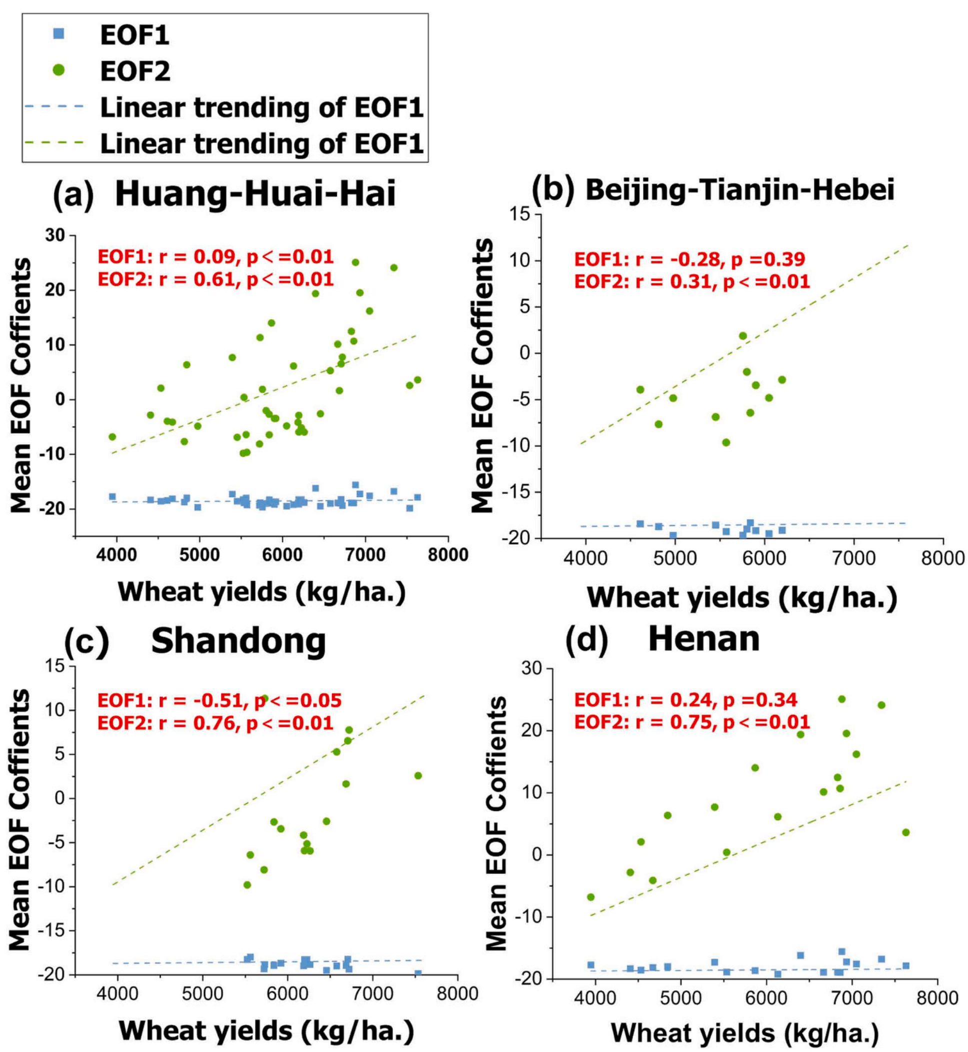

Fig. 6. Scatterplot of correlation between EOF1 and EOF2 and wheat yields in prefecture-level cities of Huang-Huai-Hai region. Data on wheat yields are derived from inter-annual grain production led by provincial statistical units through a sample survey based on municipal administrative units. (a) describes the overall scatter, trend, and correlation in the Huang-Huai-Hai. (b), (c), and (d) describe Beijing-Tianjin-Hebei, Shandong, and Henan (the subregion of Huang-Huai-Hai), respectively.

(5) Local regression results were integrated and mapped to the region center, outputting maps of intercepts, coefficients, significance tests, and R^2, facilitating parameter and spatial pattern comparisons under different windows.

In the case of the Huang-Huai-Hai region, we chose to determine the window gradient based on the size of the administrative area. The average area of counties and prefectures was calculated, and then the size of this area under the window area was treated as the size of the sliding window as the county (32 km) or city (102 km) scale.

2.3.4. Establishing the regression function of cropland fragmentation on cropland use intensity

In agricultural production function theory, the production process is directly affected by input factors such as land, labour, capital, and technology. However, CLUI management is also indirectly constrained by natural conditions (climate, topography, and soil) and regional socioeconomic conditions. These factors affect input allocation, overall production efficiency, and output levels.

Eq. (9) describes how the human CLUI at a given point is influenced by land fragmentation and other factors (climate, topography, soil, economic conditions) within a specific radius. Regression analysis helps evaluate each factor's contribution and impact, aiding in understanding the influence of agricultural production.

$$Y_{i,r} = inter + \beta_{1i}X_{i,r} + \beta_2 Z^c_{i,r} + \beta_2 Z^g_{i,r} + \beta_3 Z^s_{i,r} + \beta_4 Z^e_{i,r} + \varepsilon_{i,r} \quad (9)$$

where Y_i represents the CLUI at spatial window i within radius r, which is the explained variable or response variable. $X_{i,r}$ represents the land fragmentation within the neighbourhood window of point i at a given radius r. This variable includes indicators that describe the land landscape morphology, such as MPS, CLD, and AWMSI.

The control variables Z include several factors that may affect the CLUI at a spatial point: $Z^c_{i,r}$ represents the climate factors within the neighbourhood window of point i at a given radius r, which may include factors such as the annual average temperature. $Z^g_{i,r}$ represents topographical factors, such as altitude and field slope. $Z^s_{i,r}$ represents the soil characteristics, which are indicated by the organic matter content in the surface soil (0–5 cm). $Z^e_{i,r}$ represents economic condition factors, including GDP, population, and farming distance.

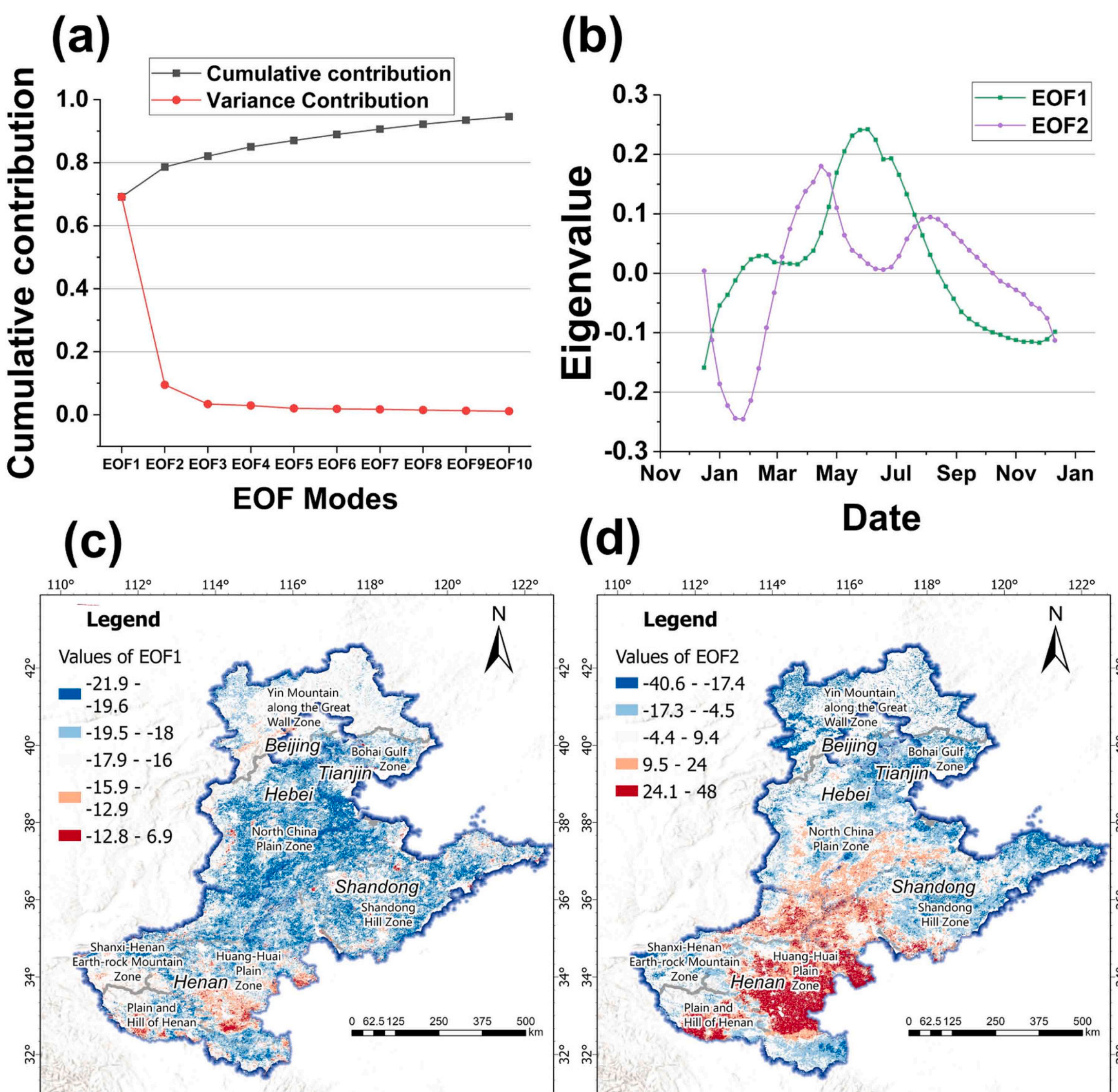

Fig. 7. EOF analysis of the time series of the LAI of cropland in the Huang-Huai-Hai region in 2010. (a) shows the contribution and cumulative contribution of different EOF modes. (b) illustrates the eigenvalue variations of the first two EOF modes over a January–December 2010 time series. (c) and (d) show the spatial visualization of EOF1 and EOF2, respectively.

β_{1i}, β_{2i}, β_{3i}, and β_{4i} are the regression coefficients of the model, representing the degree to which each independent variable affects the dependent variable.

$\varepsilon_{i,r}$ represents the error term in the model, including the part not explained by the independent variables in the model and the influence of other unobserved factors on the dependent variable.

3. Results

3.1. Spatial patterns of cropland fragmentation in the Huang-Huai-Hai region of China

The influence of topography on the distribution of cropland density (CLD) resulted in higher-density cropland observed in plain areas, particularly in the North China Plain and Huang-Huai Plain regions, and

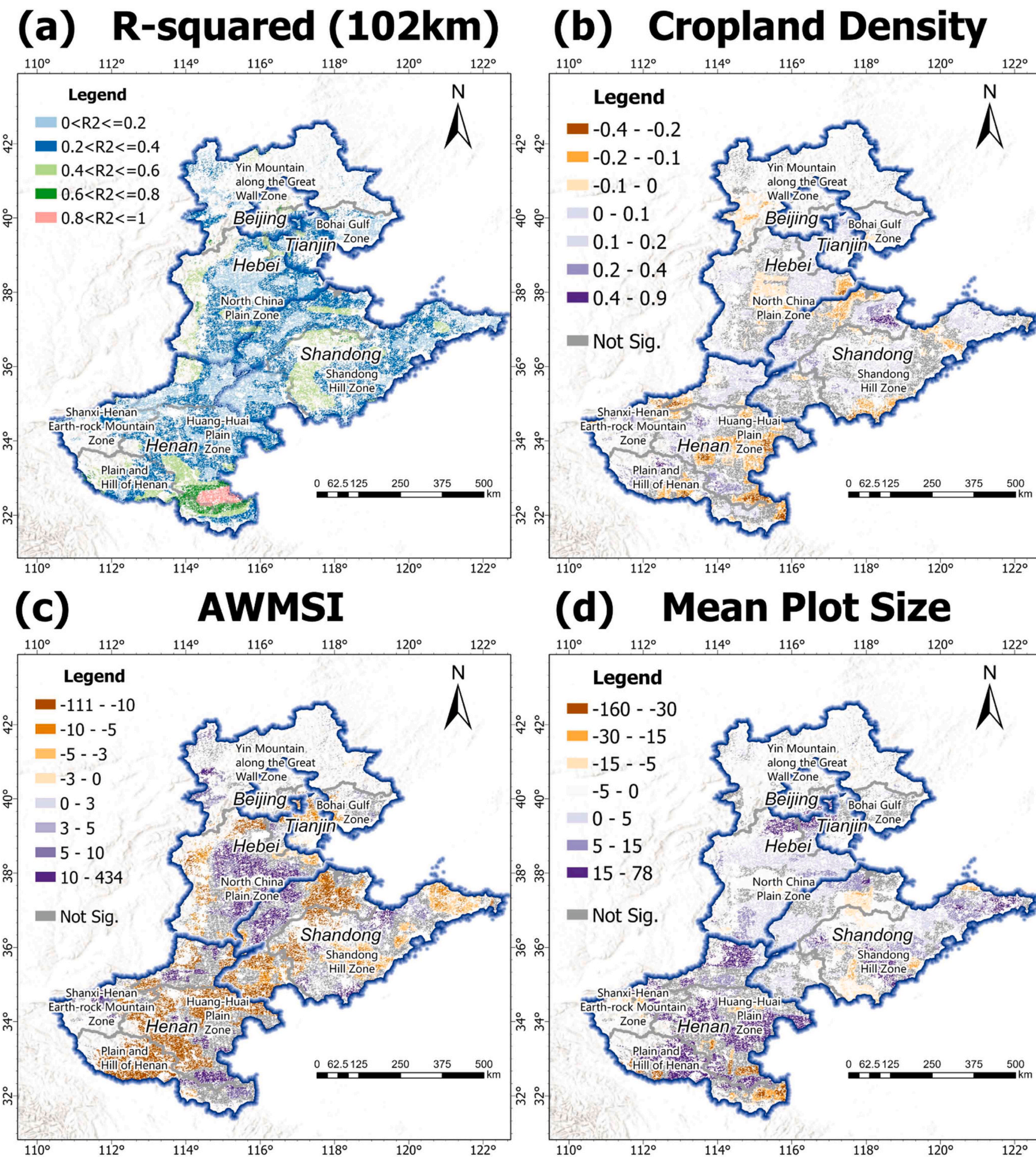

Fig. 8. Map of the sliding window regression coefficients of the effects of cropland fragmentation on cropland use intensity at the city scale (102 km). (a) R^2 spatial distribution in local linear regression based on sliding windows. (b), (c) and (d) Illustrate the spatial regression of the regression coefficients for cropland density, AWMSI, and mean plot size, respectively.

in low-density cropland primarily concentrated in the complex terrains of the Eastern Hills of Shandong, the Yinshan Mountains, the Great Wall region, and western Henan (Fig. 4a). Urban fringe areas exhibited elevated CLD, likely due to the occupation or repurposing of cropland during urbanization. The spatial autocorrelation analysis indicated that high-density cropland areas tend to cluster together (red areas: high-high clusters in Fig. 4b), particularly in plains regions. The blue areas (low-low clusters) indicate low-density cropland areas also clustered together, primarily in mountainous and hilly regions. The heterogeneous regions of high-low and low-high clusters represent transitional zones of CLD, often situated in areas transitioning from high-density to low-density cropland.

Complex topographical conditions exerted a significant influence on the Area-Weighted Mean Shape Index (AWMSI), which exhibited a spatial pattern analogous to that of CLD (Fig. 4c). The AWMSI values were lower in plains regions, particularly in areas where agriculture is a

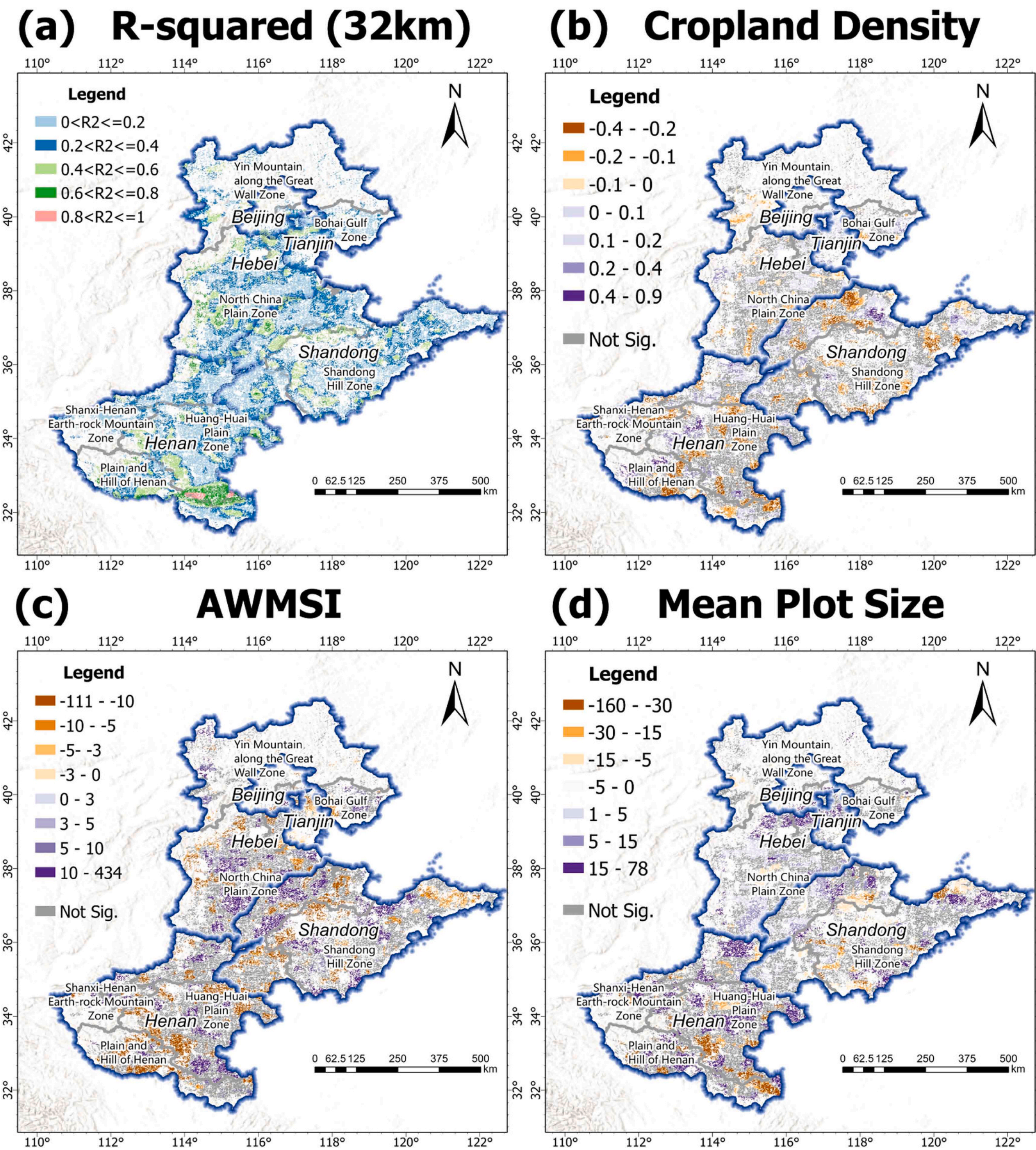

Fig. 9. Sliding window regression coefficients of the effects of cropland fragmentation on cropland use intensity at the county scale (32 km). (a) R^2 spatial distribution in local linear regression based on sliding windows. (b), (c) and (d) Illustrate the spatial regression of the regression coefficients for cropland density, AWMSI, and mean plot size, respectively.

dominant land use. In these regions, the practice of intensive cultivation and mechanisation contributed to the formation of regular patch shapes, thereby reducing fragmentation (Fig. 4d). In contrast, mountainous and hilly regions exhibit higher AWMSI values, indicating that socioeconomic and cultural factors, as well as a complex topography, contribute to the formation of more fragmented and irregular patch shapes.

As with the spatial distribution and autocorrelation of CLD, topography exerted a significant influence on the spatial pattern of the MPS (Fig. 4e,f). However, in contrast to CLD, flat terrain does not invariably correspond to larger patch areas. In the eastern plains of Henan, the MPS is relatively low, exhibiting a notable low-low clustering (indicating a low aggregation of the average patch size). This indicates that the presence of flat terrain does not necessarily result in a larger plot size. This may be attributed to the influence of intensive agricultural production and high population density, which have led to the formation of smaller and more fragmented fields. In contrast, the northern mountainous areas of Hebei, which exhibit higher vegetation coverage, demonstrate a notable clustering of MPS. This suggests that even in areas with challenging topography, larger plot sizes can emerge due to variations in land use practices or reduced population density.

Fig. 5 presents the clustering of cropland fragmentation indicators in the Huang-Huai-Hai region using the iterative self-organizing (ISO) clustering method. Fig. 5(a) shows the clustering map, while panels Fig. 5(b), (c), and (d) illustrate the distribution of CLD, AWMSI, and MPS for Clusters A, B, and C, respectively. Cluster A is predominantly located in economically underdeveloped mountainous regions, including central and eastern Shandong, northern Hebei, and western Henan. It exhibits low cropland density, indicating a scattered distribution of cropland resources; relatively high AWMSI values, suggesting less regular plot shapes; and small mean plot sizes, emphasizing the fragmented nature of cropland in these areas. The combination of low MPS, high CLD, and high AWMSI in Cluster A indicates landscapes composed of many small, irregular parcels in close proximity. Given the parcel-level cadastral boundaries, these patterns further imply a higher degree of tenure fragmentation and within-holding subdivision.

Cluster B, situated in the densely populated Huang-Huai Plain of eastern Henan, shows moderate cropland density, reflecting a balanced distribution of plots per unit area compared with other clusters. Its AWMSI values are lower than those of Clusters A and C, indicating more regular plot shapes. Cluster B also features intermediate mean plot sizes, representing dispersed, multifunctional plots operated by numerous landowners or users within relatively limited cropland areas, contributing to moderate fragmentation. The co-occurrence of moderate MPS, CLD, and AWMSI values in this cluster suggests a mixed structure, where physical regularity is higher than in Cluster A, but the dispersion of holdings among multiple operators still contributes to institutional fragmentation.

Cluster C is mainly distributed in the highly productive plains regions, such as southern Hebei and northern Jiangsu, with the highest cropland density among the three clusters, relatively low AWMSI values indicating more regular plot geometry, and the largest mean plot sizes, reflecting contiguous, intensively cropland parcels and thus the lowest degree of fragmentation. In this case, the high MPS and low AWMSI values are consistent with both physically consolidated parcels and fewer tenure boundaries within each grid cell, reducing operational complexity.

3.2. *Characteristics of cropland use intensity in the Huang-Huai-Hai region, China*

Concerning the dependability of the EOF results, survey statistics on crop yields and scatter plots are utilized to illustrate the relationship between wheat yield and EOF2 in the Huang-Huai-Hai region and its three constituent provinces (Shandong, Henan, and Beijing-Tianjin-Hebei). Additionally, correlation coefficients (R-values) and significance levels (P-values) are presented to quantify the strength and statistical significance of the observed relationship (Fig. 6). The correlation between wheat yield and EOF2 in the Huang-Huai-Hai region is moderately high ($R = 0.64$, $P \leq 0.05$), indicating that EOF2 can effectively explain the variations in wheat yield in this region. The positive correlation between wheat yield and EOF2 is more pronounced in the Shandong and Henan provinces, with R values of 0.76 and 0.75, respectively. In the Beijing-Tianjin-Hebei region, the correlation coefficient (R) for wheat yield and EOF2 is 0.32, which, although lower, is nevertheless statistically significant. EOF2 represents specific human agricultural activities, such as planting, irrigation, and fertilization, which have a direct impact on wheat growth and yield. The high correlation indicates that EOF2 effectively captures the impact of these agricultural activities on LAI, thus being highly correlated with wheat yield. The higher correlation observed in Shandong and Henan provinces serves to illustrate the close relationship between EOF2 and human agricultural activities. In regions with a high concentration of

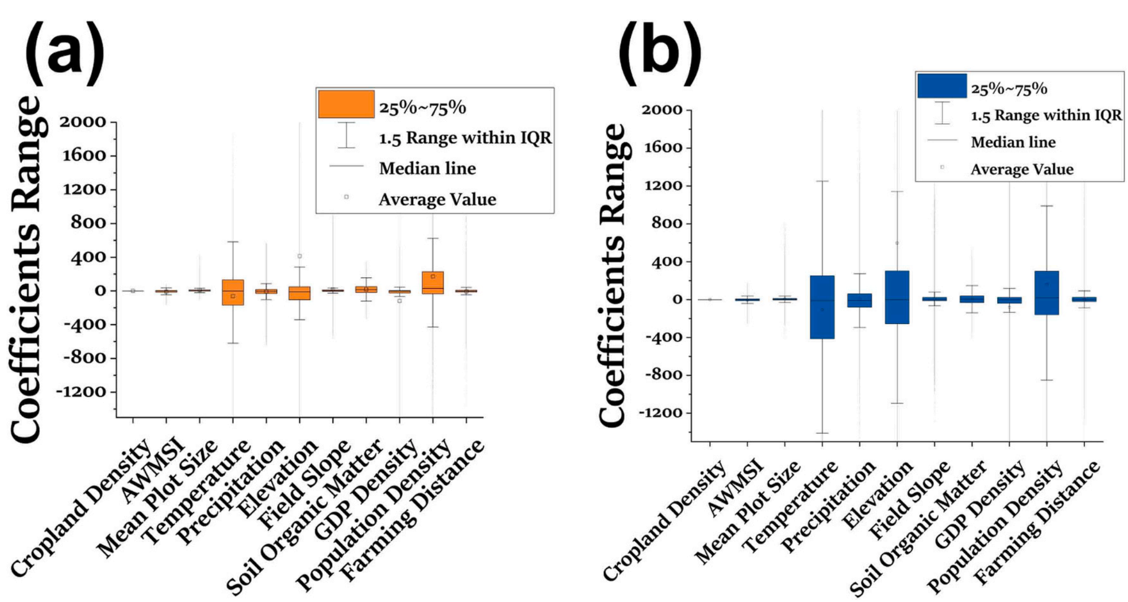

Fig. 10. (a) and (b) Represent box plots of the coefficients of the impact of cropland fragmentation and other control variables on the CLUI for sliding window sizes of 32 km and 102 km, respectively.

agricultural activities, EOF2 can explain the variations in LAI, which are reflected in wheat yield.

The spatiotemporal decomposition of Leaf Area Index (LAI) data from January–December 2010 in the Huang-Huai-Hai region using Empirical Orthogonal Function (EOF) analysis resulted in the generation of EOF mode spatial distribution maps and time coefficients. The first two EOF modes account for 63.4 % and 7.2 % of the variance, respectively, with a cumulative variance contribution rate of 70.6 % (Fig. 7a). Subsequent EOF modes account for the residual variance, but none exceed 3.6 %. This indicates that the primary patterns of variation in the dataset were represented by the first two modes.

The EOF1 mode accounts for the majority of the variation in the LAI data, primarily reflecting an annual cyclical trend of an increase in the spring and a decrease in the autumn (Fig. 7b). This is indicative of the commencement and conclusion of the vegetation growing season. From January to May 2010, the time coefficient shows an upward trajectory, reaching its zenith from April to May 2010 and subsequently declining gradually, reaching its nadir in October 2010. This suggests that the EOF1 mode predominantly reflects a substantial increase in LAI during the spring (April–May 2010), followed by a decline in the autumn (October 2010). In terms of spatial distribution, EOF1 is distributed evenly throughout the region, indicating that it reflects widespread natural variations. Notably, the majority of areas in Hebei and Shandong provinces exhibit significant negative values, while some areas in the southern Henan province show positive values. The significant negative values of EOF1 in Shandong and parts of Henan indicate a greater deviation from the regional trend, reflecting unique vegetation dynamics or growth cycles.

The EOF2 mode accounts for a smaller proportion of the variance, primarily reflecting the characteristics of specific regions at specific times. From January to April 2010, the time coefficient rapidly increases, reaching a peak from March to April 2010, after which it gradually declines from May to July 2010. There is a slight increase in August 2010, after which the coefficient decreases at a more gradual rate. The time coefficient of EOF2 peaks from March to April 2010, indicating a notable increase in the LAI in these regions during the spring, particularly in April 2010. This is consistent with the planting and growing seasons of spring crops, which are widely cultivated in the Huang-Huai-Hai region. Conversely, the time coefficient of EOF1 may be indicative of broader annual fluctuations rather than specific seasonal patterns. Furthermore, April 2010 represents a pivotal growth period for numerous crops, during which concentrated human activities such as ploughing, fertilization, and irrigation significantly influence the LAI values. Spatially, EOF1 shows a more even distribution globally (Fig. 7c). The EOF2 mode exhibited significant positive values in eastern and central Henan Province, whereas the mountainous areas in central Hebei and Shandong Provinces presented negative values (Fig. 7d). The positive value areas of EOF2 in eastern and central Henan Province exhibit a high degree of overlap with high-intensity agricultural areas, thereby indicating that this mode is closely related to human agricultural activities.

3.3. *Impacts of cropland fragmentation on cropland use intensity*

Figs. 8(a) and 9(a) depict the model's explanatory power across scales. In southern Henan and central Shandong, R^2 exceeds 0.4, indicating that the selected variables explain CLUI variations well. In Beijing, Tianjin, and northern Hebei, R^2 values range from 0.2 to 0.4, reflecting the weaker explanatory capacity in regions with more diverse land use and socio-economic structures. This illustrates the first type of spatial heterogeneity—regional differences in model performance.

Figs. 8(b–d) and 9(b–d) reveal clear spatial variation in the direction and magnitude of fragmentation effects on CLUI. Mean plot size shows significant negative impacts in the Huang-Huai Plain, Shandong hills, and Bohai Rim, where larger plots may reduce land use intensity due to decreased cropping diversity or management disruption. This negative effect is more evident at the city scale, particularly in Hebei, northern Henan, and Shandong. In contrast, positive impacts are found in the North China Plain and parts of southern Henan and eastern Shandong, suggesting that larger, regular plots can enhance efficiency through mechanization. AWMSI has negative effects in hilly areas (e.g., western Henan, southern Shandong), while its impact weakens or reverses in flatter terrain. Cropland density exhibits limited and scattered influence, indicating its lower explanatory strength compared to shape and size.

At the 102 km analysis scale (sliding window size), the negative association between mean plot size and CLUI is more prominent, meaning that within many 102 km windows, increasing average field size is linked to lower land use intensity—possibly because it reduces crop diversity or disrupts existing management patterns. This pattern suggests that, in such contexts, a higher degree of fragmentation can under certain conditions enhance land use intensity through diversification and risk dispersion. At the finer 32 km analysis scale, many regions that exhibited negative correlations at the broader scale—especially in the Huang-Huai Plain—shift to positive correlations, where larger, more contiguous plots are associated with higher cropping intensity due to more efficient coordination of machinery, labor, and inputs within smaller management zones. This indicates that targeted land consolidation measures (e.g., land integration, structure optimization) can significantly improve intensification in these local settings. Areas retaining negative effects at this finer scale are mainly in northern Hebei, western Henan, and the hilly regions of Shandong, where physical terrain constraints or fragmented ownership structures may still limit the benefits of plot enlargement.

These scale-dependent differences constitute a third type of spatial heterogeneity, indicating that the relationship between fragmentation and CLUI changes across scales due to variations in the visibility of local land-use dynamics. In sum, the spatial heterogeneity observed here includes: (1) regional variation in model explanatory power, with higher R^2 values in zones where land-use patterns are more spatially consistent and lower values in more complex or mixed-use regions; (2) spatial differences in the sign and strength of fragmentation effects on CLUI, as shown by the distinct local patterns of regression coefficients across provinces and subregions; and (3) scale-sensitive shifts in impact direction and intensity, where finer-scale analyses capture localized effects—such as land consolidation efforts or structural adjustments—that may be obscured at broader resolutions, reflecting the spatially uneven nature of fragmentation-function relationships in the Huang-Huai-Hai region.

Fig. 10(a) and (b) show how cropland fragmentation and the control variables affect the CLUI at different scales. While cropland density and AWMSI exhibit weaker and more spatially scattered effects, mean plot size consistently demonstrates stronger and more spatially coherent associations with CLUI, highlighting its statistical and practical significance in the fragmentation–intensity relationship. This is also consistent with previous studies that regard plot size as a core fragmentation indicator due to its direct link to land management efficiency and mechanization potential. Temperature and soil organic matter consistently influence the CLUI, with temperature having a strong and stable effect. Elevation and field slope have more variable effects, reflecting topographical differences. Socioeconomic factors, such as population density and GDP density, show moderate variability, indicating their context-dependent influence. Given its clearer signal and policy relevance—particularly in land consolidation and monitoring—plot size serves as a representative variable to interpret the functional impacts of fragmentation, although all indicators were included in the analysis.

4. Discussion

A comprehensive exploration of cropland fragmentation and its impacts on cropland use intensity in the Huang-Huai-Hai region was provided, employing innovative methodologies such as empirical orthogonal function analysis and sliding window regression(Fang et al., 2025). The results revealed pronounced spatial heterogeneity in cropland fragmentation, indicating a spatial structuring in which plains display more contiguous and regular land patterns, whereas mountainous areas show fragmented and irregular configurations constrained by topography and accessibility. Plains are characterized by high cropland density and regular plot shapes, closely linked to agricultural intensification, while mountainous areas exhibit low cropland density and irregular plot shapes due to topographical constraints and socioeconomic factors. Sliding window regression further uncovered strong spatial heterogeneity in the relationship between mean plot size and CLUI: in some highly mechanized plain areas, larger plot sizes were associated with lower CLUI, possibly due to simplified cropping systems and reduced management intensity; conversely, in transitional or hilly zones, larger plots tended to support higher CLUI, likely reflecting gains in operational efficiency and land-use continuity. These findings suggest that the effects of fragmentation on land use intensity are not uniform but context-dependent, highlighting the need for region-specific land management strategies that account for both physical geography and land-use practices.

4.1. Level, characteristics, and causes of cropland fragmentation in the Huang-Huai-Hai Region

Cropland fragmentation is one of the long-term concerns about cropland resource strategies in mainland China (Li et al., 2018; Du et al., 2024). Despite the high population density, studies indicate that the degree of fragmentation in the Huang-Huai-Hai region is relatively low. Comprehensive land consolidation projects and the active promotion of land transfers have significantly improved cropland fragmentation in traditional agricultural areas (Jiang et al., 2017; Zhou, Li, and Xu, 2020). According to landscape-level statistics derived from the Second National Land Survey, the average cropland plot size in the region has reached 3.6 ha, indicating moderate consolidation in comparison to more fragmented agricultural landscapes. Although notable progress has been made, the issue remains complex and heterogeneous, providing insights for other regions (Liu et al., 2023).

This study revealed that cropland fragmentation in the Huang-Huai-Hai region has a multifaceted etiology, manifesting in various forms. These include physical limitations such as topography, ownership issues, rapid urbanization, and the interplay of complex natural, social, and economic factors (Gu et al., 2023; Tan et al., 2006; Gu et al., 2025). From a physical standpoint, a region's complex terrain poses significant obstacles to the continuous distribution of cropland, leading to increased agricultural costs and heightened risks (Jiménez-Olivencia et al., 2021; Wang et al., 2020). The spatial pattern of MPS demonstrates that while topography plays a vital role, socioeconomic factors also significantly impact the fragmentation of cropland. In mountainous areas with lower population density and complex terrain, the presence of smaller MPS units and irregular plot shapes indicates a higher degree of cropland fragmentation. In contrast, in plains regions with more favorable farming conditions and land consolidation policies, larger or moderately sized MPS reflects relatively lower fragmentation levels. Regions with similar MPS values tend to cluster together, demonstrating consistent land use patterns shaped by both environmental and socioeconomic conditions. Factors such as topography (e.g., slope distribution), soil quality, water availability, and microclimatic conditions jointly influence the spatial configuration and fragmentation of cropland (Ntihinyurwa and de Vries, 2020). In hilly and mountainous areas with diverse microclimatic conditions and soil qualities, farmers may adopt smaller, dispersed plots as a coping strategy (Jiang et al., 2024; Ye et al., 2024b; Zhang et al., 2025). For example, in the mountainous areas of the Huang-Huai-Hai region (e.g., central and eastern Shandong, northern Hebei, and western Henan), small, irregularly shaped plots are sparsely distributed. These regions are frequently economically underdeveloped, with distance from grain markets and natural disasters contributing significantly to cropland fragmentation.

Land tenure structure and urbanization exert spatially differentiated influences on cropland fragmentation across the Huang-Huai-Hai region (Cai et al., 2025). Our spatial results indicate that economically underdeveloped mountainous areas—such as those in Cluster A—are characterized by small and irregular cropland parcels, reflecting high fragmentation. This pattern stems from the historical legacy of decentralized land allocation, weak market institutions, and limited collective capacity for land consolidation. In such contexts, numerous smallholders operate dispersed, multifunctional plots without access to the organizational or technological resources needed for coordinated land use (Liu et al., 2022a; Ntihinyurwa and de Vries, 2021). In contrast, some densely populated plains regions—such as eastern Henan (Cluster B)—exhibit only moderate levels of fragmentation, despite high land demand. This can be attributed to the implementation of institutional mechanisms such as land transfer markets and land consolidation programs, which have improved plot regularity and scale in high-pressure areas (Zhou et al., 2020). While ownership fragmentation persists, agricultural modernization and policy interventions have partially mitigated the negative effects of small plot sizes and scattered distribution.

Urbanization acts as an external driver that intensifies cropland fragmentation, particularly in peri-urban regions where rural land systems face growing spatial and institutional pressure (Wu et al., 2016). In southern-central Hebei, northern-central Henan, and the coastal zones of Shandong, rapid urban expansion—driven by infrastructure projects, industrial development, and real estate growth—has led to the subdivision of contiguous farmland into smaller, irregular plots (Jiang et al., 2018). This has disrupted cropland continuity, lowered land-use density, and increased shape irregularity near urban edges (Yu et al., 2018). These trends are supported by Fig. 4 and 5, where peri-urban areas exhibit small mean plot sizes, low cropland density, and high shape complexity—especially within Cluster A. Such fragmentation reflects the impact of urbanization as an exogenous spatial shock, interacting with varying levels of land governance and planning capacity. In areas lacking strong institutional safeguards, cropland fragmentation tends to be more pronounced and disorganized, while better-managed regions show more spatial coherence despite development pressure (Su et al., 2014).

4.2. Differentiated relationships between cropland fragmentation and land-use efficiency

The relationship between cropland fragmentation and cropland use intensity (CLUI) is complex and context-dependent. Although commonly assumed that land fragmentation detrimentally impacts CLUI, this does not necessarily hold in areas where small-scale farming is viable (Ntihinyurwa et al., 2019; Yu et al., 2022). Studies on cropland fragmentation in the Huang-Huai-Hai region yield several key insights with policy implications. In a given physical and socio-economic context, small-scale farms with primarily family food supply can utilize fragmented cropland to enhance the incentives for food production (Ntihinyurwa and de Vries, 2020). This suggests that small-scale farms may be viable and, during certain developmental periods, may not hinder agricultural growth.

The causes of cropland fragmentation also impact the efficacy of agricultural intensification initiatives. Fragmentation due to physical limitations, such as topography and soil quality, often requires distinct management strategies compared to fragmentation resulting from socioeconomic factors like land ownership disputes or rapid urbanization (Sklenicka, 2016; Su et al., 2014). In regions where physical limitations drive fragmentation, infrastructure improvements, technical assistance on conservation-oriented land management, and agroecological practices may enhance CLUI. Conversely, in areas affected by socioeconomic fragmentation, policies should focus on land ownership reform, promoting land leasing and consolidation through market mechanisms, and addressing urbanization pressures (Long et al., 2019). These flexible policy measures are more likely to yield positive outcomes than blanket policy recommendations (Liu et al., 2025).

Land consolidation is regarded as one of the most effective measures to address cropland fragmentation in China (Lu et al., 2019). However, general policies aimed at reducing fragmentation through large-scale land consolidation may not always be effective. Our results suggest that continued acreage upgrading on large-scale farms with good land conditions may have a more positive effect than parcel consolidation on fragmented parcels (Janus and Ertunç, 2021). Therefore, policy implementation must be adapted to the specific spatial characteristics, ecological benefits, economic benefits, and social benefits of each region.

Contemplating impacts across diverse spatial scales when developing strategies to curtail cropland fragmentation is vital to ensure efficacy in policy implementation at various levels. Our spatial analysis revealed significant differences in the impact of cropland fragmentation on CLUI across different spatial scales, as seen by e.g., (van Zanten et al., 2014). The smaller window size (32 km) captured localized effects more effectively, while the larger window size (102 km) smoothed out local heterogeneity, highlighting broader spatial trends. This revealed that the relationship between cropland fragmentation and CLUI is highly scale-dependent, emphasizing the need for policy-making and management strategies to consider scale issues. Pursuing a strategy of mega-land consolidation may not result in significant CLUI gains compared to a strategy of precise, targeted land expansion (Lefebvre et al., 2015; Verburg et al., 2008).

In fragmented mountainous areas, especially those with steep slopes and poor soils, low CLUI may not merely reflect structural inefficiencies but also indicate functional retreat in the form of land abandonment (Hong et al., 2024; Zhang et al., 2019). Cluster A, located in upland regions such as western Henan and northern Hebei, exhibits a convergence of high fragmentation (low MPS, high AWMSI), low LAI-derived CLUI, and weak EOF2 signals, reflecting limited agricultural activity and input intensity. Sliding window regression further reveals a consistently negative effect of fragmentation on CLUI in these areas (Fig. 9), reinforcing the interpretation that abandonment emerges as a rational response to biophysical constraints and low expected returns. While abandonment is not directly identified, the spatial coincidence of extreme fragmentation and low functional signals supports its inferred presence as a latent outcome of structural marginalization.

4.3. Prospects and uncertainties of the models and methods

This research contributes to the understanding of cropland fragmentation and its impact on CLUI through several innovative approaches. Firstly, the combination of LAI and EOF analysis on remotely sensed time-series data presents a novel method for quantifying CLUI capturing complex interactions between human activities and agricultural systems. Secondly, the introduction of a sliding window local linear regression method offers a robust framework for investigating the spatial heterogeneity and scale effects of cropland fragmentation. This approach enables the identification of localized patterns and relationships that traditional global regression models may overlook. Moreover, the proposed methodology can be extended to other geographical issues involving spatial heterogeneity and scale-dependent relationships (Cai et al., 2025). The application of the spatio-temporal sequence decomposition to the vegetation indices has been demonstrated to be a viable approach for differentiating the effects of various factors (Eckert et al., 2015; Lei et al., 2016; Zeng et al., 2020).

By providing a detailed understanding of the spatial and scale-dependent impacts, the findings of this research can inform the design of targeted interventions that are tailored to specific regions and scales. This, in turn, can contribute to more effective and agricultural practices, optimize land use, and enhance CLUI (Lyle, 2015). However, certain limitations and uncertainties require further investigation. The cropland fragmentation data used in the study was derived from the Second National Land Use Survey of China. While these data are representative of prevailing fragmentation patterns, the lack of time-series data limits the ability to assess the temporal evolution of fragmentation and its impacts, and may not reflect recent changes in land-use dynamics (Chen et al., 2022). Future research should incorporate more recent data and explore the dynamic relationships between fragmentation, CLUI, and agricultural CLUI over time. While the 2010 NLUSII and MODIS datasets provide the most comprehensive spatial detail available for cropland structure and function in China, we acknowledge that their age limits the direct applicability of our findings to present-day conditions. Our results should therefore be interpreted primarily as revealing enduring structural relationships rather than real-time patterns. To strengthen the policy relevance of such analyses, future research should incorporate more recent and multi-temporal datasets to capture the dynamic impacts of ongoing land consolidation, transfer, and urbanization processes.

The EOF analysis used to measure CLUI generates relative values reflecting trends rather than absolute measures, limiting cross-regional comparisons (Li et al., 2021). Developing more objective and quantifiable methods and indicators for measuring CLUI is necessary to enhance broader applicability and generalizability. Furthermore, the sliding window local linear regression method requires careful determination of an appropriate window size, as it influences the scale at which spatial patterns and relationships are captured. Future research should explore strategies for selecting the optimal window size to balance local variations and broader trends, improving the method's robustness and generalizability.

In addition, while this study incorporates several socio-economic control variables (e.g., GDP density, population density, and farming accessibility) to account for regional development conditions, we acknowledge that more detailed institutional and behavioral factors—such as household landholding decisions, land tenure arrangements, and farmer-level land management practices—remain unobserved in our analysis. These dimensions are critical for fully understanding the drivers and impacts of cropland fragmentation (Aslam and Fazal, 2025; Gu et al., 2023). Future research would benefit from integrating mixed-methods approaches, combining spatial modeling with household surveys, interviews, or institutional datasets, to capture the underlying behavioral mechanisms and governance contexts that shape fragmentation outcomes. Such extensions would further strengthen the causal interpretation and enhance the policy relevance of fragmentation research.

5. Conclusions

This study developed an integrated framework to examine how cropland fragmentation (CLF) influences cropland use intensity (CLUI) in the Huang-Huai-Hai region, combining parcel-level indicators, EOF-based LAI decomposition, and sliding-window regression. Our findings reveal clear spatial heterogeneity: plains regions (e.g., the Huang-Huai Plain) were characterized by high cropland density and larger, more regular plots, while mountainous and hilly areas contained small, irregular parcels shaped by terrain and socio-economic constraints. EOF analysis, which explained 70.6 % of the variance in LAI, confirmed that CLUI patterns are strongly associated with agricultural management practices and further constrained by topographic conditions

The relationship between fragmentation and CLUI was shown to be scale-dependent, with effects varying between broader and finer spatial resolutions. Cluster analysis further demonstrated that these outcomes are highly context-specific, differing across mountainous, transitional, and plains regions. These findings highlight the need for land governance strategies that are sensitive to both spatial scale and regional conditions, rather than relying on uniform consolidation policies.

Overall, these results demonstrate that fragmentation impacts are neither universally negative nor uniformly positive, but conditional on spatial context and analytical scale. This implies that blanket land consolidation policies are unlikely to be effective. In productive plains, targeted consolidation can enhance efficiency; in fragmented mountain regions, infrastructure and adaptive land management are more critical; and in peri-urban zones, governance mechanisms are needed to address urbanization-driven fragmentation. By highlighting enduring structural relationships rather than short-term changes, this study provides evidence-based guidance for designing region-specific and scale-sensitive land governance strategies.

CRediT authorship contribution statement

Pablo Tittonell: Writing – review & editing, Visualization, Supervision, Resources, Conceptualization. **Peichao Gao:** Software, Methodology, Formal analysis. **Changqing Song:** Supervision, Resources, Project administration, Funding acquisition. **Shuyi Ren:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leina Zhang:** Project administration, Data curation. **Sijing Ye:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of Competing Interest

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

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Data availability

The authors do not have permission to share data.

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