Title Page

Cropland abandonment in China: Patterns, drivers, and implications for food security

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Abstract: Grasping cropland abandonment patterns in China can help protect croplands, thereby ensuring the perpetuation of nationwide food security. However, the pattern of long-term cropland abandonment at the national scale remains limited. Here, we investigate the spatiotemporal patterns and drivers of cropland abandonment across China during 1990-2019 by integrating continuous long-term series of land cover, natural factors, and socioeconomic data. We find that the mean abandoned cropland area is 2.34×10^4 km^2 per year. The spatial pattern of cropland and natural factors are prime drivers of cropland abandonment, but there is a substantial variation across agricultural regions. Further analysis suggests that annual food loss due to cropland abandonment is about 7.94 billion kilograms, which could feed 19.85 million people. These findings allow for a better understanding of the spatial heterogeneity and driving forces of cropland abandonment patterns, and inspire to govern global cropland abandonment and formulate relevant policies.

Keywords: Land use change, Cropland abandonment, Driving forces, Boosted regression trees, Food security

1. Introduction

Cropland constitutes a fundamental pillar for human sustenance, and ensuring its quantity and quality is the basis for maintaining food security and social stability (Kong, 2014). Recent studies have shown that by 2030, global urban expansion will lead to cropland losses of 1.8-2.4%, with approximately 80% concentrated in Asia and Africa (Bren d'Amour et al., 2017; Li and Li, 2017). Furthermore, the enormous urbanization process characterized by rural-urban migration has led to prominent cropland abandonment in rural regions (Keenleyside et al., 2010). Cropland abandonment refers to the state of dormancy or desolation in agricultural land stemming from a lack of efficacious cultivation or management practices (Ojha et al., 2022). China is experiencing ubiquitous cropland abandonment, particularly in remote rural regions, which has seriously affects the social, economic, ecological environment and food security (Qiu et al., 2020; Chen et al., 2023). Besides, the growth of China's grain production is much lower than that of grain imports. Hence, a thorough examination of cropland abandonment serves as the basis for formulating policies aimed at the preservation of agricultural land. However, previous studies on identifying cropland abandonment are primarily based on farmer interviews and field survey data (Zhang et al., 2014; He et al., 2020). Although the field survey has high accuracy, it cannot accurately reflect the spatiotemporal patterns of cropland abandonment in detail (Li et al., 2022). Therefore, there is need to investigate the spatiotemporal pattern of cropland abandonment to reveal its driving force and impact on food security.

Remote sensing is an effective tool for identifying cropland abandonment. Since MODIS has high temporal resolution and coverage, it is favored by scholars in mapping large-scale time-series cropland (Alcantara et al., 2013; Estel et al., 2015; Löw et al., 2015). However, the data have a lower spatial resolution and short time period, affecting the accuracy of land identification and classification, which is insufficient to understand the long-term dynamics of cropland in China. To describe its pattern in detail, medium resolution images from Landsat (30m) and Sentinel-2 (10m) have become crucial for mapping abandoned cropland (Dara et al., 2018; Morell-Monzó et al., 2020). Yet, due to the limitations of large-scale image processing, scholars mostly focus on local regions and short time series, while there are few national-scale studies. Although Zhang et al. (2023) used Landsat images to explore the pattern of cropland abandonment in China, it lacked the description of the driving force of abandonment and grain production. Hence, it is necessary to use higher-resolution land cover data to monitor the pattern of cropland abandonment over a long period and to assess potential food losses.

To ensure cropland resources, it is crucial to illuminate the factors influencing cropland abandonment. Studies have shown that cropland abandonment is closely related to various elements, including the natural environment, labor force, agricultural development level, socioeconomic conditions (Meyfroidt et al., 2016; Movahedi et al., 2021). For example, cropland abandonment primarily occurs in areas with poor natural conditions, and it is frequently related to land quality and light and water supplies required for crop growth, such as cropland quality, soil, precipitation, topography and natural disasters (Arnaez et al., 2011; Díaz et al., 2011; Hou et al., 2021; Seppelt et al., 2022). In addition to natural factors, socioeconomic factors are prominent drivers. With the acceleration of urbanization, the secondary and tertiary industries have created numerous higher-income employment opportunities, transferring rural labor to the cities and exacerbating cropland abandonment (Yan et al., 2016; Huang et al., 2019; Xu et al., 2019). Furthermore, market incentives, institutions, agricultural subsidy policies and armed conflict are also important drivers (Baumann et al., 2011; Stefanski et al., 2014; Gibson et al., 2015; Olsen et al., 2021). The reform and opening up policy has enlarged urban-rural income gap in China, leading to rural population losses and exacerbating abandonment (Lai et al., 2020). Especially in mountainous areas, the natural climate, transportation and agricultural facilities are insufficient or unsuitable for crop growth and management (Wang et al., 2016). However, understanding of the spatial heterogeneity of drivers of abandonment at the national-scale remains limited.

Therefore, the objective of this study is to explore the spatiotemporal patterns and driving factors of China's cropland abandonment, and to assess the food loss due to cropland abandonment. Here we first use continuous time-series land cover data to investigate the spatiotemporal patterns of cropland abandonment over the past ~30 years and explore differences across agricultural regions. In this study, cropland abandonment is defined as cropland that has not been cultivated for two consecutive years. Second, using the boosted regression trees (BRT) method, we combine the natural environment, landscape patterns, population, and socioeconomic factors to reveal the drivers. Finally, we assessed the amount of potential food loss due to cropland abandonment, and built time-series model to predict its future trend. This study fills in the spatial distribution of China's highprecision, long-term cropland abandonment, enriches the explanation of driving factors, and clearly quantifies the food loss caused by cropland abandonment.

2. Materials and methods

2.1 Study area

This study includes 9 first-level agricultural regions and 38 secondary agricultural regions in China (Fig. 1 and Table S1). Agricultural regions are divided according to agricultural production conditions, characteristics, development directions, major issues, and the integrity of administrative units (County administrative unit), which are crucial to the management and guidance of agricultural production. Among them, the first-level agricultural regions include the Northeast Region (NER), Inner Mongolia and the Great Wall Region (IMGWR), Huang–Huai–Hai Region (HHHR), Loess Plateau Region (LPR), Middle and lower reaches of the Yangtze River drainage basin (MLYTR) and Southwest Region (SWR), South China Region (SCR), Gan–Xin Region (GXR) and Tibet Region (TBR) (He et al., 2017). They all have their advantages and characteristics. Similarly, secondary agricultural zones are a more refined division of primary agricultural zones based on agricultural production conditions.

In addition, the Hu line is the population density boundary proposed by Chinese geographer Hu Huanyong in 1935, and it is the boundary of the ecological environment. China is a traditional agricultural country with a highly uniform distribution of population and arable land. East of the Hu line is the area of concentration of population and arable land, while the west is the area of scarcity of arable land resources. Numerous studies have shown that about 90% of the country's high-quality cropland is distributed east of the Hu line due to geomorphological and natural precipitation constraints (Qiu et al., 2020). The line can better reflect the pattern of cropland abandonment.

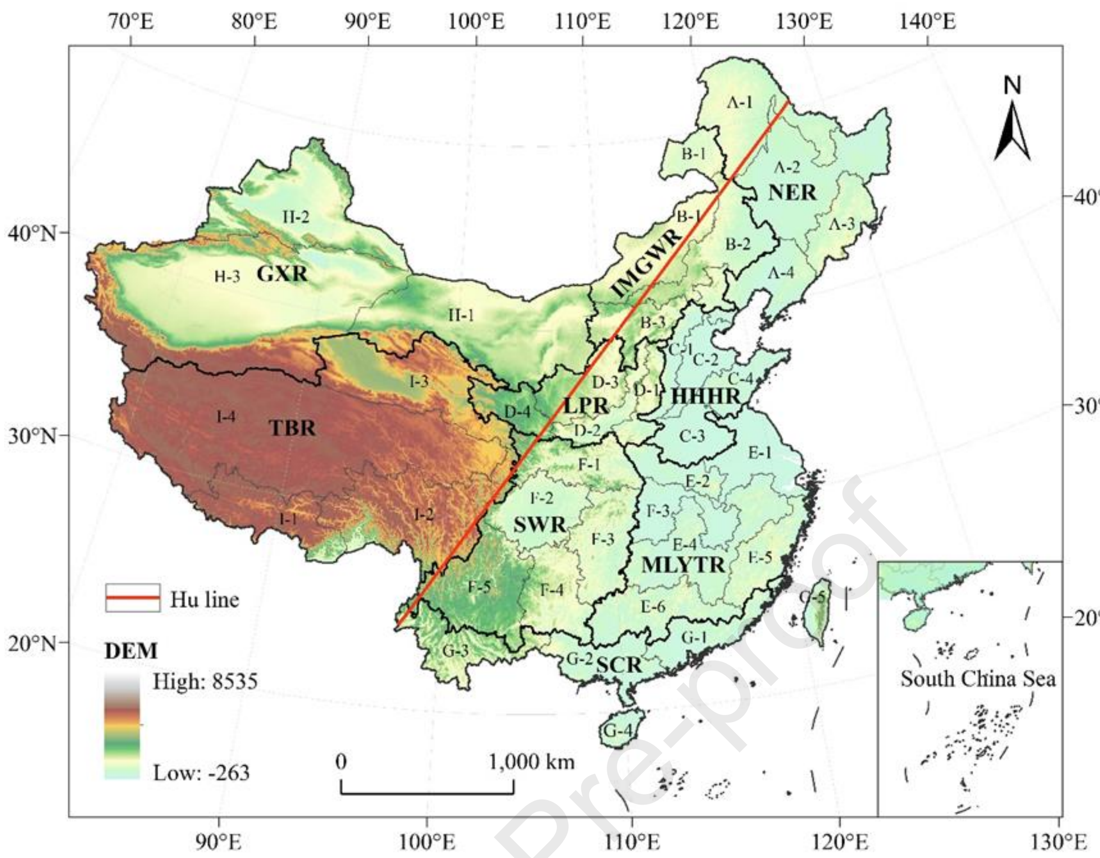


Fig. 1. Spatial division of the nine agricultural regions in China (A-1, A-2, ⋯, I-4 represent the secondary agricultural regions, see Table S1)

2.2 Data collection

This study uses data on land cover, Digital Elevation Model (DEM), meteorology, potential crop yield, population, and socioeconomic statistics (Table 1). Land cover as a data source for identifying cropland abandonment. This dataset is classified by Yang and Huang (2021) using random forest based on 335,709 Landsat images in the GEE platform and produced continuous land-cover data in China with a spatial resolution of 30 m from 1990 to 2019. The data include cropland, woodland, shrub, grassland, bare land, impervious layer, water, snow/ice, and wetland. Moreover, Yang and Huang (2021) improved the spatiotemporal consistency of China land cover dataset (CLCD) by proposing a post-processing method, including spatiotemporal filtering and logical reasoning, with an overall classification accuracy of 79.31%. To evaluate the application of CLCD in agriculture, Zhang et al. (2022) evaluated CLCD application in agriculture by verifying the accuracy of six datasets of 30 m cropland in China by collecting 30,000 samples, and the results showed that CLCD has high accuracy.

DEM, meteorology and potential crop yield as drivers of cropland abandonment. DEM is ASTER GDEM with a spatial resolution of 30 m, which are derived from geospatial data clouds (http://www.gscloud.cn/search). The precipitation, temperature and potential crop yield reflect the natural growth conditions of vegetation. The spatial resolution of this data is 1 km (2000 and 2010), which are obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/). In addition, the multiple cropping index was calculated by Liu et al. (2021) using the enhanced vegetation index (EVI) from the MOD13Q1 product with an overall accuracy of 89%, which was used to assess food losses.

Demographic, socio-economic and food production statistics are used to explain abandonment drivers and assess food losses. Demographic data comes from the fifth and sixth national census of China. Socio-economic data come from the *China Counties Statistical Yearbook (County-level)*. The food production data were obtained from the *China Statistical Yearbook* and the *National Bureau of Statistics*.

Table 1 Data description

Type	**Date and resolution**	**Source**
Land cover	1990-2020, 30 m	China land cover dataset (CLCD), http://irsip.whu.edu.cn/resources/CLCD.php
DEM	2009, 30 m	ASTER GDEM, http://www.gscloud.cn/search
Meteorology	2000, 2010, 1 km	Resource and Environment Science and Data center,
Potential crop yield	2000, 2010, 1 km	https://www.resdc.cn/
Multiple cropping index	2000, 2010, 250 m	https://doi.org/10.6084/m9.figshare.14099402
Demographic data	2000, 2010	National Bureau of Statistics, http://www.stats.gov.cn/
Socio-economic	2000, 2010	China Counties Statistical Yearbook (County-level)
Food production	2001-2020	China Statistical Yearbook and National Bureau of Statistics

2.3 Methods

2.3.1 Cropland abandonment identification

Cropland abandonment is land that has not been cultivated for at least one year (Han and Song, 2019). However, there is no uniform definition of arable land around the world according to the length of time it has been left fallow. For example, the World Food and Agriculture Organization (FAO) defines abandoned arable land as arable land that has not been used for agricultural production for more than five consecutive years. The Japanese Ministry of Agriculture, Forestry and Fisheries refers to farmland that has not been cultivated for more than one year and has no indication that it will be cultivated in the next few years as abandoned cultivated land. In addition, scholars such as Hou et al., (2021), Han and Song (2019), and Löw et al., (2018) refer to land that has not been cultivated for two, three, or four years as abandoned cropland, respectively. In view of this, we define it as land that has not been used for cultivation for two consecutive years according to the "Land Administration Law of the People's Republic of China" and the actual use of cropland. Here, we use CLCD to identify the spatiotemporal patterns of cropland abandonment over the years. To enhance the understanding and calculation process, we define cropland abandonment as the conversion of cropland to grassland, shrubs, forests, and bare land for two consecutive years. In this paper, we use the Combine tool in ArcMap 10.7 to spatially merge multi-period land cover products to identify the pattern of farmland abandonment in each period. Furthermore, we assess the cropland abandonment intensity using the abandonment ratio, i.e., the annual abandoned area divided by the initial cropland area (Shi et al., 2018; Zhu et al., 2021), as shown in Equation 1.

$$P_{T3} = \frac{A_{T3}}{A_{T1}} \times 100\% \tag{1}$$

Where, P_{T3} represents the abandonment rate in T_3 time. A_{T3} represents the cropland abandonment area in T_3 time, and A_{T1} represents the cropland area in T_1 time. In this study, we identified abandonment status for each pixel (30 m) and performed statistical summaries for primary and secondary agricultural zones.

2.3.2 Explanatory variables

Cropland abandonment is a severe land-use change phenomenon affected by the interaction of various driving factors (Müller et al., 2013; Li and Li, 2017; Li et al., 2021; Xu et al., 2021). Here, we divide the driving factors into natural factors, landscape pattern of cropland, population, and socioeconomics, with 19 factors (Table 2). Natural factors include DEM, slope, precipitation, temperature and potential crop yield, which are the basic conditions for crop growth and yield increase. DEM and slope reflects the crop growth by topography and topographic factors. Landscape patterns significantly influence cropland abandonment, such as the aggregation index (AI) and DIVISION, primarily used to reflect whether the cropland distribution is easy to manage and reduce costs. We calculated the landscape pattern index of each county-level using Fragstats 4.2 software.

Furthermore, population structure and socio-economic development are also important aspects that affect cropland abandonment (Han and Song, 2020). The population structure is frequently a direct factor determining whether to farm, such as aging, rural population, and education level (Xu et al., 2019). Here, we selected the proportion of nonagricultural population (PNAP), rural population (RP), natural growth rate (NGR), the proportion of the population over 65 years old (>65), average years of education (AYE), and the proportion of the illiteracy population (PIP) (Li et al., 2021). The socioeconomics can reflect the income of urban and rural residents and the distance from the city, so as to determine whether residents choose to engage in agriculture or go to urban employment (Deng et al., 2015). Thus, we selected the gross domestic product (GDP), urbanization rate (UR), the total power of agricultural machinery (TPAM), investment in fixed assets (IFA), distance to prefecture-level city (DisPref) and city-level administrative center (DisCity).

Table 2 Explanatory variables for cropland abandonment

Type	Variable	Description	Unit	VIF
Natural factors	DEM	The DEM mean of each county	m	5.49
	Slope	The mean slope of each county	°	4.90
	MAP	Mean annual precipitation of each county	mm	4.72
	MAT	Mean annual temperature of each county	℃	6.01
	PCY	Mean annual potential crop yield of each county	kg/ha	2.70
Landscape pattern	AI	Agglomeration index of cropland in each county, calculated using Fragstates 4.2 software	-	2.21
	DIVISION	Division index of cropland in each county, calculated using Fragstates4.2 software	-	4.37

Population	PNAP	The proportion of the nonagricultural population of each county	%	6.40
	RP	The rural population of each county	10^4	4.41
	NGR	The natural growth rate of each county	%	1.95
	>65	The proportion of the population over 65 years old in each county	%	2.20
	AYE	Average years of education of the population in each county	year	4.44
	PIP	The proportion of the illiterate population in each county	%	3.15
Socio-economics	GDP	Gross domestic product of each county	10^4 yuan	3.15
	UR	Urbanization rate, the ratio of urban population, divided by the total population in each county	%	5.21
	TPAM	Total power of agricultural machinery of each county	10^4 kilowatts	2.24
	IFA	Investment in fixed assets of each county	10^4 yuan	1.44
	DisPref	Distance to prefecture-level city administrative center	km	1.80
	DisCity	Distance to the city-level administrative center	km	1.78

In addition, to reveal the driving force of farmland abandonment, preprocessing of each independent variable is essential. We avoid the problem of collinearity among these factors using the variance inflation factor (VIF) for verification (Salmerón et al., 2018). When VIF > 7.5, it means that each factor has collinearity and should be deleted (Sheng et al., 2017; Yang et al., 2021). Table 1 shows that each variable's VIF is less than 7.5, indicating no collinearity issue among these factors, so they can be used for subsequent analysis.

2.3.3 Driver analysis of cropland abandonment

This study used Boosted regression trees (BRT) to identify the drivers of cropland abandonment. We first selected 1725 county-level cities based on the abandonment rate and explanatory variables collected and only revealed the driving forces of 2000 and 2010. BRT is a nonparametric regression method and robust machine-learning algorithm that improves the performance of a single model by fitting multiple model predictions (Elith et al., 2008; Hastie et al., 2009). BRT can capture complex, nonlinear responses and relationships of predicted variables and is widely used in climate environments and land systems (Müller et al., 2013).

The BRT method comprises a decision tree and a boosting algorithm. It does not need to consider the interaction between independent variables, so the contribution of independent variables to dependent variables and the response curve can be obtained (Smaliychuk et al., 2016). BRT operation requires four parameters: bag, tree complexity, learning rate, and the number of trees. In this paper, we used a bag score of 0.5, which means an even distribution of the total observations for training and test samples. For the remaining parameters, we evaluated several combinations (tree complexity from 1 to 6, learning rate from 0.005 to 0.025) and used 10-fold cross-validation to determine the best parameters. Thus, we set the specific parameters of BRT as follows: family = 'Laplace', tree.complexity = 5, learning.rate = 0.01, bag.fraction = 0.5. The algorithm was mainly implemented through the *R* software third-party packages "*dismo*" and "*gbm*".

2.3.4 Assess and forecast food yield losses

Grain yield is not only related to the area of cropland, but also closely related to the multiple cropping index, the ratio of grain to crop sown area and grain yield per unit area (Liu et al., 2020; Zhang et al., 2022). Here, we use Equation 2 to estimate the grain yield lost due to farmland abandonment. Due to data limitations, we integrated statistics from provinces in China and abandoned farmland to assess the amount of food loss.

$$y = s \times g \times m \times r \tag{2}$$

Where, y represents the food loss. s represents the area of cropland abandonment. g, m, and r represent grain yield per unit area, the multiple cropping index and the ratio of grain to crop sown area, respectively.

According to the grain loss assessed over the years, we use ARIMA model to predict its future trend. The ARIMA model is presented by Box and Jenkins in the early 1970s as a famous time series prediction method (Box and Jenkins, 1976). ARIMA (p, d, q) models are created by first taking the differences of the data from d degree for the stabilization process and then adding the ARMA (p, q) model. In the ARIMA (p, d, q) models, p shows the degree of the Autoregressive (AR) model, q represents the degree of the moving average (MA) model and d shows the number of differences to be taken to stabilize the data (Yonar et al., 2020). Therefore, the ARIMA model can be considered as AR (p), MA (q) or ARMA (p, q) if time series is stationary. The model can be defined as follows:

$$Y_t = \phi_1 Y_{t-1} + \phi Y_{t-2} + \cdots \phi Y_{t-p} + \alpha_1 - \theta_1 \alpha_{t-1} - \alpha_2 - \theta_2 \alpha_{t-2} - \cdots - \alpha_q - \theta_q \alpha_{t-q} \quad (3)$$

Where, ϕ_p represents the parameter values for autoregressive operator, α_q represents the error term coefficient, θ_q represents the parameter values for moving average operator, Y_t represents the time series of the original series differenced at the degree *d*. The model is implemented using open source software "*R*", including packages such as "*tseries*", "*forecas*t" and "*zoo*".

3. Results

3.1 Overall cropland abandonment trends

China's cropland area gradually decreased from 197.38×10^4 km^2 in 1992 to 188.78×10^4 km^2 in 2019, a total decrease of 8.68×10^4 km^2 (0.3×10^4 km^2 per year on average), which fully shows the severe situation of cropland (Fig. 2). Therefore, it is urgent to implement stricter farmland protection policies. Moreover, there was a short-term increase in cropland in 2012-2014, totaling 1.39×10^4 km^2. However, after 2014, it gradually decreased, with a minimum of 188.7×10^4 km^2. In terms of cropland abandonment, the area and ratio of cropland abandonment did not change significantly, with an annual average of 2.34×10^4 km^2 and 1.21%, respectively. However, 2012 and 2014 showed the lowest (1.22×10^4 km^2) and highest (3.38×10^4 km^2) values of cropland abandonment area, respectively. Also, cropland abandonment was extremely high in 2014, possibly due to the addition of new sensors from the Landsat 8 OLI during this period. Overall, the area of cropland has decreased substantially, while cropland abandonment has remained relatively stable, which may be attributed to the large amount of cropland occupied by urban development.

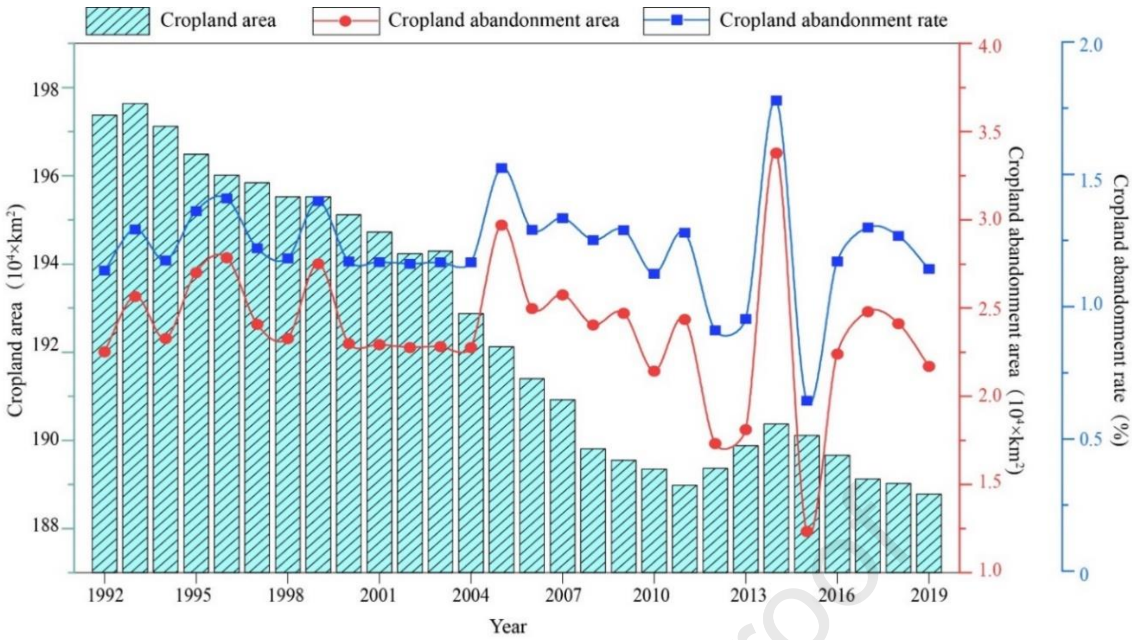


Fig. 2. Cropland abandonment in China from 1992 to 2019.

3.2 Spatial pattern of cropland abandonment at first-level agricultural region scale

Cropland abandonment is unevenly distributed among the first-level agricultural regions in China (Fig. 3a). Cropland abandonment area mainly concentrated in the Southwest Region (SWR) and Inner Mongolia and the Great Wall Region (IMGWR), with an annual average of 5.4×10^3 km^2 and 4.2×10^3 km^2, respectively, followed by Northeast Region (NER) (3.0×10^3 km^2) and the Loess Plateau Region (LPR) (3.4×10^3 km^2). However, Huang–Huai–Hai Region (HHHR) with the largest cropland area, has an abandoned area of only 0.4×10^3 km^2, which may be suitable for agricultural production and has a large agricultural population. Furthermore, regarding the abandonment rate, IMGWR (3.1%) and Tibet Region (TBR) (3.9%) were the most severe, followed by Loess Plateau Region (LPR) (2.3%) and South China Region (SCR) (2.0%), and finally HHHR (0.1%) and Yangtze River drainage basin (MLYTR) (0.7%). In addition, we count the distribution of abandoned cultivated land in latitude and longitude (Fig. 3b, c). First, the cropland abandonment in the east-west direction showed a "twin-peak" pattern, approximately 110°E (163.2 km^2) and 122°E (78.2 km^2), respectively. Moreover, the abandonment is concentrated in the central region of China (103° E-115° E), with a total of 13.6×10^3 km^2. Second, the pattern of abandonment in the south-north direction is complex, which can be divided into three stages (20° N-28° N, 34° N-37° N and 40° N-44° N), and the maximum values are 127.2 km^2, 129.0 km^2 and 141.2 km^2, respectively.

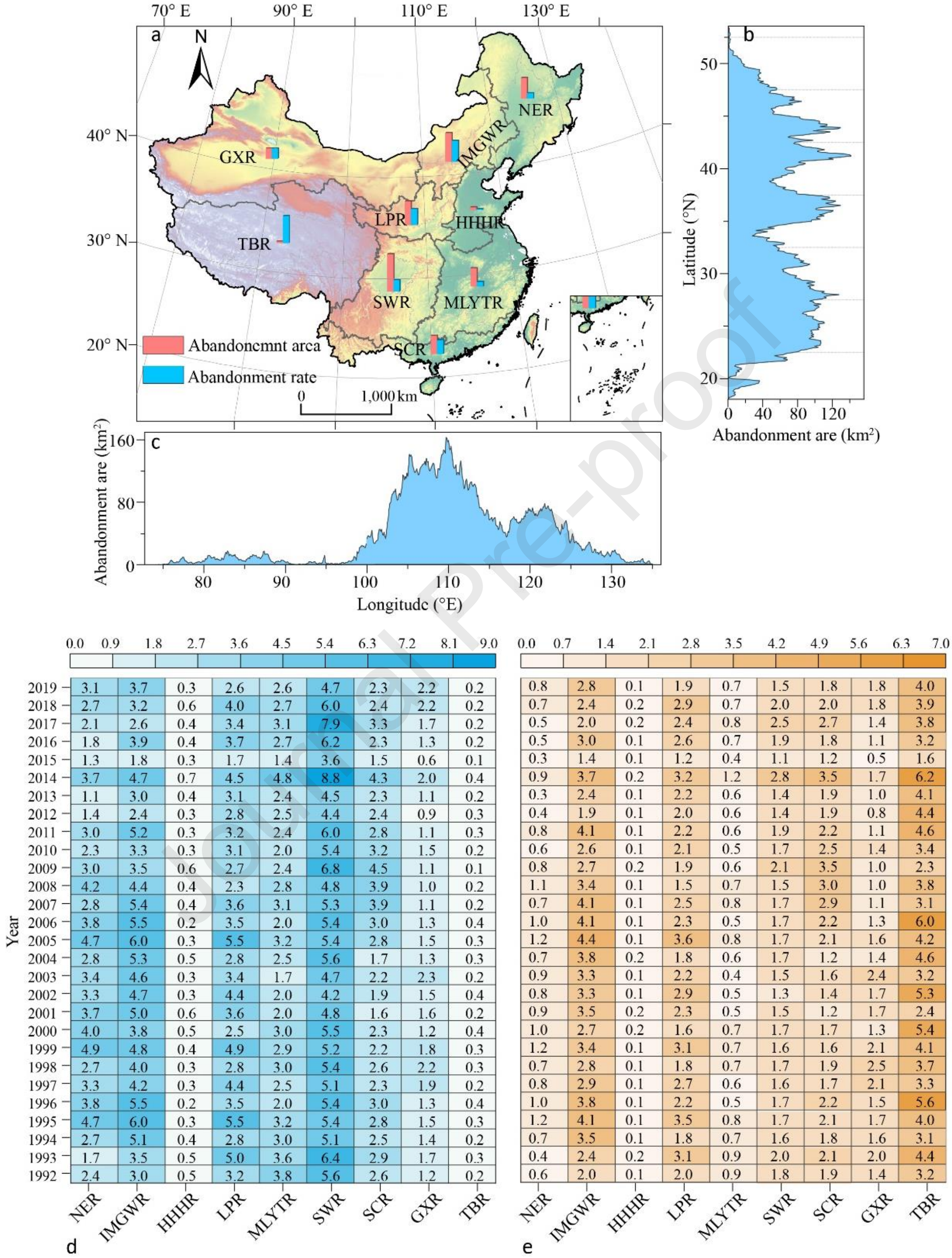


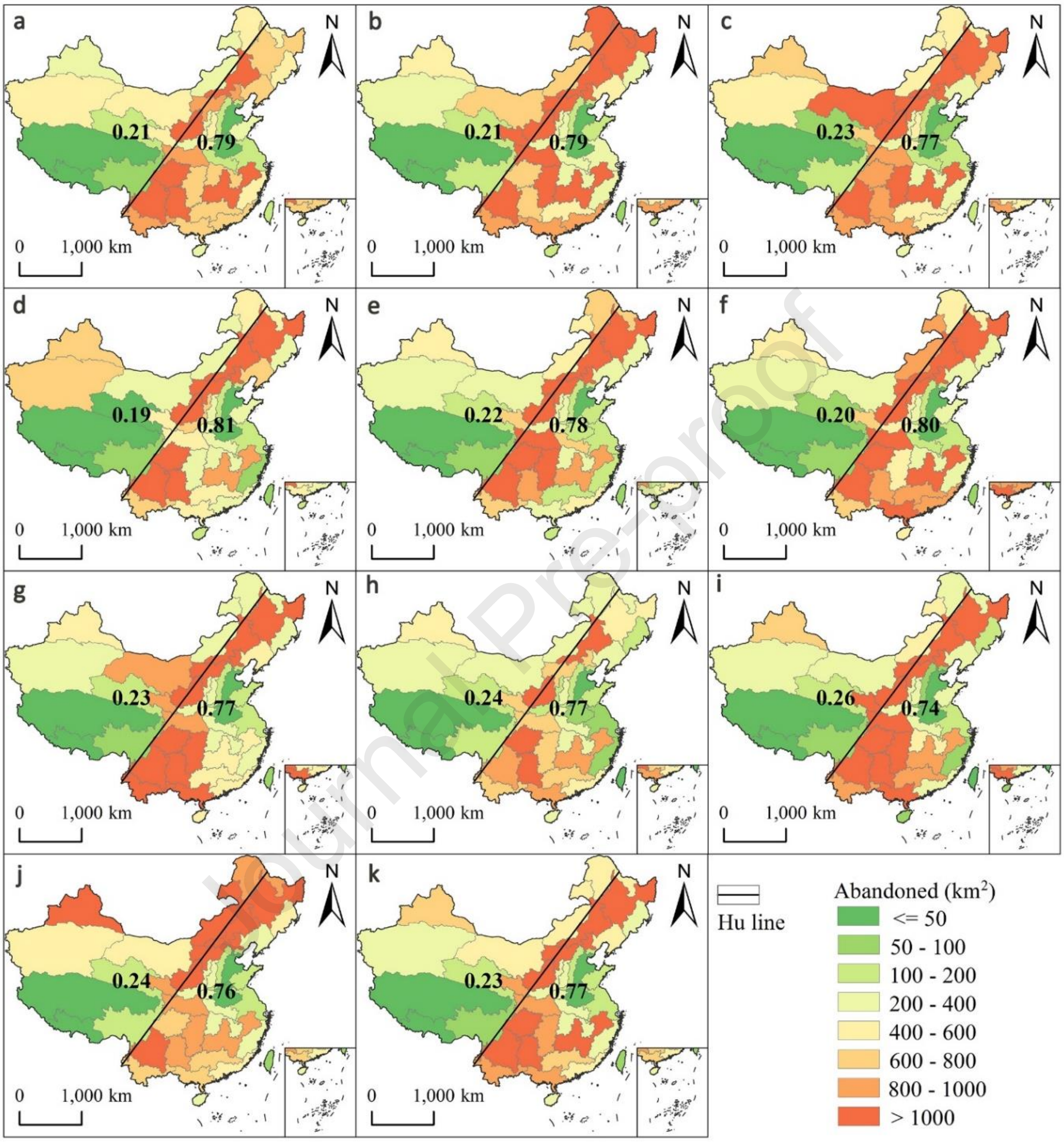
Fig. 3. Cropland abandonment in the first-class agricultural regions, 1992-2019. (a) Average of cropland abandonment area and rate in first-level agricultural regions; (b) Cropland abandonment varies in longitude. (c) Cropland abandonment varies in latitude; (d) Cropland abandonment area in each first-level agricultural regions; (e) Cropland abandonment rate in each first-level agricultural regions.

Cropland abandonment in each agricultural region was difference from 1992-2019 (Fig. 3d, e). First, the high values of NER cropland abandonment in 1999 and 2005 were 4.9×10^3 km^2 (1.2%) and 4.7×10^3 km^2 (1.2%), respectively, whereas the lowest was in 2013 at 1.1×10^3 km^2 (0.3%). The IMGWR was significantly abandoned during 2001-2007, with a maximum of 6.0×10^3 km^2. HHHR, GXR and TBR were stable, with an annual average of 0.4 × 103 km^2, 1.5 $\times10^3$ km^2 and 0.2 $\times10^3$ km^2, respectively. Second, LPR and MLYTR were severely abandoned, but during period 2014-2019, they decreased by 3.6×10^3 km^2 and 3.3×10^3 km^2, respectively. SWR is in a mountainous and hilly area, highly affected by the natural climate, infrastructure and socioeconomics, and the abandonment is prominent at 8.8×10^3 km^2.

3.3 Spatial pattern of cropland abandonment at secondary agricultural region scale

We further analyzed the spatiotemporal pattern of cropland abandonment in 38 secondary agricultural regions. Fig. 4 shows that the high value of abandonment (>1000 km^2) is concentrated near the Hu line and SWR, such as the pastoral areas in Agropastoral Region: Middle South Inner Mongolia (B-2), Agropastoral Region- Along the Great Wall (B-3), Agroforest Region: Daba Mountain (F-1), Agroforest Region: Sichuan Basin (F-2), Agropastoral Forest Region: Guizhou and Guangxi Plateau and Mountain (F-4), Agropastoral Forest Region: Sichuan Yunnan Plateau and Mountain (F-5), and Agroforest Region: South Yunnan (G-3). However, the low values are mainly located in the TBR and HHHR, such as Alpine Region: Qinghai Tibet Plateau (I-4), Agricultural Region: Hebei, Shandong, and Henan Low Plain (C-2), Agropastoral Region: South Tibet (I-1), and Agricultural Region: Huang–Huai Plain (C-3), at 6.22 km^2 (8.3 %), 9.18 km^2 (0.01%), 16.54 km^2 (4.10%) and 46.66 km^2 (0.05%). Interestingly, the east side of the Hu line was much more abandoned than the west side, at approximately 0.77 and 0.23, respectively. Moreover, the difference was most significant in 2008, at 0.86 and 0.14, respectively.

Furthermore, during 1992-2020, each secondary agricultural region's cropland abandonment was in a state of "first increase, then decrease". The Agropastoral Forest Region: Sichuan Yunnan Plateau and Mountain (F-5), the Agropastoral Forest Region: Shanxi and Shaanxi Loess Hill and Gull (D-3), and the Agroforest Region: Jiangnan Hill and Mountain (E-4) have the most significant reductions in cropland abandonment by -1.1×10^3 km^2, -1.1×10^3 km^2, and -1.2×10^3 km^2, respectively. However, a few abandoned areas show an increasing trend, 270 such as the Agropastoral Forest Region: North Xinjiang (H-2) and the Agropastoral Forest Region: Chongqing, Hubei, Hunan, and Guizhou Mountain (F-3), which increased by 226.9 km^2 and 73.9 km^2.



272

273 **Fig. 4.** Cropland abandonment in the secondary agricultural regions. (a-j) Cropland abandonment every three years in secondary agricultural regions, 1992-2019; a=1992, b=1995, c=1998 ⋯ j=2019; (k) Average annual abandoned area.

3.4 Drivers of cropland abandonment

Recognizing the driving force of abandonment helps guide reclamation policy development. Here, we explore the contribution of each driver across agricultural regions and at national scales. Fig.5 shows that the aggregation index (AI) is a critical driver of cropland abandonment in all agricultural regions, except for HHHR. The TBR is particularly significant, with AI reaching 15.5%, followed by the LPR (10.6%) and the SWR (10.4%). We found significant differences across agricultural regions. AI, mean annual precipitation (MAP), mean annual potential crop yield (PCY) and GDP are crucial driving factors affecting the cropland abandonment in NER, and they belong to the cropland landscape patterns, natural factors, and socioeconomics, respectively. IMGWR, GXR, and TBR are in the frontier regions, which are vast and sparsely populated, and the population and socioeconomic impacts on cropland abandonment are more significant than natural factors, such as PNAP, RP, NGR, >65, and GDP. However, HHHR has the most cropland, but the abandoned area and rate are very low, and most are concentrated in the high-value areas of DEM, with a relative impact of 15.9%. The drivers of LPR and SWR were similar, and the AI factor was a crucial driver (~10.5%), followed by MAP (~6.8%) and DisPref (~6.2%). Finally, in the cropland landscape patterns and natural factors in MLYTR, the vital drivers were AI, mean annual temperature (MAT), and MAP at 9.2%, 6.7% and 6.6%, respectively.

At a national level, AI is the primary driving force for cropland abandonment (18.4%), followed by PCY, MAT, and MAP, with 9.8%, 6.7%, and 6.5%, respectively. Also, the landscape pattern of cropland > natural factors > population and socioeconomics. Therefore, we found that although cropland abandonment is disturbed by population and social economy, it depends more on factors the distribution of cropland resources and natural factors in the region.

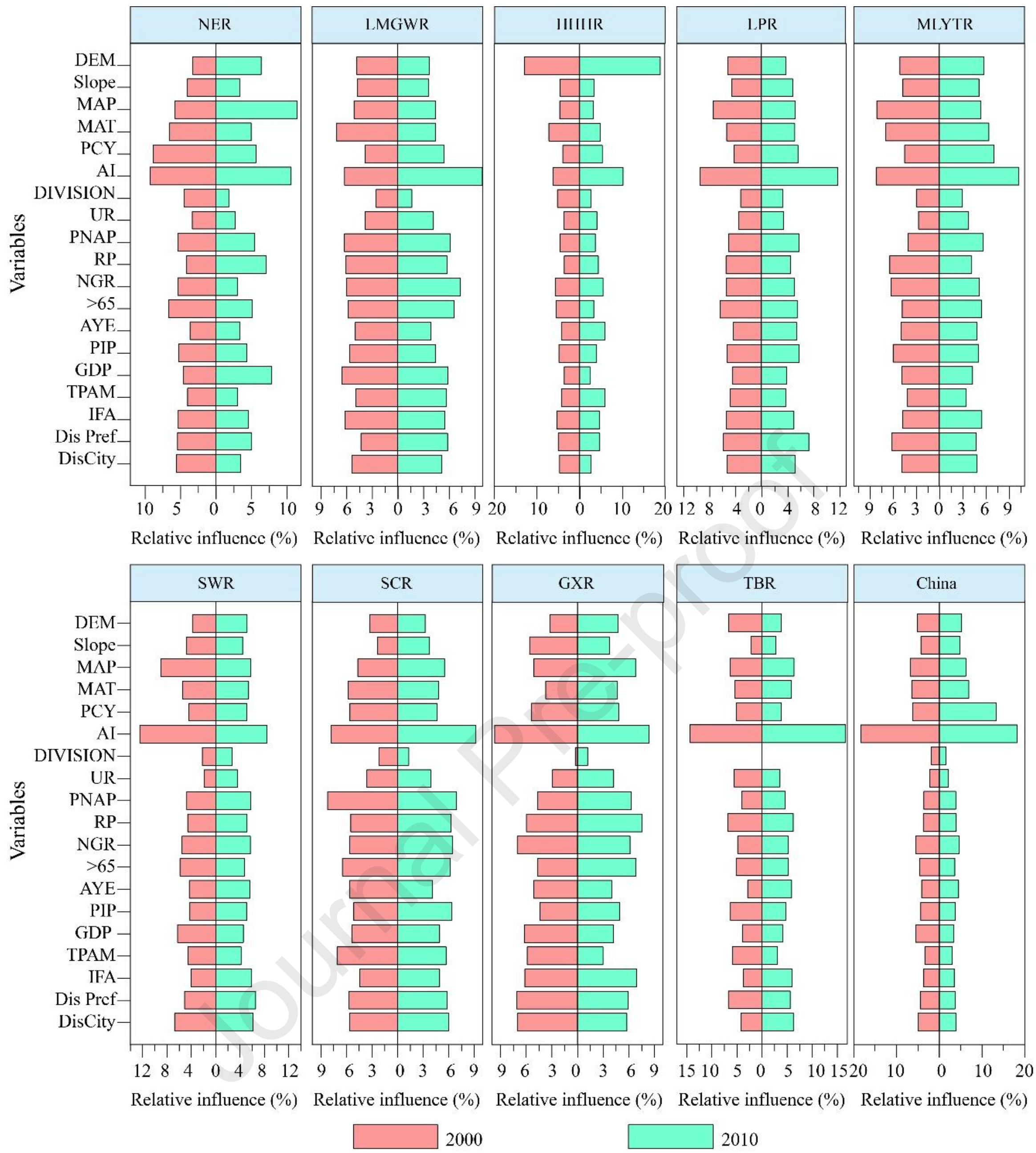


Fig. 5. Contribution of each factor to cropland abandonment. (DEM and Slope represent topographic elevation and slope, MAP and MAT represent precipitation and temperature, PCY refers to the production potential of arable land, AI and Division represent the agglomeration and fragmentation of cropland distribution; PNAP and RP refer to the proportion of non-farm population and the number of rural population, NGR and >65 are used to describe the natural population growth rate and the aging population, AYE and PIP represent years of education and illiterate population, GDP and UR represent economic development and urbanization rate, TPAM and IFA represent agricultural mechanization and fixed asset input, and DisPref and DisCity refer to distance from administrative centers of prefecture-level and county-level cities, respectively.)

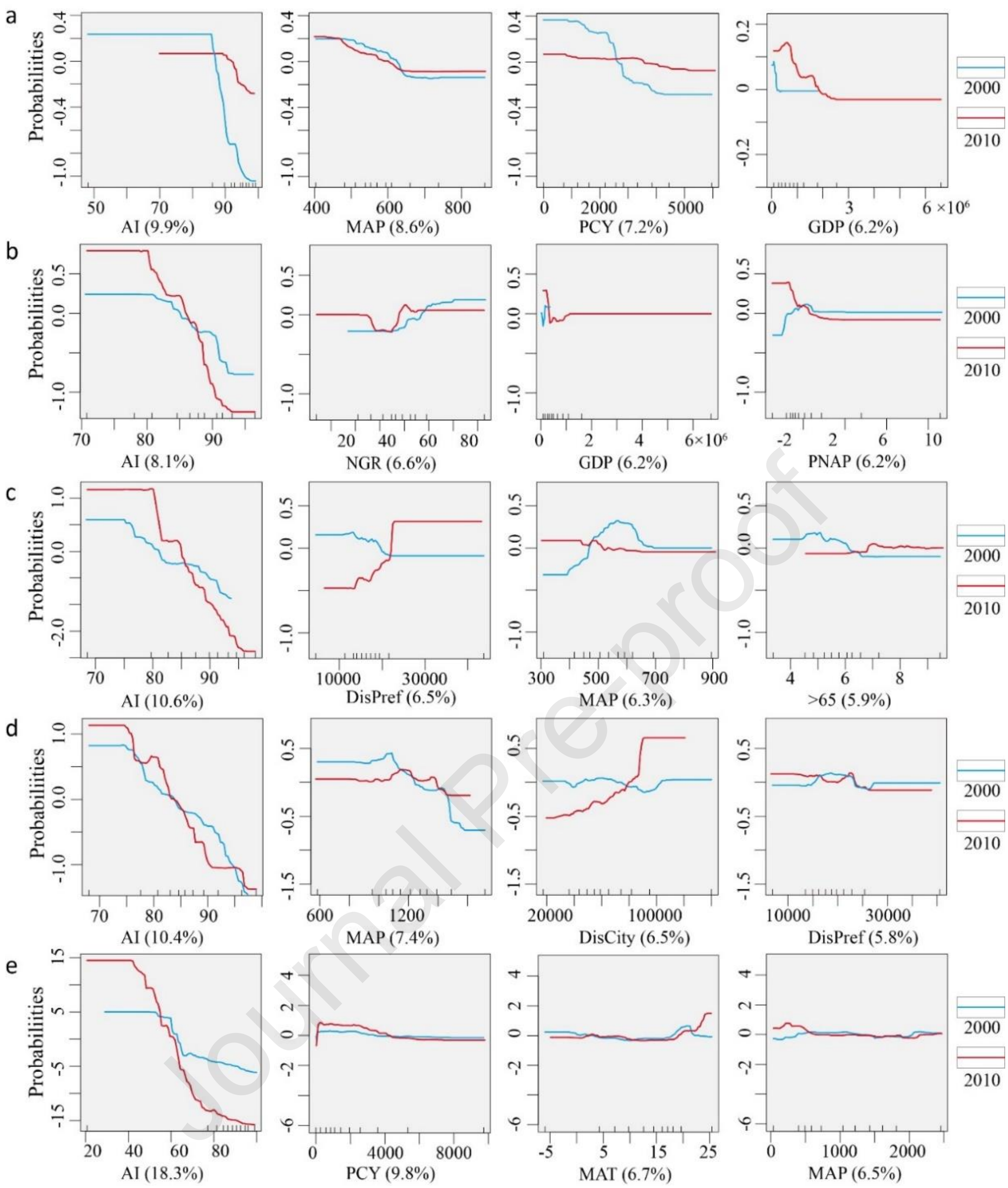


Fig. 6. The influence of explanatory variables on the probability of cropland abandonment. a-d, Marginal effect of abandoned cropland in each agricultural region. (a) NER, (b) IMGWR, (c)LPR, (d)SCR. e, Marginal effect of cropland abandonment at the national scale. Specifically, vertical axis values <0, 0, and > 0 indicate that each variable is negative, uncorrelated, and positive correlations with abandonment rate, respectively. Also, the larger the absolute value, the higher its influence.

To reveal in detail each factor's marginal effects on cropland abandonment, we took NER, IMGWR, LPR, SCR and the entire country as an example and selected four primary drivers in each region, such as AI, MAP, MAT, PCY, GDP, >65, DisPref and DisCity. Fig. 6 shows that with the increase in each driving factor, its correlation to the cropland abandonment rate will change. For example, the AI was negatively correlated with cropland abandonment at each agricultural region (~85%) and at the national scale (70%), indicating that the higher the agglomeration of cropland, the lower the abandonment. Similarly, when PCY, GDP, and MAP values increased, they were negatively correlated with abandonment rates. However, MAT shows the opposite law, i.e., with the increase in MAT, the abandonment rate increases. Interestingly, we also found that two time-period drivers exhibited different characteristics, such as DisPref (LPR) and DisCity (SWR). Fig.6 shows that the lower the DisPref and DisCity values in 2000, the higher the cropland abandonment rate. However, with urban expansion and economic development in 2010, the further away from urban areas, the more significant the abandonment.

3.5 Impact of cropland abandonment on grain yield

Generally, the large-scale cropland abandonment leads to the loss of food production and threatens food security. We combined the multiple cropping index, grain sown area ratio and grain yield per unit area of each province in China to assess the amount of grain loss from 2001 to 2019. Fig. 7 shows that the amount of food loss caused by cropland abandonment has increased overall, and the loss has increased from 6.19 billion kilograms (2001) to 8.83 billion kilograms (2019), with an average annual loss of approximately 7.94 billion kilograms. Moreover, we use the ARIMA model to predict its future trend, which shows an overall downward trend, with a loss of approximately 7.92 billion kilograms by 2030. Also, to quantify the amount of food loss satisfy how many people. Here, according to the "safety line" of 400 kilograms proposed by the Food and Agriculture Organization of the United Nations, we conclude that the annual food losses satisfy approximately 20 million people, which is equivalent to the population of Beijing or Shanghai.

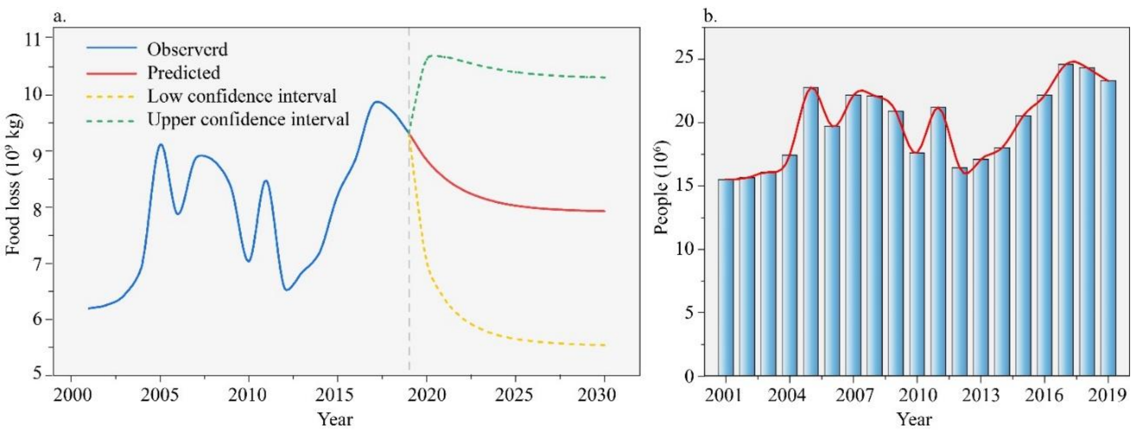


Fig. 7 Food loss assessment, forecast and total population. (a) Food loss assessment and forecast; (b) Number of population

4. Discussion

4.1 Divergent patterns of cropland abandonment

Our study fills the gap in the high-resolution, large-scale and long-term pattern of China's cropland abandonment and enriches the content of the driving forces of abandonment. Cropland is a vital basis for food production, and ensuring a specific amount of high-quality cropland crucial to maintaining food security (Tilman et al., 2011; Osei-Owusu et al., 2019). Given the pattern of cropland abandonment in China and its population of 1.4 billion, there is a clear need to understand the drivers of cropland abandonment in different regions and take better actions to protect and restore cropland to ensure food security.

This study highlights the pervasive trend of cropland abandonment in China, underscoring its considerable spatial heterogeneity. For example, the average annual cropland abandonment in China is approximately 2.34×10^{4} km^{2} (1.21%), which is about 3.8% different from the previous study (Zhu et al., 2021). Differences in results might be related to the imagery used for cropland classification. Compared with MODIS, we used higher resolution Landsat images to illustrate the characteristic of cropland dynamics in more detail. Moreover, our findings indicate that cropland abandonment is concentrated in the SWR, which is dominated by mountains and hills. Because of the challenging natural conditions, coupled with deficient transportation and infrastructure, substantial cropland abandonment is observed in the SWR, which aligns with prior studies (Li et al., 2018; Liang et al., 2020).

While Zhang et al. (2023) explored the pattern of farmland abandonment across different provinces, this scale did not describe the spatial pattern characteristics of each agricultural region (county-level scale). We found that most abandoned cropland is concentrated in the central zone (103° E-115° E), which is dominated by arid climate with low precipitation, which is not conducive to crop growth (Zhang et al., 2012). Furthermore, the economic development of this zone is more backward, resulting in an influx of rural laborers towards the eastern coastal cities, which further aggravates the abandonment. In addition, the pattern of abandonment in the north-south direction is more complex, divided into three peaks in the south (20° N-28° N), central (34° N-37° N) and north (40° N-44° N), the main reasons for which are the fragmentation of the cropland landscape in the southern region is not convenient for mechanical farming, the poor natural growth conditions of crops in the central region, and the lack of population labor in the north (Liu et al., 2017; Chen et al., 2022). Most notably, we found that the abandoned cropland was primarily near the Hu line, and the average annual abandonment rates in the east and west of the Hu line were 0.77 and 0.23, respectively. Hence, the Hu line is the boundary of population density, the natural environment, and abandoned cropland (Qiu et al., 2020).

4.2 Divergent drivers of cropland abandonment

Understanding the driving forces of cultivated land abandonment is crucial for formulating reclamation policies and ensuring food security. Studies have lacked the exploration of national-scale drivers and regional differences. Although compared with the household survey scale, the county-level scale does not precisely explain the driving force (He et al., 2020). However, our findings remain valuable by integrating numerous factors of nature, landscape configuration, population, and socioeconomics. For example, cropland abandonment in frontier areas (e.g., IMGWR, GXR and TB) is primarily related to demographic and socioeconomic factors. Owing to the adverse natural conditions, sparse population, and lagging economic development in this region, the population gradually migrated to the eastern coastal cities, resulting in the cropland abandonment (Price et al., 2015; Zhou et al., 2021). However, at the national scale, natural factors and landscape patterns had a higher impact on cropland abandonment than population and socioeconomic factors (Müller et al., 2009; Levers et al., 2018).

Interestingly, our findings show that the association between various drivers with cropland abandonment is not static (Müller et al., 2013). For example, a higher cropland agglomeration index corresponds to a lower rate of abandonment. This is likely because highly concentrated cropland resources facilitate unified mechanized management and cost efficiency, making residents more inclined towards cultivation. Furthermore, the GDP is intimately related to abandonment, i.e., areas with backward economic development have lower levels of mechanization and farmer’s income, which are more likely to lead to cropland abandonment.

The driving forces behind abandonment also differ across time periods. For example, in 2010, the farther from the city, the higher the abandonment rate of cropland, which had the opposite result from 2000. Several explanations for this phenomenon exist. First, in 2010, the cropland around the city was reduced to a minimum, restricted by the cropland protection policy. Second, far from the city, the economic development is backward, and the income gap between urban and rural areas is significant, which is easy to attract laborers to give up farming. However, the primary reason is that the closer the city is, the more willing residents are to move to the city to work for higher wages.

4.3 Implications for food security and uncertainty

Prior studies have focused on the identification and driving forces of cropland abandonment, but few have explored the potential impact of this phenomenon on food security (Tian et al., 2021). Cropland is a vital basis for food production, and ensuring a specific amount of high-quality cropland crucial to maintaining food security. Although the Chinese government has issued policies such as Compensation for Cropland Occupation, Protection of Prime Cropland, and Construction of High-standard Prime Cropland, cropland abandonment still poses a serious threat to food security due to natural and socio-economic factors (Zhang et al., 2023). We found that an average annual food loss of 7.94 billion kilograms, equivalent to the total amount of food (wheat, paddy and rice) imported each year. Hence, government departments should develop reclamation policies according to the pattern and driving force of abandoned cropland and improve farmers' engagement in agricultural production, for example, by improving the basic conditions and facilities of cropland, and adjusting the cropland layout. Furthermore, the primary reason for abandonment is closely related to residents' income; therefore, it is possible to adjust the land planting structure and increase the agricultural output value of cropland. Potential strategies may also include innovating the sales and distribution mechanisms of agricultural products, bolstering the marketing of locally distinctive farm products, and resolving issues related to single-market channels and poor circulation. By boosting farmers' income and enhancing the overall efficiency of cropland use, farmers' enthusiasm for agricultural production can be revitalized.

We found that cropland abandonment mostly occurred in SWR, LPR, IMGWR and NER regions, which are affected by fragmentation of cropland resources, low precipitation and large labor exodus. In contrast, the HHHR and MLYTR regions are rich in cropland resources and have a suitable natural climate, which facilitates large-scale crop production. Moreover, with the development of urbanization, the utilization rate of agricultural machinery and fertilizers has increased, enhancing the level of farmland intensification and compensating to some extent for the food loss due to the reduction of cropland (Hu et al., 2020; Wang et al., 2021). Therefore, to ensure food security, local governments should not only strictly implement the cropland protection system, but also strengthen the quality of cropland to improve the intensive use of cropland (Lin and Huang, 2019).

The acquisition of highly precise spatial distribution data for grain production is pivotal for estimating national-scale grain loss. In this study, we used statistical data from provincial units to estimate the amount of grain loss, which is important for cropland conservation. However, the method cannot be accurate to pixel units, which inevitably leads to errors in the results. In view of this, we combined remote sensing and statistical data to recalculate the amount of grain loss in 2001 and 2010, so as to verify the reasonableness of the results. It is worth noting that the remote sensing data mainly refer to the potential crop yield and multiple cropping index of farmland in each image element, while the statistical data refer to the ratio of grain to crop sown area. Fig. 8 demonstrates that the trends of potential crop yield loss and grain loss for each province are largely congruent. The correlation between the two time periods is 0.94 and 0.88, respectively, demonstrating that despite minor mismatches with the statistical data, they do not alter our conclusions.

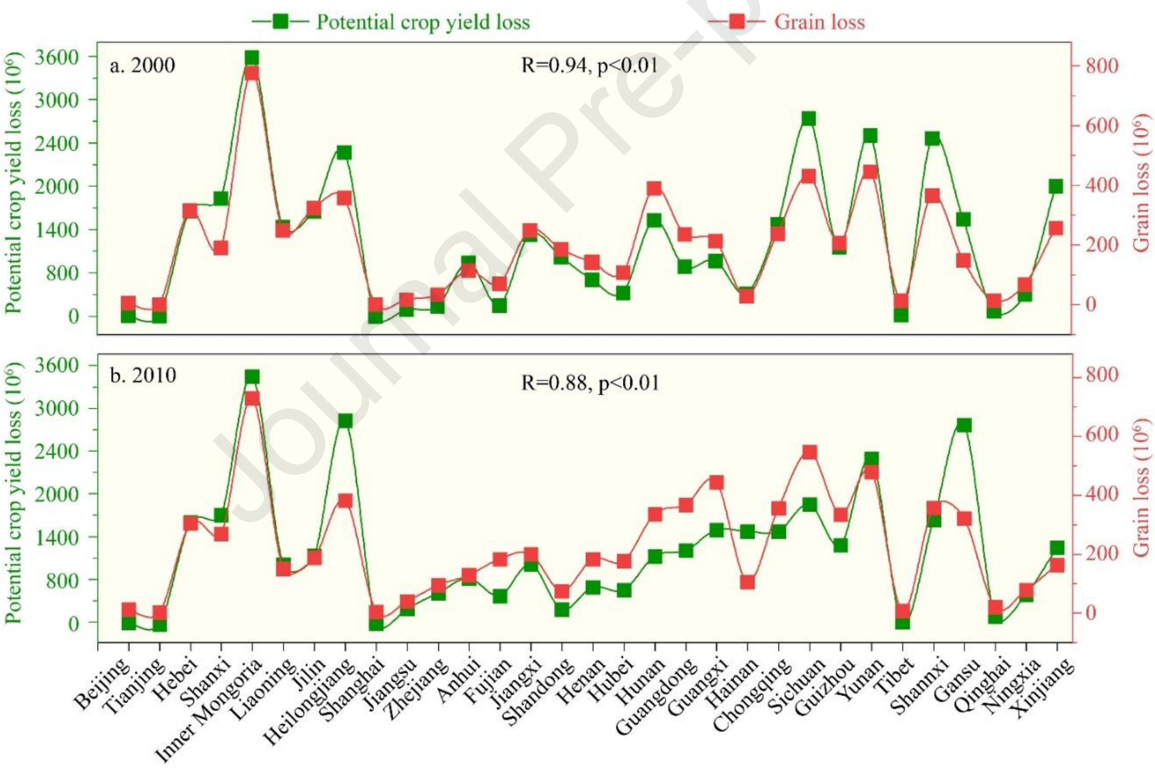


Fig. 8 Comparative analysis of potential crop yield loss and grain loss.

4.4 Limitations and future directions

This study has several limitations. First, we considered individual pixels as complete land units and assessed only the major land cover changes for each pixel. However, due to the limitation of Landsat image resolution

(30 m), we did not consider the fluctuation of land cover area within a single pixel, leading to errors in the assessment of abandonment results. Second, this study failed to reveal the driving factors of abandonment in detail. Cropland abandonment is influenced by natural, demographic, socioeconomic, policy, land rent, and labor cost factors. Despite we combined various types of factors and used machine learning algorithms to explain the relative and marginal effects of each factor on abandonment, which is of great value in understanding the drivers of cropland abandonment. Studies have shown that the income level of rural residents often determines whether they abandon their land. However, we did not collect statistical survey data on agricultural subsidies and farming costs. Finally, this study lacks a more accurate model for assessing food yield losses. Although we combined statistical data and used the provincial scale to roughly assess the grain yield loss caused by the abandonment of cropland, it is difficult to accurately assess the final result due to the different characteristics of each region. In the future, we will use higher resolution images and sub-pixel analysis methods to better understand the changes in cropland within each pixel, thus improving the granularity and accuracy of the assessment. In addition, combining long time series statistics and remote sensing data to more scientifically assess the impact of abandonment on food security and provide data support for the formulation of arable land protection policies.

5. Conclusion

This study used continuous long-term land-cover data from 1990 to 2019 to investigate the spatiotemporal patterns and regional differences in cropland abandonment. Furthermore, we explored their drivers using the BRT method by combining natural factors, landscape patterns, population, and socioeconomic data. Overall, this study fills the gap in the high-resolution, large-scale and long-term pattern of China's cropland abandonment and enriches the content of the driving forces of abandonment.

Our findings indicate that, on average, China experiences an annual cropland abandonment of 2.34 × 104 , with the majority of these abandonments concentrated in the inland regions, e.g., SWR and IMGWR. This phenomenon is because of the poor level of economic development and natural conditions. Moreover, cropland abandonment is distributed near the Hu line. However, due to the interference of natural, landscape, population, and socioeconomic factors, cropland abandonment east of the Hu line is much more than in the west, with a difference of approximately 54%. Interestingly, AI was the primary driving force affecting cropland abandonment, different from previous studies, and a significant spatial heterogeneity occurred across agricultural regions. Moreover, as the AI of cropland landscape pattern increases, it is negatively correlated with the abandonment rate.

This study grasps the overall abandonment pattern and driving force, and provides practical implications for guiding cropland reclamation. Overall, a large amount of cropland has been abandoned all year round, posing hidden threats to national food security and directly hindering the implementation of rural revitalization plans. Moreover, we found that the annual food loss due to the cropland abandonment is about 7.94 billion kilograms, which can feed 19.85 million people. Hence, government departments should develop reclamation policies according to the pattern and driving force of abandoned cropland and improve farmers' engagement in agricultural production.

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Supplementary data

Supplemental information can be found attached.

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