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# Composite driving mechanisms of farmland abandonment in plains and mountainous areas of China from a 1-km grid perspective

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ABSTRACT

Reducing farmland abandonment is essential for protecting farmland resources and ensuring national food security. The driving mechanisms of farmland abandonment in China at the 1-km grid scale remain insufficiently understood. In this study, a composite theoretical framework integrating natural factors, socioeconomic factors, and cultivation conditions was developed to explain farmland abandonment at the grid scale. Fifteen driving variables, together with a 1-km gridded dataset of farmland abandonment ratio (the proportion of abandoned farmland relative to the total farmland area), were modelled using random forest models. The SHAPley additive explanations algorithm was applied to quantify both the individual effects and interaction effects. The results revealed that in 2019, the overall farmland abandonment ratio in China was 4.49%, with higher rates observed in mountainous areas (6.26%) than in the plains (2.22%). Stable hotspots of farmland abandonment emerged in the agro-pastoral transition zone between the northern arid and semiarid regions and the Loess Plateau, in the southeastern coastal region, in the southwestern mountainous region, and around the Beijing–Tianjin–Hebei urban agglomeration. Distinct driving mechanisms of farmland abandonment were observed between plains and mountainous areas. Increased farmland density mitigated abandonment risk across both terrains by strengthening large-scale farming and organizational structure. In plains, farmland abandonment was governed mainly by labour, location, and organizational structure. Engineering improvements and institutional support weakened the effects of climatic and topographic factors. The influence of ageing was both stage-specific and bidirectional. In mountainous areas, farmland abandonment was driven mainly by strong coupling among climatic conditions, topography, and service accessibility. The effects of climatic conditions were amplified by their interactions with slope and altitude, resulting in the formation of a chain that extends from natural stress to mechanization constraints and ultimately to cost accumulation. The dominant driving factors of farmland abandonment varied regionally. Natural factors dominated in western high-altitude, cold, and arid areas. Socioeconomic factors dominated in the plains and rapidly urbanizing regions. Cultivation conditions were dominant in hilly regions and areas characterized by fragmented farmland. This study enhances the understanding of farmland abandonment from a grid-scale perspective and provides guidance for regionalized governance strategies.

## 1. Introduction

Food security is closely linked to economic development and social stability (Gao et al., 2025; Willett et al., 2019; Ye et al., 2020). Its vulnerability has been increasingly amplified under the combined influence of global population growth, increased consumption structure, and intensified extreme climate events (Chai et al., 2024; Lesk et al., 2016; Wan et al., 2021). As the material foundation of the food supply system, the quantity and quality of farmland directly affect the sustainability of agricultural productivity and human well-being (Cui et al., 2018; Du et al., 2024; Jiang et al., 2024a; Ren et al., 2022). Farmland abandonment generally refers to the cessation of regular cultivation and management activities, with the land remaining idle or semi-idle for a certain period (Dara et al., 2018; Li and Li, 2017). It has been widely

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observed in many parts of the world, particularly in Europe, East Asia, and mountainous or marginal agricultural regions undergoing socioeconomic transformation and rural depopulation (Lee et al., 2021; Levers et al., 2018; Song et al., 2025b; Terres et al., 2015). The environmental and socioeconomic consequences of farmland abandonment are often characterized by notable trade-offs. On the one hand, the reduction in cultivation disturbances can facilitate the recovery of soil physicochemical properties, promote natural vegetation succession, and enhance biodiversity and habitat connectivity (Crawford et al., 2022; Liu et al., 2025a; Romero-Díaz et al., 2017; Zabel et al., 2019; Zang et al., 2025). In many marginal landscapes, farmland abandonment has also been associated with ecosystem restoration and increased carbon sequestration potential (Gellrich et al., 2007). On the other hand, the decline in active cultivation may reduce regional agricultural production capacity and weaken local food security, while also reshaping rural livelihoods and land use structures (Lasanta et al., 2017; Ojha et al., 2022; Springmann et al., 2018). In some regions, unmanaged abandoned lands may additionally increase the risk of wildfires, invasive species spread, or other secondary ecological hazards (Lecina-Diaz et al., 2023).

China shoulders a substantial responsibility to sustain high food production to feed its large population, making the effective utilization of farmland critically important for national food security (Jiang et al., 2024b; Liu et al., 2023a; Ye et al., 2022a; Zhao et al., 2021). However, farmland abandonment has become increasingly widespread under rapid urbanization and demographic ageing (Fang et al., 2026; Hou et al., 2021; Liu and Zhou, 2021). Although long-standing national policies (such as permanent basic farmland protection, agricultural subsidies, and high-standard farmland construction) have been implemented, farmland abandonment in some areas has not been fundamentally alleviated and, in certain localities, continues to expand and intensify (Guo et al., 2023; Wang et al., 2023; Ye et al., 2022b). A deep understanding of the spatial patterns and driving mechanisms of farmland abandonment constitutes an essential foundation for integrating food security, ecological restoration, and sustainable rural transformation.

Research on spatial quantitative assessments of farmland abandonment has evolved mainly along two interrelated paths. The first research path focuses on identifying abandoned farmland through remote sensing data (Guo et al., 2023; Liu et al., 2025b; Lou et al., 2025; Prishchepov et al., 2025). Multitemporal analyses using MODIS, Landsat, and Sentinel imagery have been enhanced by the advent of cloud computing and advanced change detection algorithms, thereby increasing the accuracy and temporal continuity of mapping (Dara et al., 2018; Liu et al., 2025b). This approach faces persistent challenges including parcel fragmentation, land-cover confusion, and difficulties in distinguishing intentional abandonment from land use transitions, particularly in mountainous areas (Li et al., 2022; Zhu et al., 2021). A second research path adopts microlevel survey methods, including household questionnaires, plot-based sampling, and meta-analytical approaches. The spatial patterns of farmland abandonment, as well as the effects of natural endowments, policy interventions, and farmer decision-making on abandonment behaviour have been revealed (Wang et al., 2022, 2023; Yan et al., 2016). The limited sample size and spatial coverage of these studies constrain their ability to reveal large-scale spatial patterns. Based on these paths, many studies at the administrative unit scale rely on remote sensing identification or survey data aggregated at the county or township level to examine the spatiotemporal dynamics and driving forces of farmland abandonment (Guo et al., 2023; Li et al., 2025). Such studies effectively integrate official statistical data and are advantageous for characterizing large-scale patterns and mechanisms. However, the coarse spatial resolution of administrative units tends to obscure within-unit heterogeneity (masking contrasts between high- and low-abandonment areas) and limits the ability to capture parcel-level processes. In recent years, the Third National Land Use Survey of China, which is derived from high-resolution remote sensing imagery with a spatial resolution better than 1 m and large-scale field investigations, has created new opportunities (Song et al., 2025b). Through official statistical definitions, the dataset at the plot scale provides authoritative estimates of abandoned farmland. Aggregating parcel-level information into 1-km grid cells for nationwide spatial analysis provides a practical balance between retaining fine-scale spatial information and enabling consistent large-scale spatial modelling. Moreover, 1-km grid analysis has been widely used in large-scale studies of farmland abandonment and land use change (Levers et al., 2018; Hong et al., 2024), demonstrating its suitability for capturing broad spatial patterns and drivers of agricultural land abandonment.

To explore the driving mechanisms of farmland abandonment, both linear (e.g., OLS, GWR and PCA) and nonlinear analytical methods have been widely applied (Guo et al., 2023; Hong et al., 2024; Kosmas et al., 2015; Wang et al., 2023; Yan et al., 2016). Explanatory variables generally include natural factors (e.g., elevation, slope, soil fertility and texture, climatic conditions, and exposure to extreme events), socioeconomic factors (e.g., rural labour outmigration and opportunity cost, fluctuations in agricultural input and grain prices and population ageing), cultivation conditions (e.g., travel time to roads or markets, distance to mechanized roads, and farmland contiguity) and policy drivers (e.g., land transfer market, and institutional or subsidy influences). Previous studies have revealed distinct driving mechanisms of farmland abandonment between plains and mountainous areas (He et al., 2020; Zhang et al., 2014). In mountainous and remote zones, abandonment is constrained mainly by fragmented terrain, poor soil fertility, and insufficient infrastructure, whereas in peri-urban and agriculturally dominant plains, nonmarginal farmland abandonment is often influenced by labour outmigration, changes in relative profitability, and increasing land use competition (Baumann et al., 2011; Ren et al., 2023; Song et al., 2025a; Wang et al., 2020; Zhang et al., 2014). Beyond statistical approaches, land use simulation models have also been applied to analyse farmland abandonment processes. CLUE-based models have been used to link socioeconomic and biophysical drivers with spatial land use allocation processes and to simulate future patterns of agricultural land abandonment under different scenarios, while platforms such as LUISA integrate demographic, economic, and environmental drivers to project regional abandonment dynamics (Perpiña Castillo et al., 2020; Song et al., 2024b; Verburg and Overmars, 2009). However, these approaches have limited capacity to examine the synergistic and complex threshold effects among multiple factors, as well as their interaction mechanisms. Identifying interaction structures helps reveal which combinations of conditions lead to high abandonment risk, thereby supporting more targeted regional policies, while single-factor interventions may have limited effectiveness (Terres et al., 2015). Several studies have attempted to explore these relationships. By employing Tobit models with interaction and moderation analyses, Song et al. (2024a) examined the influence of farmland transfer on abandonment at the village level and found that its effect is stronger in areas with fewer full-time agricultural labourers, more abundant farmland resources, a higher share of high-quality farmland, and more land transfers with rent. In addition, Song et al. (2025b), using Tobit and quantile regression models, showed that as farmland abandonment deepens, the mitigating effect of favourable cultivation conditions strengthens, while the promoting role of socioeconomic factors weakens. Nevertheless, interactions among natural, socioeconomic, and cultivation factors remain insufficiently explored, and the linear structure of Tobit models limits their ability to capture nonlinear characteristics. The SHAPley additive explanations algorithm, a tree-based machine learning method, enables the quantification of nonlinear couplings and threshold-dependent interactions among driving variables (Lundberg et al., 2018). This approach provides a more refined understanding of the synergistic and heterogeneous mechanisms underlying farmland abandonment and helps support more targeted regional policy interventions.

The core objective of this study was to investigate the spatial patterns and driving mechanisms of farmland abandonment in China from a 1-

km grid perspective. We hypothesize that the drivers of farmland abandonment interact in a nonlinear manner, and that the joint effects of multiple dimensions shape the spatial patterns of abandonment. First, a theoretical framework for the composite driving mechanisms of farmland abandonment was developed, integrating fifteen driving variables categorized into natural factors, socioeconomic factors, and cultivation conditions, all of which were harmonized to a 1-km grid. Second, the spatial pattern of farmland abandonment was analysed, and key hotspot regions requiring targeted attention were identified. Third, random forest regression and the SHAP algorithm were employed to quantify both the individual and interaction effects of the driving factors, thereby revealing the nonlinear and synergistic dynamics underlying farmland abandonment. In the discussion section, the relationships between policy-related indicators and the fifteen driving variables were examined at the provincial scale to assess the potential influence of the absence of explicit policy indicators in the framework. Region-specific policy insights were inferred from the identified driver patterns, which may provide references for mitigating farmland abandonment in different regions. This study enhanced the understanding of farmland abandonment drivers at a fine spatial resolution and provided actionable insights for farmland protection and national food security.

## 2. Theoretical framework for grid-scale farmland abandonment driving mechanisms

Within the existing theoretical framework of resource allocation and land use transition, farmland abandonment can be regarded as a rational choice made by farmers or agricultural entities under multiple constraints. In essence, it represents a decision to withdraw from or reduce the intensity of cultivation on the basis of a trade-off among returns, costs, and opportunity costs (Baumann et al., 2011; Li and Li, 2017; Song et al., 2025b). Accordingly, the framework can be structured on the basis of the individual effects of natural factors, socioeconomic factors and cultivation conditions, while emphasizing the interactions and context dependencies among them (Fig. 1).

First, natural factors constitute the fundamental constraints of agricultural production by shaping the potential yield and risk structure, thereby influencing both the probability and spatial pattern of farmland abandonment. *ALT* and *Slope* affect thermal and moisture conditions, soil depth, erosion risk, and the accessibility of mechanized farming (Li et al., 2021; Terres et al., 2015; Yan et al., 2016). *MAP* and *MAT* jointly determine the hydrothermal balance and stress intensity during the crop-growing period (Guo et al., 2023). *SOC*, as an integrated indicator of soil fertility and water-holding capacity, increases the potential yield ceiling, buffers against drought and flood stresses, and reduces the uncertainty of marginal returns on agricultural inputs, thereby suppressing abandonment (Du et al., 2026; Liu et al., 2022). These natural endowments set the upper limit and fluctuation range of agricultural output, which in turn affect both the upper bound and the stability of land rent. When the expected net return falls below management and opportunity costs, farmland parcels are more likely to become abandoned or remain fallow for longer durations (Fig. 2).

Second, according to new labour migration theory, socioeconomic factors indirectly reshape the relative profitability of agriculture by altering opportunity costs, market expectations, and organizational patterns, thereby influencing the FAR (He et al., 2020; Xu et al., 2019). *PCGDP* generally enhances nonagricultural employment opportunities and returns, increasing the opportunity cost of farming. In the absence of scale economies and adequate service support, high *PCGDP* tends to increase abandonment. High *PCGDPdiff* amplifies labour outmigration and local labour shortages, accelerating the withdrawal of marginal land (Yan et al., 2016). *PCFA* reflects the scale of land available per labor and potential economies of scale. High *PCFA* can reduce fixed costs, improve machinery utilization efficiency, and enhance organizational efficiency, thereby reducing unit costs and suppressing abandonment. However, in regions suffering from severe labour shortages or high plot fragmentation, land may exceed labour capacity, resulting in poor field management or selective abandonment (Terres et al., 2015). When dominated by nonagricultural sources, increased *Income* often increases external opportunity returns and reduces agricultural labour input, thereby increasing abandonment. Conversely, when income growth is accompanied by improved agricultural efficiency and service accessibility,

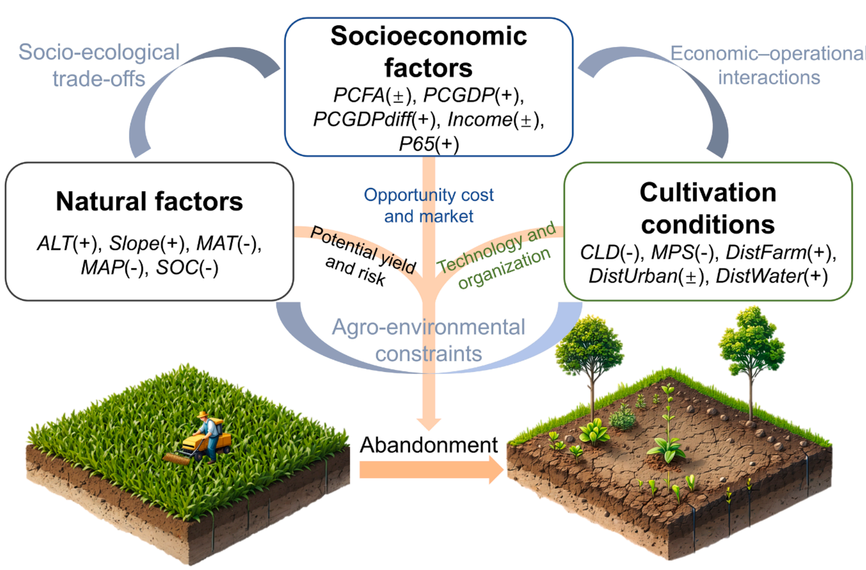


**Fig. 1.** Theoretical framework illustrating the driving effects of natural factors, socioeconomic factors, and cultivation conditions on farmland abandonment, as well as the interactions among them. *ALT* represents altitude; *Slope* represents slope of farmland plots; *MAT* represents temperature; *MAP* represents precipitation; *SOC* represents soil organic carbon content; *PCGDP* represents per capita gross domestic product; *PCGDPdiff* represents the gap in *PCGDP* compared with the most developed region, reflecting the potential economic benefits that could be obtained by migrating to more developed areas; *PCFA* represents per capita farmland area; *Income* represents per capita disposable income; *P65* represents the proportion of the population over 65 years old, reflecting the level of aging in the rural population; *MPS* represents mean plot size; *CLD* represents farmland density; *DistFarm* represents the distance from farmland to the nearest building; *DistUrban* represents the distance from farmland to the nearest city; and *DistWater* represents the distance from farmland to the nearest water body. (+) and (-) denote positive and negative effects, respectively, of the variables on the FAR. (±) indicates a possible bidirectional effect.

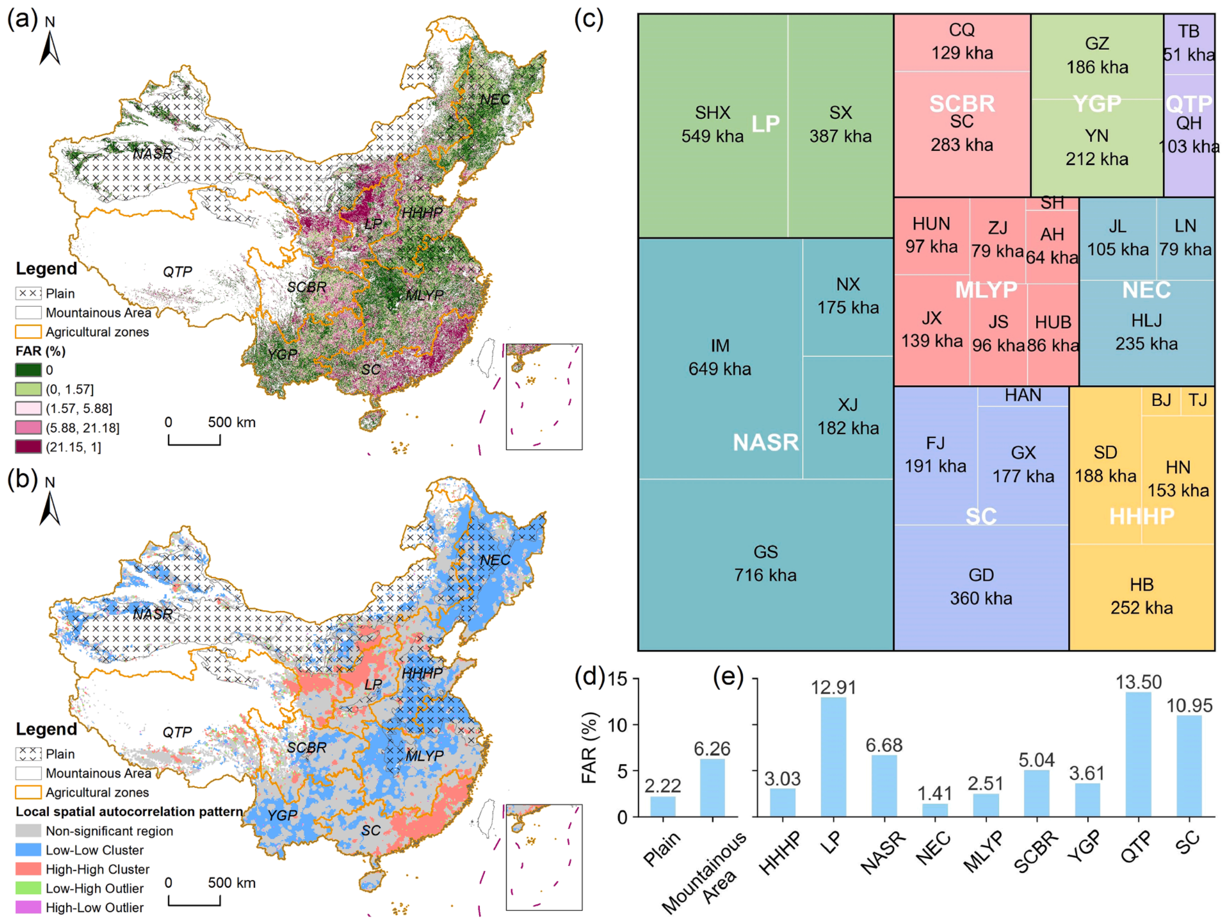


**Fig. 2.** Spatial pattern and regional statistics of farmland abandonment in China. (a) 1-km grid-based FAR map. (b) 10-km grid-based local spatial autocorrelation pattern of the FAR. (c) Abandoned farmland area across agricultural zones and provinces. (d–e) FAR of plain, mountain area, and agricultural zones. NASR represents the northern arid and semiarid regions, including Xinjiang Uygur Autonomous Region (XJ), Inner Mongolia Autonomous Region (IM), Ningxia Hui Autonomous Region (NX), and Gansu (GS). NEC represents the Northeast China Plain, including Heilongjiang (HLJ), Jilin (JL), and Liaoning (LN). LP represents the Loess Plateau, including Shanxi (SX) and Shaanxi (SHX). HHHP represents the Huang–Huai–Hai Plain, including Henan (HN), Hebei (HB), Shandong (SD), Beijing (BJ) and Tianjin (TJ). MLYP represents the Middle–Lower Yangtze Plain, including Hubei (HUB), Hunan (HUN), Jiangxi (JX), Anhui (AH), Zhejiang (ZJ), Jiangsu (JS) and Shanghai (SH). SC represents southern China, including Guangdong (GD), Guangxi Zhuang Autonomous Region (GX), Fujian (FJ) and Hainan (HAN). YGP represents the Yunnan–Guizhou Plateau, including Yunnan (YN) and Guizhou (GZ). SCBR represents the Sichuan Basin and surrounding regions, including Sichuan (SC) and Chongqing (CQ). QTP represents the Qinghai–Tibet Plateau, including Tibet Autonomous Region (XZ) and Qinghai (QH).

abandonment may decrease (Shi et al., 2018). *P65* reflects the level of population ageing and the potential constraints it imposes on agricultural labour availability and farming capacity, which may increase the FAR (Ren et al., 2023). However, in areas with well-developed land transfer markets, entrusted farming, or enhanced public services, such negative effects may be partly mitigated (Xu et al., 2019).

Third, cultivation conditions directly affect production costs by shaping the feasibility of technological adoption and organizational arrangements. On the basis of ground rent theory, better cultivation conditions contribute to higher profits, motivating farmers to cultivate more farmland and expand their grain production (Hou et al., 2021; Song et al., 2025b). High *MPS* generally facilitates mechanized operations and the optimization of working routes, which dilutes fixed costs and reduces the marginal cost of field management, thereby suppressing abandonment (Ye et al., 2024a). High *CLD* indicates more concentrated plots, shorter operational turnover, and better accessibility to agricultural services, all of which typically suppress abandonment (Song et al., 2025a; Ye et al., 2024b). High *DistFarm* increases labour and supervision costs and complicates field monitoring and security management, which is expected to increase the FAR (Zhang et al., 2016). Low *DistUrban* generally increases the circulation of agricultural inputs and outputs, accessibility to agricultural services, and price discovery, thus potentially reducing abandonment (Gellrich et al., 2007). It can also increase abandonment tendencies when high non-agricultural returns or strong expectations of land conversion prevail (Hou et al., 2021). High *DistWater* reduces irrigation convenience and drought-buffering capacity, and increases abandonment under arid or highly variable climatic conditions.

Crucially, the above three categories of factors exhibit multilevel interactions and threshold effects (Terres et al., 2015). There are socio-ecological trade-offs between natural factors and socioeconomic factors. The adverse effects of natural factors can be amplified when nonagricultural opportunities expand, as lower potential yields and higher risk premiums are more likely to trigger abandonment under high opportunity costs (Li et al., 2021). Moreover, natural factors and cultivation conditions have reshaped the agro-environmental constraints. When mechanization and service systems are well developed, the cost increases induced by unfavourable natural factors can be partially offset, thereby reducing farmers' sensitivity to environmental constraints (Xu et al., 2025; Yan et al., 2016). Regions with high compatibility between natural endowments and cultivation conditions tend to maintain more stable farmland utilization. There are economic–operational interactions between cultivation conditions and socioeconomic factors. Large-scale and organized farming can reduce transaction and management costs through route optimization and labour specialization, allowing for marginal plots to be included within viable production sets (Song et al., 2025b). However, under the persistent net out-migration of rural labour, even with technological substitution, the potential gains from mechanization may not be fully realized if maintenance and operational services remain inaccessible (Chen et al., 2023). Therefore, farmland abandonment should be understood as a dynamic process shaped by the three constraints of natural factors, socioeconomic factors, and cultivation conditions, among which interaction effects exist. Identifying these interaction effects can help reveal the combinations of constraints that lead to high abandonment risk, thereby providing a basis for more targeted and differentiated policy interventions.

## 3. Materials and methods

### 3.1. Data source

The data used in this study included land use data, official Chinese statistical data, and remote sensing data. Land use data were employed to extract abandoned farmland and the attribute characteristics of farmland parcels. The official statistical data and remote sensing data were used to represent the natural factors, socioeconomic factors, and cultivation conditions. All the datasets were standardized to a 1-km grid resolution. Owing to the spatial coverage limitations of the datasets, Hong Kong, Macao, and Taiwan were excluded from the analysis.

The land use data characterizing farmland were derived from the Third National Land Use Survey of China (NLUS III), released in 2021. On the basis of the farmland plots from the NLUS III dataset, a 1-km gridded dataset was constructed, including variables such as farmland density (*CLD*), mean plot size (*MPS*), and FAR. We identified "uncultivated cultivated land" in the NLUS III dataset in 2019 as abandoned farmland, defined as farmland where farming practices and production activities have ceased but that could be directly restored for agricultural purposes (Song et al., 2025b). This category in the NLUS III classification system and does not include cultivated land under planned fallow programs or land converted through ecological restoration policies (e.g., cropland-to-forest or cropland-to-grassland), nor land that would require substantial engineering measures to be restored to cultivation (https://www.mnr.gov.cn/zt/td/dscqggtdc/zl/201906/t20190604_2439983.html). In addition, the topographic type was considered a key factor influencing the mechanisms driving farmland abandonment and was used for spatial zonation. The Digital Mountain Map of China dataset classified China into plains and mountainous areas, and the former included relatively flat regions such as plateaus and basins (Nan et al., 2022).

Fifteen factors from three dimensions (natural factors, socioeconomic factors, and cultivation conditions) were considered (Table 1). The natural factors included altitude (*ALT*), slope, mean annual temperature and precipitation (*MAT* and *MAP*), and soil organic carbon (*SOC*). The *ALT* and *Slope* data were derived from the ASTER Global Digital Elevation Model (GDEM) with an original spatial resolution of 30 m. The *Slope* data were extracted through masking on the basis of farmland plot data. The *MAT* and *MAP* data were spatially downscaled from the CRU TS v4.02 dataset using WorldClim data and validated against observations from 496 national meteorological stations across China, achieving a spatial resolution of 1 km. The *SOC* data were obtained from the high-resolution global soil dataset developed by Shangguan et al. (2014), which also has a spatial resolution of 1 km. The socioeconomic factors include per capita gross domestic product (*PCGDP*), *PCGDP* gap with the most developed region within the province (*PCGDPdiff*), per capita farmland area (*PCFA*), per capita disposable income (*Income*), and the proportion of the population aged over 65 (*P65*). The *PCGDP*, *PCGDPdiff*, and *Income* data were sourced from the China County Statistical Yearbook. The *PCFA* data were calculated on the basis of the 1-km population grid from the LandScan dataset and

**Table 1**
Definitions of driving variables.

| Type | Variable | Variable definition | Source |
|---|---|---|---|
| Natural factors | *ALT* | Altitude of each grid cell (m) | Abrams et al. (2015) |
| | *Slope* | Mean slope of farmland plots within each grid cell (°) | Calculated based on *ALT* |
| | *MAT* | Mean annual temperature (°C) | Peng (2024a) |
| | *MAP* | Mean annual precipitation (mm) | Peng (2024b) |
| | *SOC* | Soil organic carbon content (%) | Shangguan et al. (2014) |
| Socioeconomic factors | *PCGDP* | Per capita gross domestic product (yuan) | China County Statistical Yearbook 2020 (https://data.cnki.net/Yearbook/) |
| | *PCGDPdiff* | *PCGDP* gap with the most developed region within the province (yuan) | Calculated based on *PCGDP* |
| | *PCFA* | Per capita farmland area (ha) | Lebakula et al. (2025) (https://landscan.ornl.gov/) |
| | *Income* | Per capita disposable income (yuan) | China County Statistical Yearbook 2020 (https://data.cnki.net/Yearbook/) |
| | *P65* | Proportion of the population over 65 years old | Seventh National Population Census of China (https://www.stats.gov.cn/english) |
| Cultivation conditions | *MPS* | Mean plot size (ha) | NLUS III; Ye et al. (2024) |
| | *CLD* | Farmland density (ha) | NLUS III; Ye et al. (2024) |
| | *DistFarm* | Mean distance from farmland to the nearest building (km) | Zanaga et al. (2021) |
| | *DistUrban* | Mean distance from farmland to the nearest city (km) | Liu et al. (2024) |
| | *DistWater* | Mean distance from farmland to the nearest water body (km) | Chen et al. (2015) |

farmland area data from NLUS III (Lebakula et al., 2025). The *P65* data were derived from the Seventh National Population Census of China and were calculated at the township or subdistrict level. The cultivation conditions include factors such as *MPS*, *CLD*, and the mean distance from farmland to the nearest building, city and water body (*DistFarm*, *DistUrban* and *DistWater*). The *MPS* and *CLD* data were calculated from farmland plot data on the basis of the NLUS III dataset. The *DistFarm* data were calculated on the basis of WorldCover maps for 2020, which provided land cover information for 2020 at a spatial resolution of 10 m (Zanaga et al., 2021). The *DistUrban* data were calculated on the basis of the global urban built-up area in 2019 (Liu et al., 2024). The *DistWater* data were calculated on the basis of the GlobeLand30 dataset (2020 edition) developed by Chen et al. (2015). Boxplots illustrating the spatial distribution and variability of these 15 factors across agricultural zones in China were provided in Fig. S1, while results of the multicollinearity test among the factors are reported in Table S1.

### 3.2. Farmland abandonment ratio

Farmland abandonment ratio (FAR) is defined as the proportion of abandoned farmland area to total farmland area, and is used to represent and quantify the degree of farmland abandonment (Eq. 1), where $A_{abnd}$ denotes the abandoned farmland area and $A_{tot}$ denotes the total farmland area (Song et al., 2025b). Both $A_{abnd}$ and $A_{tot}$ were derived from the spatial dataset of the NLUS III, which provides parcel-level land use polygons interpreted from high-resolution remote sensing imagery and large-scale field investigations. Specifically, $A_{abnd}$ represents the area of uncultivated cultivated land. $A_{tot}$ represents the total cultivated land area (including paddy fields, irrigated land, and dryland). In this study, FAR was calculated at a 1-km grid resolution. Both variables were calculated by aggregating the areas of the corresponding land use polygons within each 1-km grid cell using GIS. FAR was calculated only for grid cells containing farmland ($A_{tot} > 0$); grid cells without farmland were excluded. Under this definition, FAR $= 0$ indicates no abandonment, whereas $0 <$ FAR $\leq 100\%$ represents the intensity of farmland abandonment within the grid cell.

$$FAR = A_{abnd}/A_{tot} \times 100\% \tag{1}$$

### 3.3. Random forest model

The random forest (RF) model is an ensemble learning algorithm that constructs multiple decision regression trees using randomly sampled subsets of the data and feature space, and aggregates their outputs through averaging to generate the final prediction (Breiman, 2001). Compared with a single decision tree, RF substantially improves regression and classification performance and is particularly effective in capturing complex nonlinear relationships and interactions among variables. In addition, RF is robust to multicollinearity and does not require strict assumptions about the distribution of explanatory variables, making it well suited for analysing the multidimensional drivers of farmland abandonment.

In this study, the RF regression model was employed to examine the relationships between natural factors, socioeconomic factors, and cultivation conditions and the FAR in plains and mountainous areas. Specifically, for both terrain types, grid cells with a nonzero FAR were used to construct the modelling datasets. To evaluate the robustness and generalization ability of the model, a fivefold cross-validation procedure was conducted by randomly partitioning each dataset into five approximately equal subsets. The model was trained and validated in five iterations. In each iteration, four subsets were used for training, and the remaining subset was used for validation. The final model performance was evaluated by averaging the determination coefficient ($R^2$) across the five folds. The detailed results were presented in Table S2.

### 3.4. SHAPley additive explanations

The SHAP (SHAPley additive explanations) method is a game theory–based framework for model interpretability. Its core idea is to regard the model prediction as the total payoff generated by the cooperation of all features and to quantify the importance of each feature by computing its marginal contribution across all possible subsets of features (Lundberg and Lee, 2017). Tree SHAP is particularly suitable for tree-based models, offering both efficiency and exactness while satisfying key properties such as local additivity and consistency (Lundberg et al., 2018). The SHAP value for feature $j$ is defined as follows (Eq. 2), where $N = \{1, \ldots, M\}$ denotes the complete set of features, $S$ represents a subset of features that does not include feature $j$, and $f_S$ denotes the model trained or evaluated based solely on the subset $S$ (or equivalently, the conditional expectation when other features are masked). This formulation captures the average marginal contribution of feature $j$ across all possible coalitions.

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(M - |S| - 1)!}{M!} \left[ f_{S \cup \{j\}}(x_{S \cup \{j\}}) - f_S(x_S) \right] \tag{2}$$

In addition, the SHAP framework allows for the total contribution to be further decomposed into main effects and interaction effects, thereby identifying nonlinear interaction structures among features. The second-order interaction effect represents the additional contribution to the prediction when two features occur together. A positive interaction SHAP value indicates that the joint presence of the two features increases the prediction beyond the sum of their individual main effects, whereas a negative value implies a suppressing or compensatory interaction. The second-order interaction SHAP value is calculated using Eq. 3, where $\Phi_{i,j}$ denotes the second-order interaction SHAP value between features $i$ and $j$, and $\Phi_i$ ($\Phi_j$) refers to the main effect SHAP value of feature $i$ ($j$). This formulation compares the change in each feature's main effect when the other feature is considered versus excluded and then takes their symmetric average.

$$\Phi_{i,j} = \frac{1}{2}\left( \phi_i^{(+j)} - \phi_i^{(-j)} + \phi_j^{(+i)} - \phi_j^{(-i)} \right) \tag{3}$$

## 4. Results

### 4.1. Spatial pattern of farmland abandonment

The spatial distribution of farmland abandonment revealed that the abandoned areas were mainly concentrated in the northern arid and semiarid regions, the Loess Plateau, southern China, and the Huang–Huai–Hai Plain. Provinces such as Gansu, Inner Mongolia, Shaanxi, Shanxi, and Guangdong each had more than 300 kha of abandoned farmland (Fig. 1c). At the national scale, the overall FAR was 4.49%, with notable differences across terrain types (Fig. 1d). The FAR in the plains was only approximately 2.22%, whereas that in the mountainous areas reached 6.26%, approximately 2.8 times higher than that in the plains. Among the agricultural zones, the Qinghai–Tibet Plateau had the highest FAR (13.50%), followed by southern China (10.95%). The Loess Plateau and Sichuan Basin and surrounding region showed moderate levels (6.68% and 5.04%, respectively), whereas the northern arid and semiarid regions, northeast China, Huang–Huai–Hai Plain, and the Middle–Lower Yangtze Plain showed relatively low rates (all below 3%).

At the grid scale, approximately 80% of the grid cells containing farmland were no more than 65 ha (Fig. S2). Farmland abandonment in China followed a pattern of wide coverage but low intensity. More than 70% of the grids exhibited a FAR less than 5%, yet they contributed less than 20% of the total abandoned area. Grids with low FAR were widely distributed across China but accounted for a relatively small proportion of the total abandoned area, whereas a limited number of grids with high FAR contributed a large share of the total abandonment. Spatially, farmland abandonment showed a pronounced mountain-high and plain-low gradient. Higher FAR values were observed in the southeastern coastal region, the northwestern agro-pastoral ecotone, and the southwestern mountainous region. The local spatial autocorrelation results revealed stable high-high clusters in the agro-pastoral transition zone between the northern arid and semiarid regions and the Loess Plateau, in the southeastern coastal region, in the southwestern mountainous region, and around the Beijing–Tianjin–Hebei urban agglomeration. The first two areas exhibited a clear belt-like clustering pattern, whereas farmland abandonment in the southwestern mountainous region was more scattered and occurred at a lower overall intensity. In contrast, the northeastern region, the North China Plain, the Middle–Lower Yangtze Plain, and the Yunnan–Guizhou Plateau manifested distinct low-low cold spots, indicating a strong tendency towards spatial clustering and neighbourhood spillover effects. These clustering patterns describe the spatial distribution of FAR. Considering the clear mountain–plain gradient in FAR, the driving mechanisms of farmland abandonment in these two terrain types were further analysed in Sections 4.2–4.3 using the RF–SHAP framework.

### 4.2. Driving mechanisms of farmland abandonment in plains and mountainous areas

Together, natural factors, socioeconomic factors, and cultivation conditions explained 51–54.4% of the variation in farmland abandonment (Table S2). The relative importance of each factor and the marginal effects derived from single-variable SHAP values were shown (Fig. 3). In general, *CLD* was the most influential determinant in both the plains and mountainous areas, with the SHAP value showing a consistently decreasing effect with increasing size. The increase in *CLD* had a stable diminishing effect on abandonment risk, with a significant reduction observed as the farm size expanded from the small to medium scale. The turning point where the SHAP value changed from positive to negative occurred at a much smaller scale in mountainous areas (∼20 ha) than in plains (∼40 ha). *DistFarm* ranked among the top factors in both terrains. *DistUrban* exhibited positive effects at low values that rapidly diminished with increasing distance, reflecting the opportunity-cost effect driven by peri-urban urbanization. *ALT* increased the risk of abandonment in both terrains. *Slope* had a near-zero effect on plains but shifted from negative to positive in mountainous areas, with a turning point at approximately 10°. *P65* displayed a U-shaped relationship in both terrains: the abandonment risk decreased sharply at low levels (<15%), became negative at mid-levels, and then turned positive again at high levels (>30%). The sensitivity range differed by terrain: plains were more sensitive in the low-value range, whereas mountains were more sensitive in the high-value range.

In plains, the factor ranking was dominated by labour and location, with *P65* and *DistUrban* having greater importance, whereas natural factors contributed less. *DistFarm* exhibited a U-shaped relationship, indicating dual risks from both excessive proximity (reflecting nonagricultural attraction and higher land rents) and excessive remoteness (limited access to services). Along the gradient where *DistUrban* was low, the SHAP value in plains declined faster and more steeply, highlighting a stronger sensitivity of abandonment to peri-urban opportunity costs. Mountainous areas were influenced mainly by natural factors and *DistFarm*. The SHAP value of *MAP* followed a U-shaped pattern. *MAT* changed from negative to positive and increased rapidly above 15 °C. *Slope* and *ALT* were highly important and, together with climatic variables, amplified both cultivation cost and yield uncertainty. The SHAP value of *DistFarm* in mountainous areas increased almost monotonically, indicating that longer distances to farm service facilities significantly elevated the risk of abandonment—in contrast to the U-shaped effect observed in plains. The positive effect of low *DistUrban* was weaker in mountainous areas, suggesting that urban opportunity-cost effects were less direct than the constraints imposed by natural conditions and service inaccessibility were.

### 4.3. Interaction effects among driving factors

On the basis of the SHAP interaction contributions, systematic differences were observed between plains and mountainous areas in terms of both interaction intensity and hotspot structure (Fig. 4). Plains generally showed weaker interactions and more dispersed hotspots, indicating that farmland abandonment in the plains was primarily

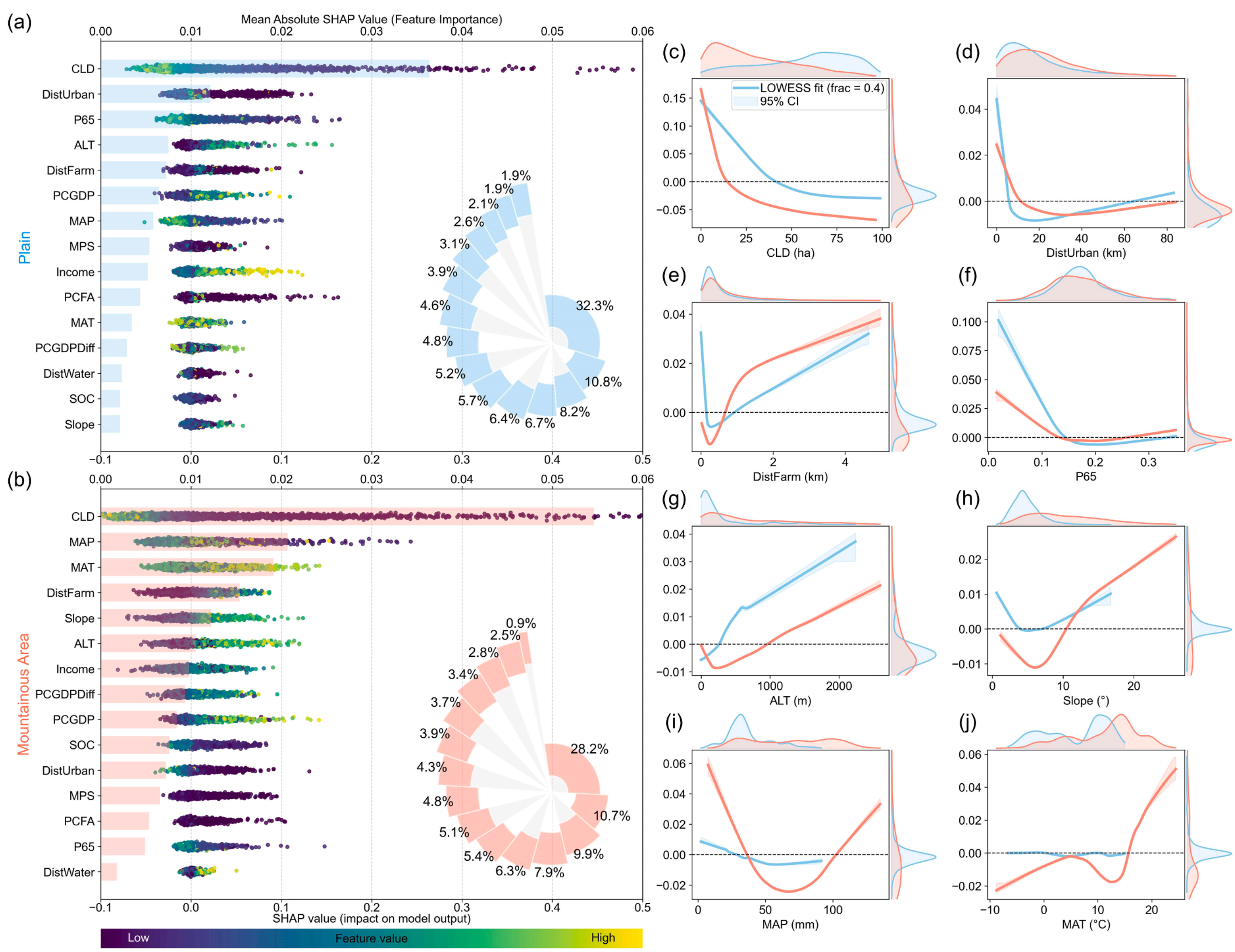


**Fig. 3.** Importance of 15 driving factors and marginal effects of key variables on the basis of SHAP values. (a–b) Scatter plots of SHAP values and bar charts of feature importance for plains and mountainous areas, together with rose charts showing the proportional contribution of each driving factor. (c–j) Marginal effect plots of relatively important features, displaying the data distribution, LOWESS-fitted trend lines, and 95% confidence intervals generated from 200 bootstrap samples.

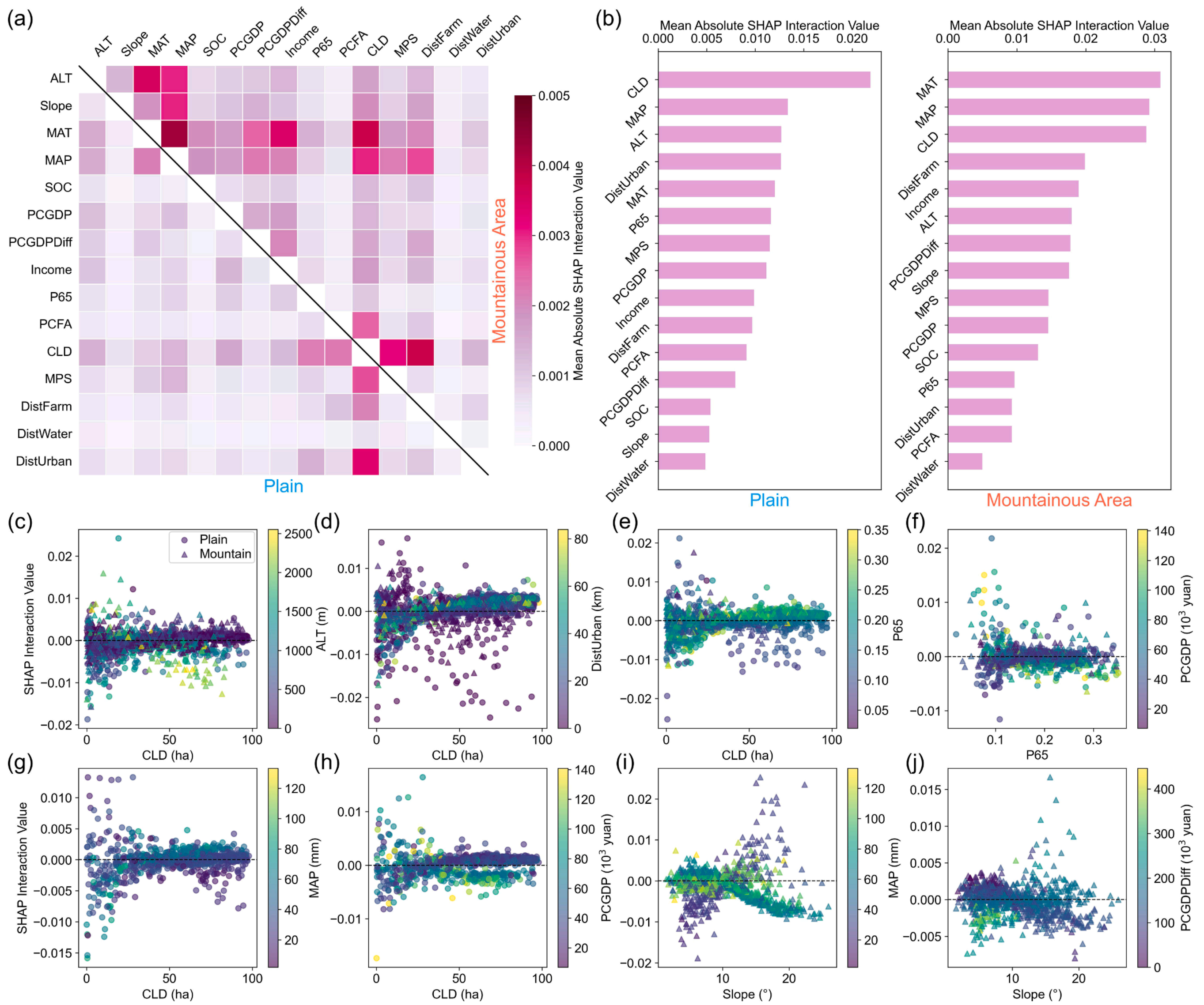


**Fig. 4.** Interaction effect intensity among driving factors and scatterplots of variable interactions. (a) Heatmaps showing the interaction effects between driving factors in plains and mountainous areas. (b) Bar charts summarizing the statistical strength of factor-pair interactions for plains and mountainous areas. (c–j) SHAP scatterplots of high-value interactions between selected driving variables. (c–d) include both plains and mountainous areas; (g–h) represent driving mechanisms in plains; and (i–j) represent driving mechanisms in mountainous areas.

controlled by a few structural factors. Engineering and institutional conditions appeared to weaken the effects of climate–topography coupling. In terms of interaction importance, *CLD*, *MAP*, *ALT*, *DistUrban*, *MAT*, *P65*, and *MPS* were among the top factors. The hotspots revealed several key patterns. Interactions between *CLD* and *DistFarm/DistUrban/MPS* reflected the bidirectional regulation of abandonment through organizational structure and accessibility. The coupling of *MAP* with *ALT/MAT* represented conditional natural effects that persisted despite engineering interventions. The joint effect of *P65* with *DistUrban/PCGDP* highlighted the coupled influence of ageing and urban opportunity. Mountainous areas exhibited higher overall interaction intensities and more spatially concentrated hotspots. *MAT*, *MAP*, and *CLD* ranked as the top three interactive factors, followed by *DistFarm*, *Income*, *ALT*, *PCGDPdiff*, and *Slope*. The dominant relationships were characterized by the central role of *MAT–MAP* hydrothermal coupling, the amplified combined effects of *Slope/ALT* with climatic factors, and the synergistic buffering between *CLD* and *DistFarm/DistUrban/MPS*, which promoted connected cultivation and improved service accessibility in fragmented terrain.

Both plains and mountainous areas showed threshold-reversal type interactions. When *CLD* exceeded approximately 30 ha, the SHAP interaction values between high *ALT* and *CLD* became strongly negative (Fig. 4c). These findings indicated that under high density conditions, the net effect of high *ALT* decreased. Moreover, the SHAP interaction values between high *DistUrban*, high *P65*, and *CLD* changed from negative to positive (Fig. 4d–e), suggesting that increased farmland density converted the effects of remoteness and aging from suppression to enhancement of abandonment risk. With increasing *P65*, the SHAP interaction values between high *PCGDP* and *P65* changed from positive to negative (Fig. 4f). In plains, as *CLD* increased, the SHAP interaction between high *MAP* and *CLD* shifted from negative to positive (Fig. 4g), whereas that between high *PCGDP* and *CLD* changed from positive to negative (Fig. 4h). In mountainous areas, as *Slope* increased, the SHAP interaction between high *MAP* and *Slope* turned from positive to negative (Fig. 4i), and that between high *PCGDPdiff* and *Slope* changed from negative to positive (Fig. 4j).

## 5. Discussion

### 5.1. Comparison of the spatial pattern of farmland abandonment with existing studies

In this study, the most detailed land use dataset available in China was used, excluding the impacts caused by ecological conversion programs and crop planting adjustments. A 1-km gridded spatial pattern study of abandoned farmland in China was supplemented from an official statistical perspective. In this study, we reported that the national FAR in 2019 was 4.49%, which was broadly consistent with the county-level estimate of 4.07% derived by Song et al. (2025b) based on the same dataset. Both the grid-scale and county-scale analyses revealed similar spatial patterns. Hotspots of farmland abandonment were concentrated mainly in the southeastern coastal region, the northwestern agro-pastoral ecotone, and the southwestern mountainous region, forming distinct belt-like and clustered patterns. Farm household survey data and remote sensing results have been comparable (Guo et al., 2023; Long et al., 2025; Wang et al., 2023; Yan et al., 2016; Zhu et al., 2021). Zhu et al. (2021) estimated a national FAR between 3.68% and 6.89%, whereas Li et al. (2022) reported a value of 6.4%, both of which align closely with the results of this study. Spatially, large areas of abandoned farmland were observed in the northwest and southwest, with the northern region exhibiting the greatest total abandoned area (Hong et al., 2024; Yan et al., 2016; Zhang et al., 2023). High FAR values were found mainly in southern China, particularly along the southeastern coast (Long et al., 2025). However, the remote sensing data tended to underestimate abandonment in the northern arid and semiarid regions, especially in Gansu Province, which accounted for a large proportion of the abandoned farmland area. This highlights the challenges associated with detecting abandoned farmland from satellite observations, especially in arid areas where farmland is embedded within a grassland background (Tong et al., 2020).

### 5.2. Composite driving mechanisms of farmland abandonment

By integrating both individual and interaction effects, farmland abandonment in China can be conceptualized as a composite mechanism, which is typically shaped by organizational structure and differentiated by scenario-specific environmental thresholds. Compared with studies conducted at the administrative scale, our grid-scale results placed greater emphasis on the influence of *CLD* on farmland abandonment. Specifically, more fragmented and sparsely distributed plots were more likely to be abandoned. Increased *CLD* reduced field boundaries and transition costs, enhanced the efficiency and accessibility of socialized agricultural services, and strengthened large-scale and organized farm operations across both terrains. Even a transition from a small to medium scale could markedly reduce the risk of abandonment (Guo et al., 2023; Kosmas et al., 2015). It was consistent with the findings of Terres et al. (2015) in Europe. However, the management requirements of the large-scale organizational structure reshaped traditional constraints related to locational marginality and labour availability, introducing new cost and governance thresholds. Without adequate labour support and service systems, farmland structure optimization might exacerbate the spatial vulnerability of agricultural operations (Hou et al., 2021). The interaction effects further indicated that increasing *CLD* (particularly beyond the threshold of 30 ha) intensified resource and service disparities under conditions of labour shortage (high *P65*) and remote location (high *DistUrban*). In these areas, a lack of sufficient labour and service support reduced the operational feasibility of agriculture, making it potentially less sustainable than it was in smallholder-dominated regions (Ren et al., 2025).

In plains, the driving mechanisms of farmland abandonment were characterized mainly by labour, location, and organizational structure. Engineering improvements and institutional support weakened the effects of climatic and topographic factors (Levers et al., 2018). *P65*, *DistUrban*, and *CLD* constituted the primary explanatory framework. The positive effect of low *DistUrban*, together with its rapid decay, pointed to a spatial gradient of factor siphoning (Hou et al., 2021). The U-shaped relationship of *P65* indicated that the influence of ageing on farmland abandonment was both stage specific and bidirectional. These findings contrast with those of farm household surveys, in which ageing generally has a positive relationship with the FAR (Hong et al., 2024; Lee et al., 2021). These findings highlight the advantages of nonlinear models and demonstrate that large-scale grid analyses are able to identify generalized mechanisms and threshold effects of cross-regional spatial heterogeneity. At low to moderate levels of ageing, a moderate proportion of the elderly population was often associated with rich farming experience and a strong attachment to land. This maintained a certain level of cultivation stability and thus suppressed abandonment as *P65* increased (Liu et al., 2023b). As ageing has increased, labour shortages, reduced agricultural capacity, and broken inheritance and land transfer chains have made farm operations unsustainable, resulting in a sharp increase in abandonment risk (Xu et al., 2019). High *PCGDP* promoted farmland abandonment, but its influence was conditional. In highly ageing areas, strengthened collective management, the introduction of industrial and commercial capital and the embedding of socialized agricultural services changed the direction of economic enrichment effects, shifting them from enhancement to suppression of abandonment risk (Tian et al., 2023). Under high *CLD* and mature factor markets, the improved efficiency of capital and service allocation helped reduce basic operational costs and uncertainty. An institutional and organizational environment that mitigated abandonment was fostered (Chen et al., 2025). Notably, under high *CLD*, high precipitation (especially extreme precipitation) could increase the risk of abandonment.

In mountainous areas, farmland abandonment was driven mainly by strong coupling among climatic conditions, topography, and service accessibility. The direct stimulating effect of proximity to urban areas was limited, as abandonment in mountain areas was more sensitive to natural constraints and service inaccessibility than to urban attraction (Guo et al., 2023; Li et al., 2021; Zhang et al., 2014). Compared with plains, mountainous areas exhibited stronger dependence on and vulnerability to service networks. The greater the distance to socialized agricultural services, the more difficult it became to organize production and secure inputs, resulting in a higher abandonment risk (Yan et al., 2016). The effects of climatic conditions were amplified by their interactions with *Slope* and *ALT*, resulting in the formation of a chain that extends from natural stress to mechanization constraints and ultimately to cost accumulation. The threshold-reversal phenomenon in these interactions indicated that appropriate matching among crop systems, institutional arrangements, and engineering measures could transform heavier precipitation burdens into buffering water supplies. It relied on the joint support of soil and water conservation, farm roads, small-scale irrigation, and adaptive cropping systems. Moreover, with increasing *Slope*, the effects of regional economic disparity tended to increase. This led to factor outflows and service imbalances, thereby increasing abandonment risk (Hou et al., 2021; Todde et al., 2024).

Compared with Europe, farmland abandonment in both regions was influenced by a combination of natural, socioeconomic, and cultivation factors. In many regions, rural out-migration, population aging, and declining agricultural profitability reduced the availability of labor and weakened farmers' incentives to maintain cultivation, which increased the likelihood of land abandonment. At the same time, natural factors such as climate and terrain shaped farmland suitability and productivity, thereby affecting farmers' land use decisions (Terres et al., 2015). These similarities indicated that farmland abandonment was a common outcome of broader rural transformation processes associated with economic development and structural changes in agriculture. Some differences were also observed between the two regions. In China, particularly in mountainous areas, natural constraints such as steep slopes, high elevation, and limited accessibility played a stronger role in shaping abandonment patterns. In contrast, studies in Europe generally emphasized structural and institutional factors, including farm economic viability, agricultural policy frameworks, and historical land use transitions (Lasanta et al., 2017; Levers et al., 2018). For example, in the Swiss Alps, high cultivation costs relative to agricultural returns encouraged farmers to abandon marginal land (Gellrich et al., 2007), while in parts of Eastern Europe, institutional transition and rural economic restructuring following the post-socialist period were identified as important drivers (Baumann et al., 2011).

### 5.3. Relationship between policy-related indicators and fifteen driving variables

Due to the limited availability of spatially explicit policy data, policy-related indicators could only be obtained at the provincial level. To examine how these macro-level policy indicators related to the factors included in the RF–SHAP framework, a provincial-scale analysis was conducted using three commonly reported indicators: land transfer rate, land transfer price, and rural revitalization subsidy per unit area. Multiple linear regression models were constructed for each policy indicator using the fifteen factors representing natural factors, socioeconomic conditions, and cultivation conditions. All three models were statistically significant, with adjusted $R^2$ values ranging from 0.55 to 0.73, indicating that the set of fifteen factors explained a substantial proportion of the spatial variation in these policy indicators (Table S3). These results suggested that, at the provincial scale, the selected variables already captured much of the spatial information reflected by the aggregated policy measures. In other words, these policy indicators largely represented outcomes of underlying differences in natural factors, socioeconomic conditions, and cultivation conditions, rather than independent drivers beyond the framework.

The standardized regression coefficients further revealed systematic and interpretable relationships between the policy indicators and framework variables (Table S4). The land transfer rate was positively associated with *Income* (0.66) and *MPS* (0.47), but negatively associated with accessibility-related variables such as *DistFarm* (−0.34) and *DistWater* (−0.3), indicating that provinces with better economic conditions and more favorable production environments tended to exhibit more active land transfer. The land transfer price showed negative associations with *DistFarm* (−1.00), *SLP* (−0.10), and *PCGDPdiff* (−0.24), while positive associations were observed with *PCGDP* (0.18), *Income* (0.64), and *MPS* (0.33). This pattern reflected the combined influence of accessibility, terrain constraints, and regional economic conditions on land value formation. The rural revitalization subsidies were positively associated with *ALT* (0.83), *DistFarm* (0.17), and *DistUrban* (0.18), but negatively associated with several variables reflecting economic and cultivation conditions, including *Income* (−0.46), *PCGDP* (−0.18), and *CLD* (−0.54). This suggested that subsidies tended to be allocated to regions with higher elevation, lower income levels, and lower farmland contiguity, which generally faced greater structural constraints on agricultural production.

Overall, these results indicated that the spatial variation in the three policy indicators could largely be explained by the combined effects of natural factors, socioeconomic conditions, and cultivation conditions, further supporting the representativeness of the variables included in the grid-scale RF–SHAP framework for capturing regional differences.

### 5.4. Regionalized governance recommendations for farmland abandonment

Based on the RF–SHAP framework, the dominant drivers of farmland abandonment across nine agricultural zones in China were explored (Fig. 5). Natural factors dominated in western high-altitude, cold, and arid areas. Socioeconomic factors dominated in the plains and rapidly urbanizing regions. Cultivation conditions were dominant in hilly regions and areas characterized by fragmented farmland. Accordingly, different intervention strategies can be inferred.

In the Northeast China Plain, the results suggest that factors related to farmland quality and operational conditions are closely associated with the spatial pattern of farmland abandonment. In this context, measures such as high-standard farmland construction and black soil conservation may help improve land productivity and cultivation conditions (Wan et al., 2026; Xu et al., 2025). The distance between farmland and nearby settlements or farm buildings may also influence operational efficiency. Areas around large farms show relatively better performance, whereas abandonment remains more evident in low-density rural–forest–grassland ecotones and at the outer margins of reclamation zones (Fig. S1). In the northern arid and semiarid region, water availability and cultivation conditions appear to be important constraints. Approaches such as water-saving irrigation technologies (e.g., drip or sprinkler systems) and soil-testing-based fertilization could potentially help improve resource-use efficiency. For ecologically fragile or marginal plots, farmland retirement and ecological compensation

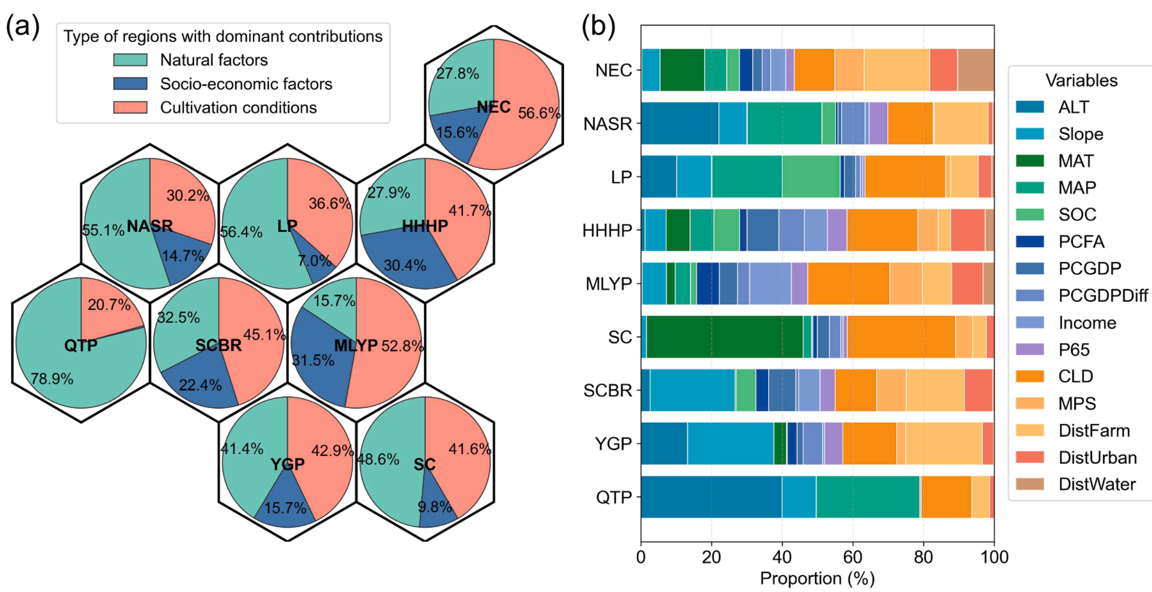


**Fig. 5.** Dominant contributions of nine agricultural zones at the 1-km grid scale in China. (a) The pie charts represent the fractional contributions of the three types of driving factors. (b) Proportions of dominant factors within each region.

programs have been discussed as possible management options (Yuan et al., 2025). In addition, ecological protection initiatives (such as grassland restoration, desertification control, and ecological red-line policies) may indirectly shape farmers' land use decisions by limiting cultivation intensity or encouraging ecological restoration, which may contribute to farmland withdrawal in environmentally sensitive areas. In the Loess Plateau, topography and soil erosion risks are closely related to farmland abandonment patterns. Measures such as terrace construction, soil and water conservation, and ecological adjustment programs that convert cropland to forest or grassland have been widely discussed as ways to reduce cultivation risks on sloping lands (Song et al., 2025a). In the Huang–Huai–Hai Plain, where mechanized agriculture is more prevalent, farmland standardization, improved irrigation–drainage systems, and the development of socialized agricultural service networks may help reduce mechanization barriers and production costs. Supporting technologies such as unmanned agricultural machinery and grain-drying facilities could also contribute to improving operational efficiency. In addition, instruments such as target-price insurance or contract farming may help stabilize the returns of high multiple-cropping systems. In the middle–lower Yangtze Plain and southern China, small-scale water storage and drainage facilities, crop–livestock integration models, and machinery adapted to complex terrain may contribute to improving resource-use efficiency and system resilience (Han et al., 2026; Jiang et al., 2026). In areas exposed to multiple climatic hazards, tools such as weather-index insurance may help disperse production risks. In the Yunnan–Guizhou Plateau and the Sichuan Basin and surrounding regions, steep terrain and fragmented plots appear to be important constraints. In such contexts, terrace farming, diversified farming systems, and locally adapted mechanization technologies may help improve cultivation feasibility. In the Sichuan Basin and surrounding regions where population aging is relatively pronounced (Fig. S1), collective management arrangements, the participation of industrial and commercial capital, and the provision of socialized agricultural services have been suggested as possible ways to alleviate rural labour shortages (Chen et al., 2025). In the Qinghai–Tibet Plateau, ecological functions remain particularly important. Marginal farmlands are often considered in the context of ecological withdrawal and integration into grass–livestock production systems. In suitable areas, small-scale trials of cold-tolerant and short-season crops may be explored while avoiding high-cost compulsory cultivation (Li et al., 2021). Large-scale ecological protection policies, including nature reserve expansion and ecological restoration programs, may also reshape local land use incentives and indirectly influence farmland abandonment patterns in ecologically fragile regions.

These findings suggest several broader directions that may be relevant for farmland management at the national level. First, improving land tenure stability and facilitating farmland transfer markets may support moderate-scale management and land trusteeship, which could help reduce abandonment pressures associated with rural labour out-migration (Song et al., 2024a). In plains, policies that promote moderate-scale management, land transfer, and agricultural service systems may be particularly effective in mitigating labour shortages and improving operational efficiency. Second, combining engineering measures with technological improvements may help lower production costs and labour demand on marginal plots. For example, high-standard farmland construction and mechanization may be more relevant in plains, whereas terrace engineering, soil and water conservation, terrain-adapted mechanization, and small-scale machinery may be more applicable in mountainous areas. In mountainous regions, priority should also be given to improving rural infrastructure and service accessibility and implementing ecological management for marginal lands. In arid zones, water-saving irrigation and drought-tolerant crop varieties may further enhance agricultural adaptability. Third, policy instruments such as minimum purchase prices, target-price insurance, and income insurance may contribute to stabilizing farmers' income expectations. Strengthening public agricultural services and rural infrastructure may also improve accessibility and enhance the resilience of farming systems under both economic and ecological policy contexts.

### 5.5. Limitations and future research

This study provides new insights into the spatial patterns and driving mechanisms of farmland abandonment in China at the 1-km grid scale. The RF–SHAP framework offers a transferable analytical tool with broader applicability to other regions experiencing farmland abandonment. By incorporating region-specific datasets, the framework can identify the interactions among natural factors, socioeconomic factors, cultivation conditions, and policy influences that shape abandonment dynamics, thereby providing evidence to support region-specific policy design. Several limitations should be acknowledged.

First, this study relied on a single cross-sectional year due to the availability of the national land use survey dataset. Consequently, climatic conditions were represented by annual mean temperature and precipitation, which capture the general climatic background influencing agricultural production but cannot reflect interannual variability or seasonal dynamics that may affect crop growth and water stress during specific growing periods. Future studies incorporating multi-year datasets and more detailed climatic indicators (e.g., seasonal or monthly variables) would help better capture the temporal variability of hydrothermal conditions and reveal the dynamic evolution and persistence of farmland abandonment patterns.

Second, although this study integrated multiple drivers from natural, socioeconomic, and cultivation dimensions, some potentially relevant factors were not included due to data availability constraints. In particular, spatially consistent information on policy implementation intensity and farmers' participation in specific agricultural programs is limited, especially at the national 1-km grid scale, and high-resolution datasets on irrigation intensity, irrigation infrastructure, or spatially explicit agricultural water withdrawal are also not currently available at a consistent national scale. As a result, these factors could not be explicitly incorporated into the analysis. Future research could benefit from integrating large-scale land use datasets with spatial policy and institutional data derived from large-scale farm or household surveys, as well as high-resolution datasets on irrigation and agricultural water use when such data become available. This would help better capture farmers' decision-making processes and further deepen the understanding of the drivers of farmland abandonment.

Third, although the RF–SHAP framework is well suited for capturing nonlinear relationships and complex interactions among variables, it remains primarily a data-driven approach. While the SHAP framework improves interpretability by quantifying the contributions and interactions of variables, the results should be interpreted as correlational evidence rather than causal inference. Future studies could integrate process-based or agent-based models with causal inference frameworks to better capture micro-level behavioural mechanisms and further examine the causal pathways underlying farmland abandonment.

## 6. Conclusions

This study investigated the spatial patterns and driving mechanisms of farmland abandonment in China at a 1-km grid scale by integrating natural factors, socioeconomic factors, and cultivation conditions within an RF–SHAP framework. The results reveal that farmland abandonment in China exhibits clear spatial heterogeneity and is shaped by the joint effects and interactions among multiple drivers.

Farmland abandonment displayed a pronounced mountain–plain gradient, with significantly higher abandonment rates in mountainous areas than in plains. Across both terrains, farmland density emerged as the most influential factor, indicating that improved land contiguity and moderate-scale farming can effectively reduce abandonment risk by strengthening organizational efficiency and facilitating agricultural service provision. However, the mechanisms underlying abandonment differed substantially between terrains. In plains, farmland abandonment was governed mainly by labour, location, and organizational structure. Engineering improvements and institutional support weakened the effects of climatic and topographic factors. The influence of ageing was both stage-specific and bidirectional. In mountainous areas, farmland abandonment was driven mainly by strong coupling among climatic conditions, topography, and service accessibility. The effects of climatic conditions were amplified by their interactions with slope and altitude, resulting in the formation of a chain that extends from natural stress to mechanization constraints and ultimately to cost accumulation.

These findings highlight that farmland abandonment should be understood as a composite socio-ecological process shaped by nonlinear interactions among environmental constraints, economic incentives, and cultivation conditions. Accordingly, management strategies should adopt region-specific approaches. In plains, policies that promote moderate-scale management, land transfer, and agricultural service systems may help mitigate labour shortages and improve operational efficiency. In mountainous regions, priority should be given to improving infrastructure and service accessibility, supporting terrain-adapted mechanization, and implementing ecological management for marginal lands. Overall, the grid-scale RF–SHAP framework provides a useful approach for revealing the complex mechanisms of farmland abandonment and offers evidence to support differentiated farmland governance strategies aimed at safeguarding agricultural sustainability and food security.

## CRediT authorship contribution statement

**Bin Du:** Writing – review & editing, Visualization, Data curation. **Peichao Gao:** Writing – review & editing, Methodology. **Guoli Wang:** Validation, Investigation, Data curation. **Shuyi Ren:** Writing – review & editing, Methodology. **Changqing Song:** Writing – review & editing, Supervision, Funding acquisition. **Sijing Ye:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation. **Longfeng Weng:** Validation, Investigation, Data curation. **Jiayi Jiang:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Declaration of Competing Interest

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

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2026.108138.

## Data availability

Data will be made available on request.

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