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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 $2.34 \times 10^4$ 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

48 driving force of abandonment and grain production. Hence, it is necessary to use higher-resolution land cover

49 data to monitor the pattern of cropland abandonment over a long period and to assess potential food losses.

50 To ensure cropland resources, it is crucial to illuminate the factors influencing cropland abandonment. Studies

51 have shown that cropland abandonment is closely related to various elements, including the natural environment,

52 labor force, agricultural development level, socioeconomic conditions (Meyfroidt et al., 2016; Movahedi et al.,

53 2021). For example, cropland abandonment primarily occurs in areas with poor natural conditions, and it is

54 frequently related to land quality and light and water supplies required for crop growth, such as cropland quality,

55 soil, precipitation, topography and natural disasters (Arnaez et al., 2011; Díaz et al., 2011; Hou et al., 2021;

56 Seppelt et al., 2022). In addition to natural factors, socioeconomic factors are prominent drivers. With the

57 acceleration of urbanization, the secondary and tertiary industries have created numerous higher-income

58 employment opportunities, transferring rural labor to the cities and exacerbating cropland abandonment (Yan

59 et al., 2016; Huang et al., 2019; Xu et al., 2019). Furthermore, market incentives, institutions, agricultural

60 subsidy policies and armed conflict are also important drivers (Baumann et al., 2011; Stefanski et al., 2014;

61 Gibson et al., 2015; Olsen et al., 2021). The reform and opening up policy has enlarged urban-rural income gap

62 in China, leading to rural population losses and exacerbating abandonment (Lai et al., 2020). Especially in

63 mountainous areas, the natural climate, transportation and agricultural facilities are insufficient or unsuitable

64 for crop growth and management (Wang et al., 2016). However, understanding of the spatial heterogeneity of

65 drivers of abandonment at the national-scale remains limited.

66 Therefore, the objective of this study is to explore the spatiotemporal patterns and driving factors of China's

67 cropland abandonment, and to assess the food loss due to cropland abandonment. Here we first use continuous

68 time-series land cover data to investigate the spatiotemporal patterns of cropland abandonment over the past

69 ~30 years and explore differences across agricultural regions. In this study, cropland abandonment is defined as

70 cropland that has not been cultivated for two consecutive years. Second, using the boosted regression trees (BRT)

71 method, we combine the natural environment, landscape patterns, population, and socioeconomic factors to

72 reveal the drivers. Finally, we assessed the amount of potential food loss due to cropland abandonment, and

73 built time-series model to predict its future trend. This study fills in the spatial distribution of China's high-

74 precision, long-term cropland abandonment, enriches the explanation of driving factors, and clearly quantifies

75 the food loss caused by cropland abandonment.

## 2. Materials and methods

### 2.1 Study area

78 This study includes 9 first-level agricultural regions and 38 secondary agricultural regions in China (Fig. 1 and

79 Table S1). Agricultural regions are divided according to agricultural production conditions, characteristics,

80 development directions, major issues, and the integrity of administrative units (County administrative unit),

81 which are crucial to the management and guidance of agricultural production. Among them, the first-level

82 agricultural regions include the Northeast Region (NER), Inner Mongolia and the Great Wall Region (IMGWR),

83 Huang–Huai–Hai Region (HHHR), Loess Plateau Region (LPR), Middle and lower reaches of the Yangtze

84 River drainage basin (MLYTR) and Southwest Region (SWR), South China Region (SCR), Gan–Xin Region

85 (GXR) and Tibet Region (TBR) (He et al., 2017). They all have their advantages and characteristics. Similarly,

86 secondary agricultural zones are a more refined division of primary agricultural zones based on agricultural

87 production conditions.

88 In addition, the Hu line is the population density boundary proposed by Chinese geographer Hu Huanyong in

89 1935, and it is the boundary of the ecological environment. China is a traditional agricultural country with a

90 highly uniform distribution of population and arable land. East of the Hu line is the area of concentration of

91 population and arable land, while the west is the area of scarcity of arable land resources. Numerous studies

92 have shown that about 90% of the country's high-quality cropland is distributed east of the Hu line due to

93 geomorphological and natural precipitation constraints (Qiu et al., 2020). The line can better reflect the pattern
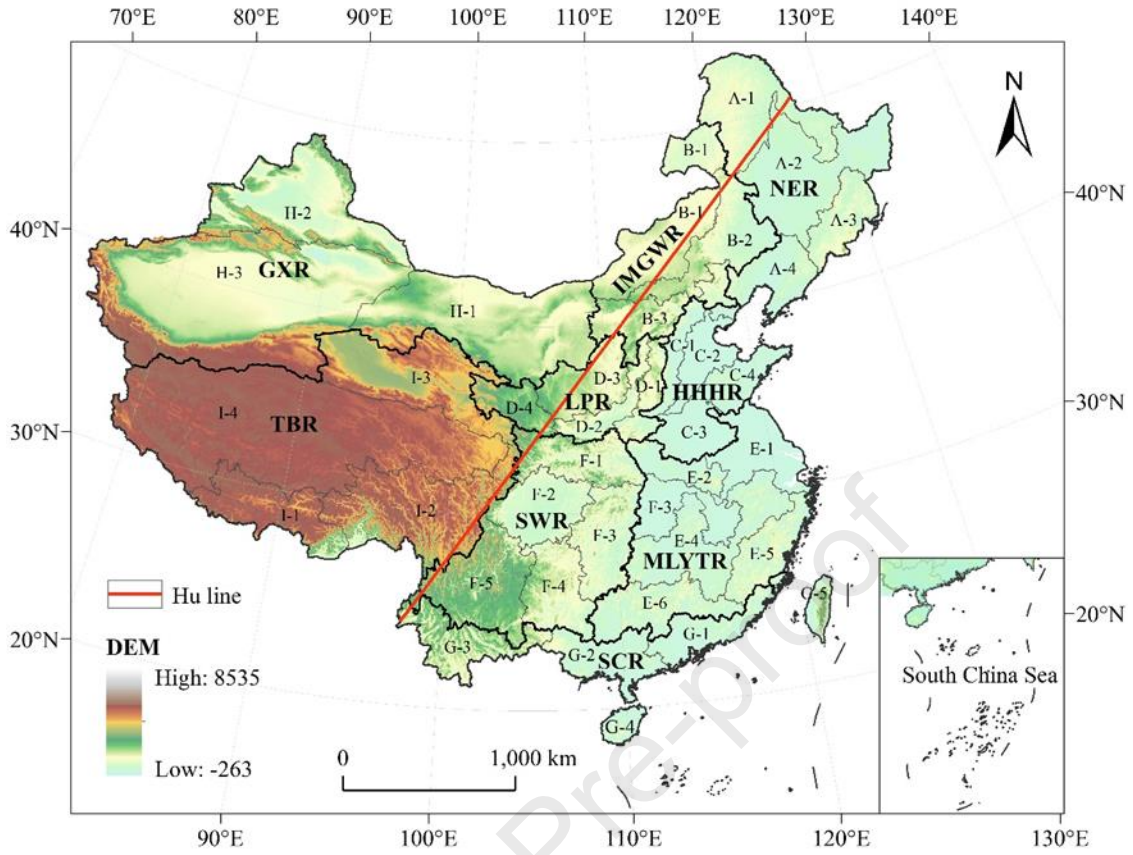
94 of cropland abandonment.

**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

108    datasets of 30 m cropland in China by collecting 30,000 samples, and the results showed that CLCD has high

109    accuracy.

110    DEM, meteorology and potential crop yield as drivers of cropland abandonment. DEM is ASTER GDEM with

111    a spatial resolution of 30 m, which are derived from geospatial data clouds (http://www.gscloud.cn/search). The

112    precipitation, temperature and potential crop yield reflect the natural growth conditions of vegetation. The

113    spatial resolution of this data is 1 km (2000 and 2010), which are obtained from the Resource and Environmental

114    Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/). In addition, the multiple

115    cropping index was calculated by Liu et al. (2021) using the enhanced vegetation index (EVI) from the

116    MOD13Q1 product with an overall accuracy of 89%, which was used to assess food losses.

117    Demographic, socio-economic and food production statistics are used to explain abandonment drivers and

118    assess food losses. Demographic data comes from the fifth and sixth national census of China. Socio-economic

119    data come from the *China Counties Statistical Yearbook (County-level)*. The food production data were obtained

120    from the *China Statistical Yearbook* and the *National Bureau of Statistics*.

121

**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 |

122

123 **2.3 Methods**

124 *2.3.1 Cropland abandonment identification*

125 Cropland abandonment is land that has not been cultivated for at least one year (Han and Song, 2019). However,

126 there is no uniform definition of arable land around the world according to the length of time it has been left

127 fallow. For example, the World Food and Agriculture Organization (FAO) defines abandoned arable land as

128 arable land that has not been used for agricultural production for more than five consecutive years. The Japanese

129 Ministry of Agriculture, Forestry and Fisheries refers to farmland that has not been cultivated for more than one

130 year and has no indication that it will be cultivated in the next few years as abandoned cultivated land. In

131 addition, scholars such as Hou et al., (2021), Han and Song (2019), and Löw et al., (2018) refer to land that has

132 not been cultivated for two, three, or four years as abandoned cropland, respectively. In view of this, we define

133 it as land that has not been used for cultivation for two consecutive years according to the "Land Administration

134 Law of the People's Republic of China" and the actual use of cropland. Here, we use CLCD to identify the

135 spatiotemporal patterns of cropland abandonment over the years. To enhance the understanding and calculation

136 process, we define cropland abandonment as the conversion of cropland to grassland, shrubs, forests, and bare

137 land for two consecutive years. In this paper, we use the Combine tool in ArcMap 10.7 to spatially merge multi-

138 period land cover products to identify the pattern of farmland abandonment in each period. Furthermore, we

139 assess the cropland abandonment intensity using the abandonment ratio, i.e., the annual abandoned area divided

140 by the initial cropland area (Shi et al., 2018; Zhu et al., 2021), as shown in Equation 1.

141
$$P_{T3} = \frac{A_{T3}}{A_{T1}} \times 100\%$$
(1)

142 Where, $P_{T3}$ represents the abandonment rate in $T_3$ time. $A_{T3}$ represents the cropland abandonment area in $T_3$ time,

143 and $A_{T1}$ represents the cropland area in $T_1$ time. In this study, we identified abandonment status for each pixel

144 (30 m) and performed statistical summaries for primary and secondary agricultural zones.

145 *2.3.2 Explanatory variables*

146 Cropland abandonment is a severe land-use change phenomenon affected by the interaction of various driving

147 factors (Müller et al., 2013; Li and Li, 2017; Li et al., 2021; Xu et al., 2021). Here, we divide the driving factors

148 into natural factors, landscape pattern of cropland, population, and socioeconomics, with 19 factors (Table 2).

149 Natural factors include DEM, slope, precipitation, temperature and potential crop yield, which are the basic

150 conditions for crop growth and yield increase. DEM and slope reflects the crop growth by topography and

151 topographic factors. Landscape patterns significantly influence cropland abandonment, such as the aggregation

152 index (AI) and DIVISION, primarily used to reflect whether the cropland distribution is easy to manage and

153 reduce costs. We calculated the landscape pattern index of each county-level using Fragstats 4.2 software.

154 Furthermore, population structure and socio-economic development are also important aspects that affect

155 cropland abandonment (Han and Song, 2020). The population structure is frequently a direct factor determining

156 whether to farm, such as aging, rural population, and education level (Xu et al., 2019). Here, we selected the

157 proportion of nonagricultural population (PNAP), rural population (RP), natural growth rate (NGR), the

158 proportion of the population over 65 years old (>65), average years of education (AYE), and the proportion of

159 the illiteracy population (PIP) (Li et al., 2021). The socioeconomics can reflect the income of urban and rural

160 residents and the distance from the city, so as to determine whether residents choose to engage in agriculture or

161 go to urban employment (Deng et al., 2015). Thus, we selected the gross domestic product (GDP), urbanization

162 rate (UR), the total power of agricultural machinery (TPAM), investment in fixed assets (IFA), distance to

163 prefecture-level city (DisPref) and city-level administrative center (DisCity).

164 **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 | °C | 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 |

165

166  In addition, to reveal the driving force of farmland abandonment, preprocessing of each independent variable is

167  essential. We avoid the problem of collinearity among these factors using the variance inflation factor (VIF) for

168  verification (Salmerón et al., 2018). When VIF > 7.5, it means that each factor has collinearity and should be

169  deleted (Sheng et al., 2017; Yang et al., 2021). Table 1 shows that each variable's VIF is less than 7.5, indicating

170  no collinearity issue among these factors, so they can be used for subsequent analysis.

171  ***2.3.3 Driver analysis of cropland abandonment***

172  This study used Boosted regression trees (BRT) to identify the drivers of cropland abandonment. We first

173  selected 1725 county-level cities based on the abandonment rate and explanatory variables collected and only

174  revealed the driving forces of 2000 and 2010. BRT is a nonparametric regression method and robust machine-

175  learning algorithm that improves the performance of a single model by fitting multiple model predictions (Elith

176  et al., 2008; Hastie et al., 2009). BRT can capture complex, nonlinear responses and relationships of predicted

177  variables and is widely used in climate environments and land systems (Müller et al., 2013).

178　　The BRT method comprises a decision tree and a boosting algorithm. It does not need to consider the interaction

179　　between independent variables, so the contribution of independent variables to dependent variables and the

180　　response curve can be obtained (Smaliychuk et al., 2016). BRT operation requires four parameters: bag, tree

181　　complexity, learning rate, and the number of trees. In this paper, we used a bag score of 0.5, which means an

182　　even distribution of the total observations for training and test samples. For the remaining parameters, we

183　　evaluated several combinations (tree complexity from 1 to 6, learning rate from 0.005 to 0.025) and used 10-

184　　fold cross-validation to determine the best parameters. Thus, we set the specific parameters of BRT as follows:

185　　family = 'Laplace', tree.complexity = 5, learning.rate = 0.01, bag.fraction = 0.5. The algorithm was mainly

186　　implemented through the *R* software third-party packages "*dismo*" and "*gbm*".

187　　**2.3.4 Assess and forecast food yield losses**

188　　Grain yield is not only related to the area of cropland, but also closely related to the multiple cropping index,

189　　the ratio of grain to crop sown area and grain yield per unit area (Liu et al., 2020; Zhang et al., 2022). Here, we

190　　use Equation 2 to estimate the grain yield lost due to farmland abandonment. Due to data limitations, we

191　　integrated statistics from provinces in China and abandoned farmland to assess the amount of food loss.

192　　$$y = s \times g \times m \times r \qquad (2)$$

193　　Where, *y* represents the food loss. *s* represents the area of cropland abandonment. *g*, *m*, and *r* represent grain

194　　yield per unit area, the multiple cropping index and the ratio of grain to crop sown area, respectively.

195　　According to the grain loss assessed over the years, we use ARIMA model to predict its future trend. The

196　　ARIMA model is presented by Box and Jenkins in the early 1970s as a famous time series prediction method

197　　(Box and Jenkins, 1976). ARIMA ($p$, $d$, $q$) models are created by first taking the differences of the data from d

198　　degree for the stabilization process and then adding the ARMA (p, q) model. In the ARIMA (p, d, q) models, p

199　　shows the degree of the Autoregressive (AR) model, q represents the degree of the moving average (MA) model

200　　and d shows the number of differences to be taken to stabilize the data (Yonar et al., 2020). Therefore, the

201　　ARIMA model can be considered as AR (p), MA (q) or ARMA (p, q) if time series is stationary. The model can

202　　be defined as follows:

203
$$Y_t = \phi_1 Y_{t-1} + \phi Y_{t-2} + \cdots \phi Y_{t-p} + \alpha_1 - \theta_1 \alpha_{t-1} - \alpha_2 - \theta_2 \alpha_{t-2} - \cdots - \alpha_q - \theta_q \alpha_{t-q} \qquad (3)$$

204    Where, $\phi_p$ represents the parameter values for autoregressive operator, $\alpha_q$ represents the error term coefficient,

205    $\theta_q$ represents the parameter values for moving average operator, $Y_t$ represents the time series of the original

206    series differenced at the degree $d$. The model is implemented using open source software "$R$", including

207    packages such as "$tseries$", "$forecast$" and "$zoo$".

208    ## 3. Results

209    ### 3.1 Overall cropland abandonment trends

210    China's cropland area gradually decreased from $197.38 \times 10^4$ km$^2$ in 1992 to $188.78 \times 10^4$ km$^2$ in 2019, a total

211    decrease of $8.68 \times 10^4$ km$^2$ ($0.3 \times 10^4$ km$^2$ per year on average), which fully shows the severe situation of cropland

212    (Fig. 2). Therefore, it is urgent to implement stricter farmland protection policies. Moreover, there was a short-

213    term increase in cropland in 2012-2014, totaling $1.39 \times 10^4$ km$^2$. However, after 2014, it gradually decreased,

214    with a minimum of $188.7 \times 10^4$ km$^2$. In terms of cropland abandonment, the area and ratio of cropland

215    abandonment did not change significantly, with an annual average of $2.34 \times 10^4$ km$^2$ and 1.21%, respectively.

216    However, 2012 and 2014 showed the lowest ($1.22 \times 10^4$ km$^2$) and highest ($3.38 \times 10^4$ km$^2$) values of cropland

217    abandonment area, respectively. Also, cropland abandonment was extremely high in 2014, possibly due to the

218    addition of new sensors from the Landsat 8 OLI during this period. Overall, the area of cropland has decreased

219    substantially, while cropland abandonment has remained relatively stable, which may be attributed to the large

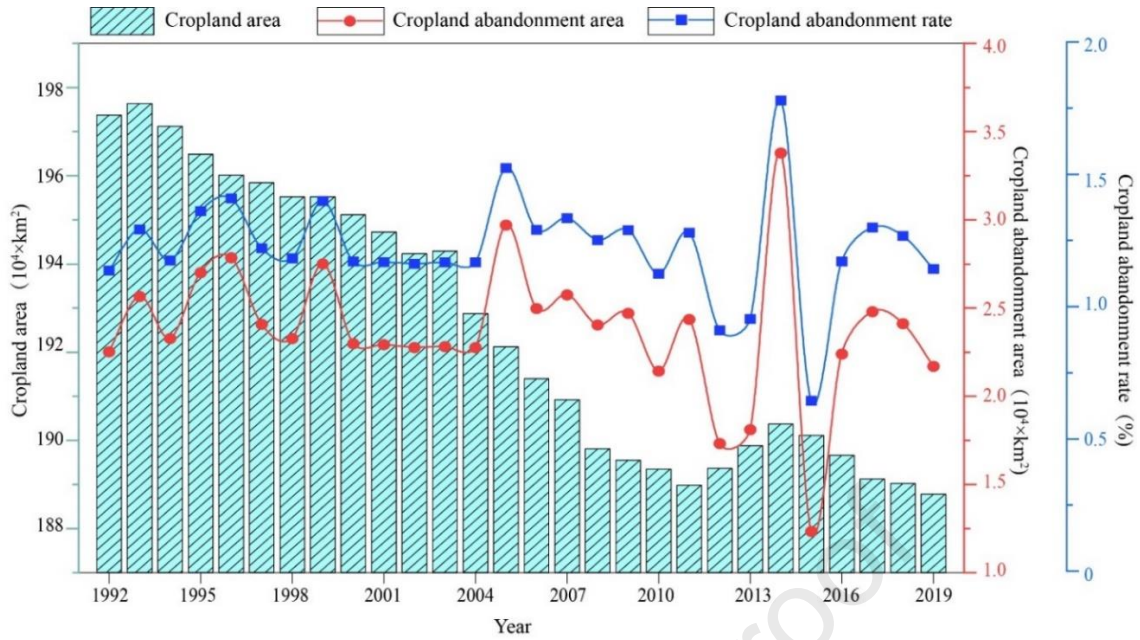220    amount of cropland occupied by urban development.

221

**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 $5.4 \times 10^3$ km$^2$ and $4.2 \times 10^3$ km$^2$, respectively, followed by Northeast Region (NER) ($3.0 \times 10^3$ km$^2$) and the Loess Plateau Region (LPR) ($3.4 \times 10^3$ km$^2$). However, Huang–Huai–Hai Region (HHHR) with the largest cropland area, has an abandoned area of only $0.4 \times 10^3$ 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 $13.6 \times 10^3$ 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.
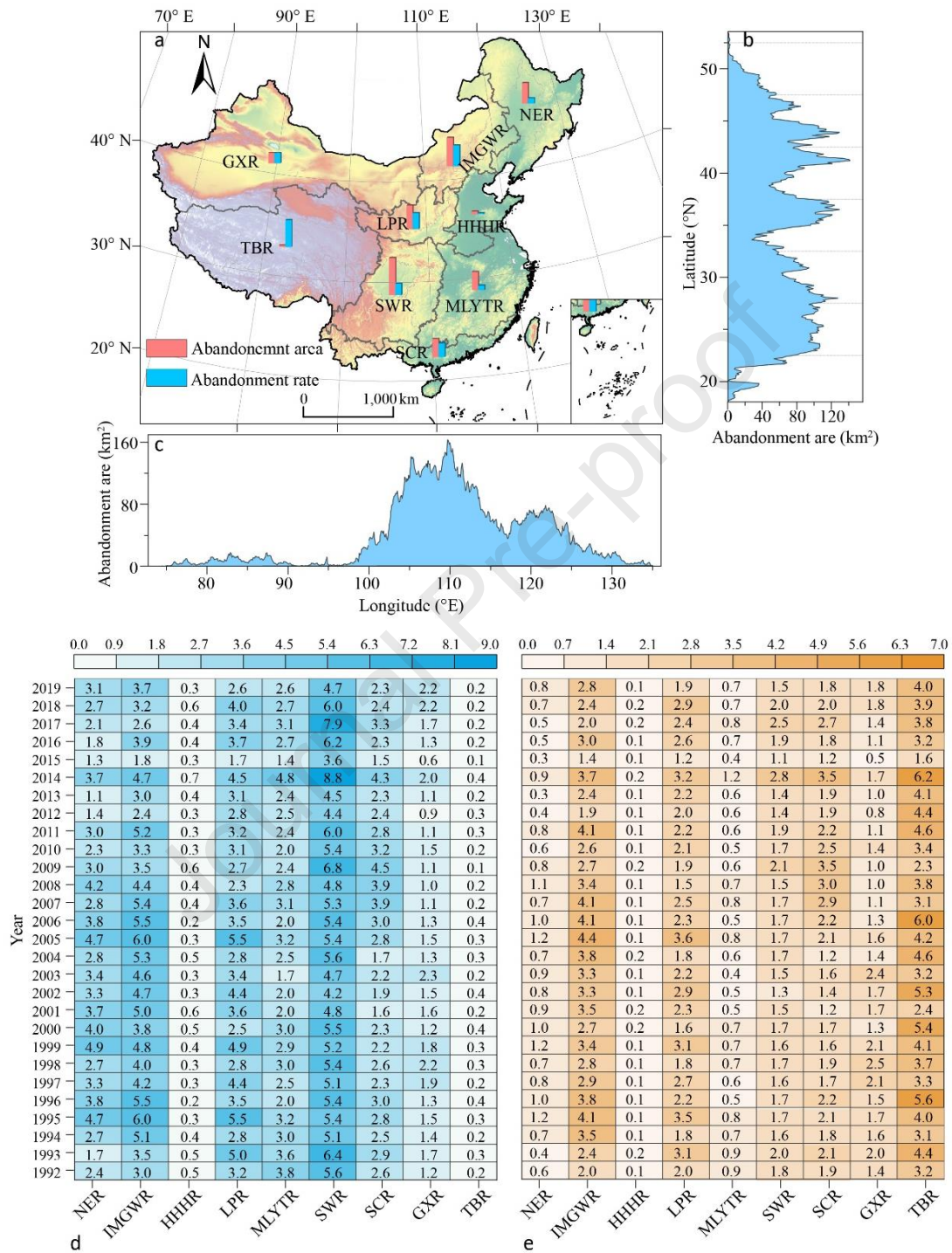


**Fig. 3.** Cropland abandonment in the first-class agricultural regions, 1992-2019. (a) Average of cropland abandonment area and rate in first-level agricultural regions; (b) Cropland abandonment varies in longitude. (c) Cropland abandonment varies in latitude; (d) Cropland abandonment area in each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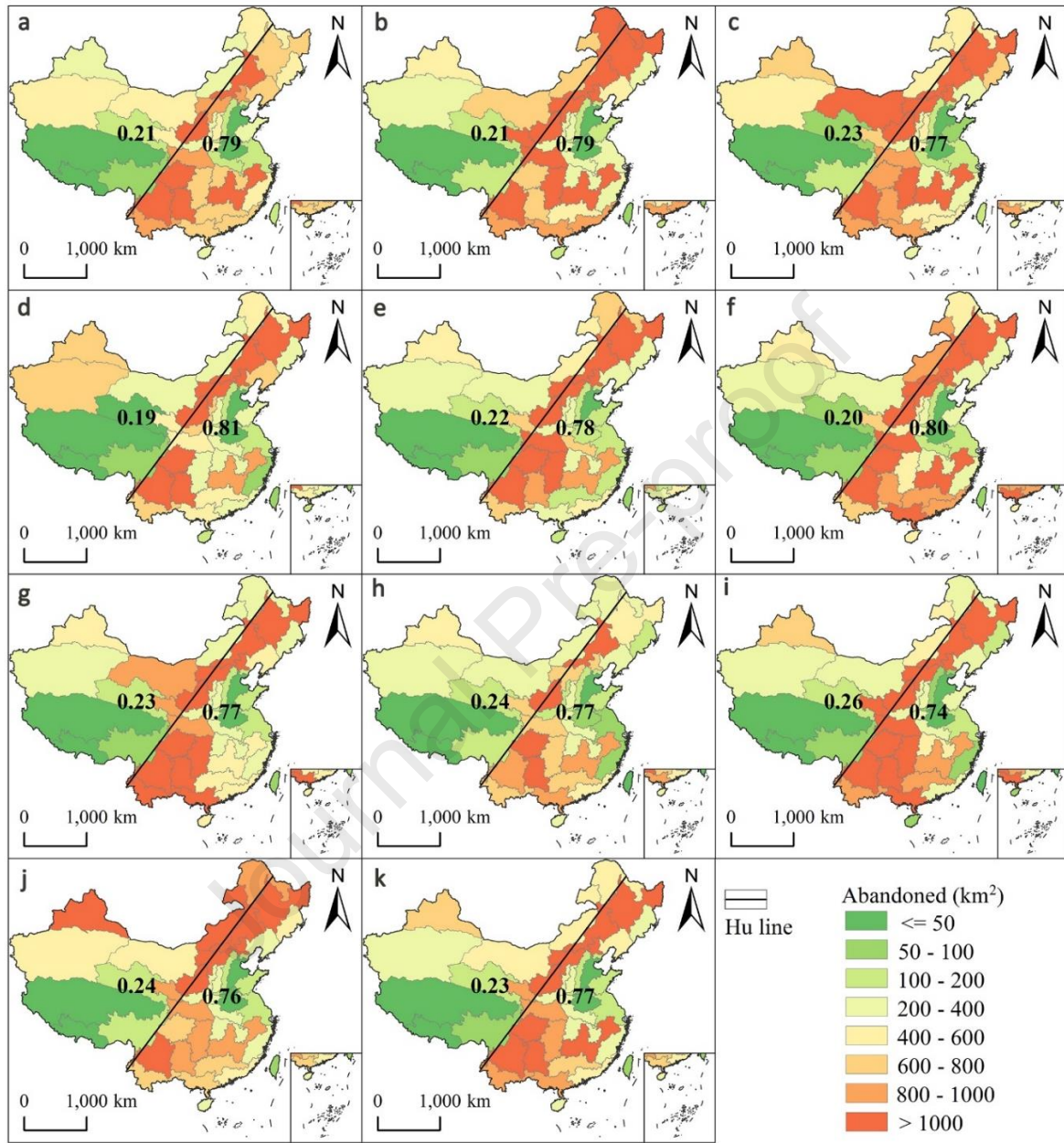
244    Cropland abandonment in each agricultural region was difference from 1992-2019 (Fig. 3d, e). First, the high

245    values of NER cropland abandonment in 1999 and 2005 were $4.9 \times 10^3$ km$^2$ (1.2%) and $4.7 \times 10^3$ km$^2$ (1.2%),

246    respectively, whereas the lowest was in 2013 at $1.1 \times 10^3$ km$^2$ (0.3%). The IMGWR was significantly abandoned

247    during 2001-2007, with a maximum of $6.0 \times 10^3$ km$^2$. HHHR, GXR and TBR were stable, with an annual average

248    of $0.4 \times 10^3$ km$^2$, $1.5 \times 10^3$ km$^2$ and $0.2 \times 10^3$ km$^2$, respectively. Second, LPR and MLYTR were severely

249    abandoned, but during period 2014-2019, they decreased by $3.6 \times 10^3$ km$^2$ and $3.3 \times 10^3$ km$^2$, respectively. SWR

250    is in a mountainous and hilly area, highly affected by the natural climate, infrastructure and socioeconomics,

251    and the abandonment is prominent at $8.8 \times 10^3$ km$^2$.

252    **3.3 Spatial pattern of cropland abandonment at secondary agricultural region scale**

253    We further analyzed the spatiotemporal pattern of cropland abandonment in 38 secondary agricultural regions.

254    Fig. 4 shows that the high value of abandonment (>1000 km$^2$) is concentrated near the Hu line and SWR, such

255    as the pastoral areas in Agropastoral Region: Middle South Inner Mongolia (B-2), Agropastoral Region- Along

256    the Great Wall (B-3), Agroforest Region: Daba Mountain (F-1), Agroforest Region: Sichuan Basin (F-2),

257    Agropastoral Forest Region: Guizhou and Guangxi Plateau and Mountain (F-4), Agropastoral Forest Region:

258    Sichuan Yunnan Plateau and Mountain (F-5), and Agroforest Region: South Yunnan (G-3). However, the low

259    values are mainly located in the TBR and HHHR, such as Alpine Region: Qinghai Tibet Plateau (I-4),

260    Agricultural Region: Hebei, Shandong, and Henan Low Plain (C-2), Agropastoral Region: South Tibet (I-1),

261    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%)

262    and 46.66 km$^2$ (0.05%). Interestingly, the east side of the Hu line was much more abandoned than the west side,

263    at approximately 0.77 and 0.23, respectively. Moreover, the difference was most significant in 2008, at 0.86 and

264    0.14, respectively.

265    Furthermore, during 1992-2020, each secondary agricultural region's cropland abandonment was in a state of

266    "first increase, then decrease". The Agropastoral Forest Region: Sichuan Yunnan Plateau and Mountain (F-5),

267    the Agropastoral Forest Region: Shanxi and Shaanxi Loess Hill and Gull (D-3), and the Agroforest Region:

268    Jiangnan Hill and Mountain (E-4) have the most significant reductions in cropland abandonment by $-1.1 \times 10^3$

269    km$^2$, $-1.1 \times 10^3$ km$^2$, and $-1.2 \times 10^3$ 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,

271    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

274    years in secondary agricultural regions, 1992-2019; a=1992, b=1995, c=1998 ⋯ j=2019; (k) Average annual

275    abandoned area.

276  **3.4 Drivers of cropland abandonment**

277  Recognizing the driving force of abandonment helps guide reclamation policy development. Here, we explore

278  the contribution of each driver across agricultural regions and at national scales. Fig.5 shows that the aggregation

279  index (AI) is a critical driver of cropland abandonment in all agricultural regions, except for HHHR. The TBR

280  is particularly significant, with AI reaching 15.5%, followed by the LPR (10.6%) and the SWR (10.4%). We

281  found significant differences across agricultural regions. AI, mean annual precipitation (MAP), mean annual

282  potential crop yield (PCY) and GDP are crucial driving factors affecting the cropland abandonment in NER,

283  and they belong to the cropland landscape patterns, natural factors, and socioeconomics, respectively. IMGWR,

284  GXR, and TBR are in the frontier regions, which are vast and sparsely populated, and the population and

285  socioeconomic impacts on cropland abandonment are more significant than natural factors, such as PNAP, RP,

286  NGR, >65, and GDP. However, HHHR has the most cropland, but the abandoned area and rate are very low,

287  and most are concentrated in the high-value areas of DEM, with a relative impact of 15.9%. The drivers of LPR

288  and SWR were similar, and the AI factor was a crucial driver (~10.5%), followed by MAP (~6.8%) and DisPref

289  (~6.2%). Finally, in the cropland landscape patterns and natural factors in MLYTR, the vital drivers were AI,

290  mean annual temperature (MAT), and MAP at 9.2%, 6.7% and 6.6%, respectively.

291  At a national level, AI is the primary driving force for cropland abandonment (18.4%), followed by PCY, MAT,

292  and MAP, with 9.8%, 6.7%, and 6.5%, respectively. Also, the landscape pattern of cropland > natural factors >

293  population and socioeconomics. Therefore, we found that although cropland abandonment is disturbed by

294  population and social economy, it depends more on factors the distribution of cropland resources and natural
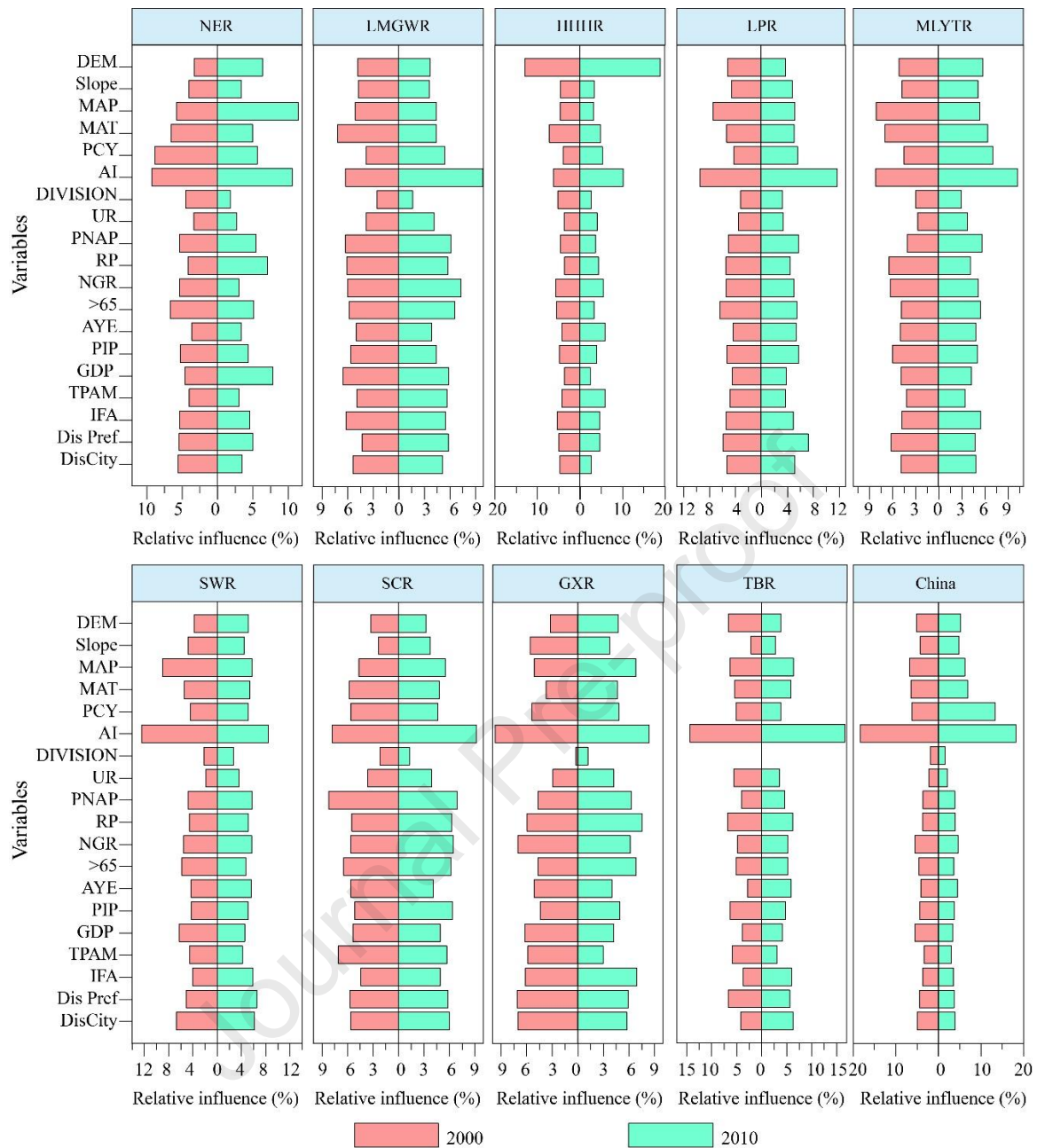
295  factors in the region.

**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.)
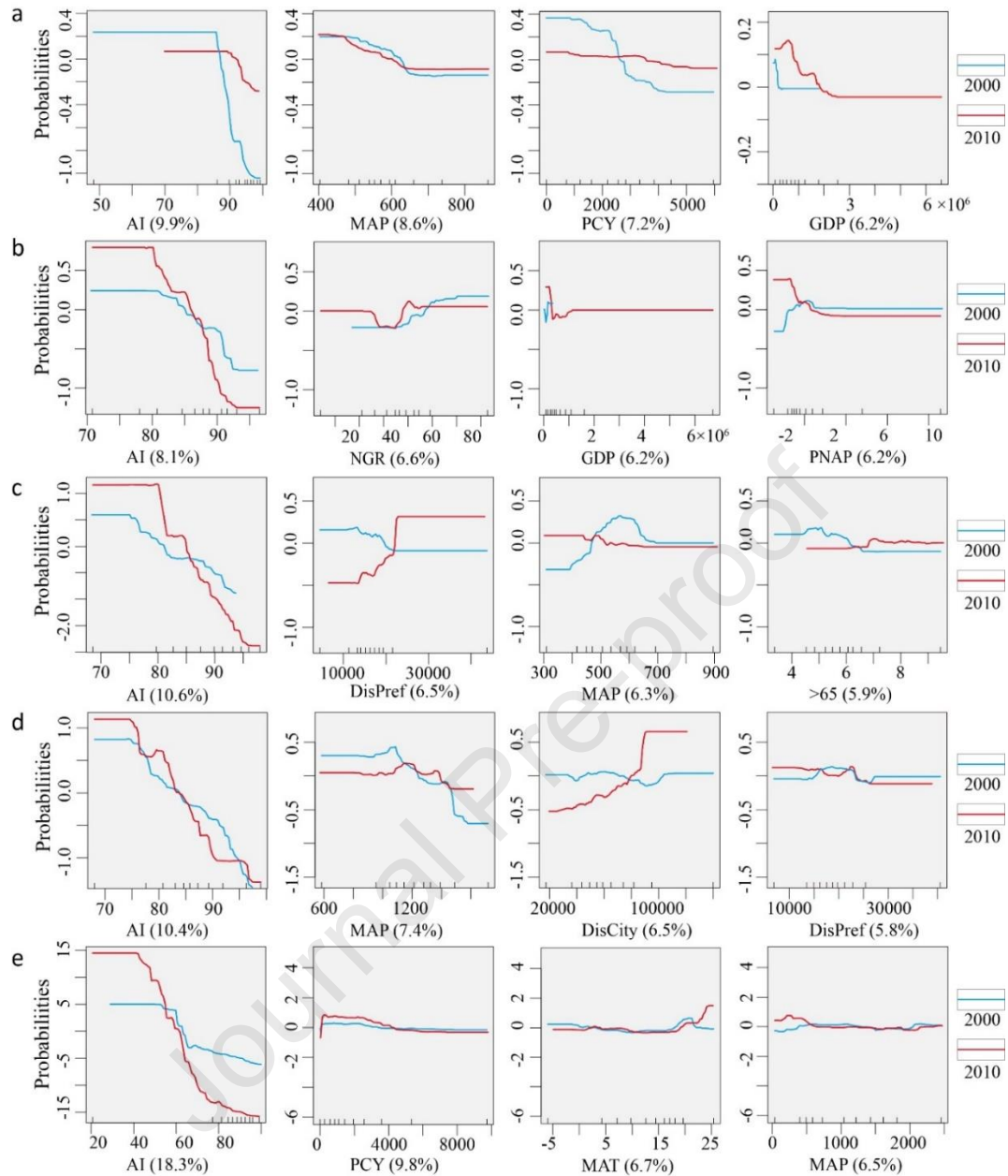
305

**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

315    abandonment at each agricultural region (~85%) and at the national scale (70%), indicating that the higher the

316    agglomeration of cropland, the lower the abandonment. Similarly, when PCY, GDP, and MAP values increased,

317    they were negatively correlated with abandonment rates. However, MAT shows the opposite law, i.e., with the

318    increase in MAT, the abandonment rate increases. Interestingly, we also found that two time-period drivers

319    exhibited different characteristics, such as DisPref (LPR) and DisCity (SWR). Fig.6 shows that the lower the

320    DisPref and DisCity values in 2000, the higher the cropland abandonment rate. However, with urban expansion

321    and economic development in 2010, the further away from urban areas, the more significant the abandonment.

322    **3.5 Impact of cropland abandonment on grain yield**

323    Generally, the large-scale cropland abandonment leads to the loss of food production and threatens food security.

324    We combined the multiple cropping index, grain sown area ratio and grain yield per unit area of each province

325    in China to assess the amount of grain loss from 2001 to 2019. Fig. 7 shows that the amount of food loss caused

326    by cropland abandonment has increased overall, and the loss has increased from 6.19 billion kilograms (2001)

327    to 8.83 billion kilograms (2019), with an average annual loss of approximately 7.94 billion kilograms. Moreover,

328    we use the ARIMA model to predict its future trend, which shows an overall downward trend, with a loss of

329    approximately 7.92 billion kilograms by 2030. Also, to quantify the amount of food loss satisfy how many

330    people. Here, according to the "safety line" of 400 kilograms proposed by the Food and Agriculture Organization

331    of the United Nations, we conclude that the annual food losses satisfy approximately 20 million people, which

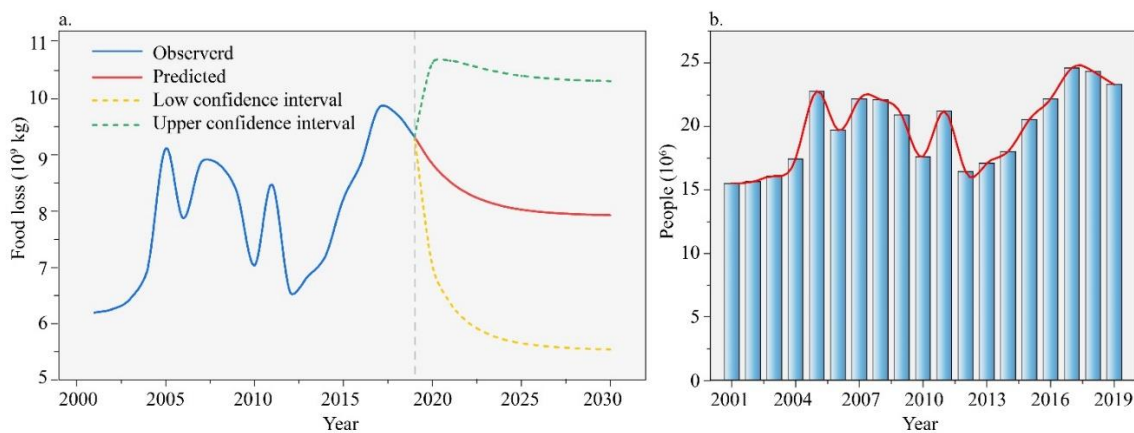332    is equivalent to the population of Beijing or Shanghai.

333



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

335    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 $2.34 \times 10^4 \, km^2$ (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

362 region, and the lack of population labor in the north (Liu et al., 2017; Chen et al., 2022). Most notably, we found

363 that the abandoned cropland was primarily near the Hu line, and the average annual abandonment rates in the

364 east and west of the Hu line were 0.77 and 0.23, respectively. Hence, the Hu line is the boundary of population

365 density, the natural environment, and abandoned cropland (Qiu et al., 2020).

366 **4.2 Divergent drivers of cropland abandonment**

367 Understanding the driving forces of cultivated land abandonment is crucial for formulating reclamation policies

368 and ensuring food security. Studies have lacked the exploration of national-scale drivers and regional differences.

369 Although compared with the household survey scale, the county-level scale does not precisely explain the

370 driving force (He et al., 2020). However, our findings remain valuable by integrating numerous factors of nature,

371 landscape configuration, population, and socioeconomics. For example, cropland abandonment in frontier areas

372 (e.g., IMGWR, GXR and TB) is primarily related to demographic and socioeconomic factors. Owing to the

373 adverse natural conditions, sparse population, and lagging economic development in this region, the population

374 gradually migrated to the eastern coastal cities, resulting in the cropland abandonment (Price et al., 2015; Zhou

375 et al., 2021). However, at the national scale, natural factors and landscape patterns had a higher impact on

376 cropland abandonment than population and socioeconomic factors (Müller et al., 2009; Levers et al., 2018).

377 Interestingly, our findings show that the association between various drivers with cropland abandonment is not

378 static (Müller et al., 2013). For example, a higher cropland agglomeration index corresponds to a lower rate of

379 abandonment. This is likely because highly concentrated cropland resources facilitate unified mechanized

380 management and cost efficiency, making residents more inclined towards cultivation. Furthermore, the GDP is

381 intimately related to abandonment, i.e., areas with backward economic development have lower levels of

382 mechanization and farmer's income, which are more likely to lead to cropland abandonment.

383 The driving forces behind abandonment also differ across time periods. For example, in 2010, the farther from

384 the city, the higher the abandonment rate of cropland, which had the opposite result from 2000. Several

385 explanations for this phenomenon exist. First, in 2010, the cropland around the city was reduced to a minimum,

386 restricted by the cropland protection policy. Second, far from the city, the economic development is backward,

387 and the income gap between urban and rural areas is significant, which is easy to attract laborers to give up

388    farming. However, the primary reason is that the closer the city is, the more willing residents are to move to the

389    city to work for higher wages.

390    **4.3 Implications for food security and uncertainty**

391    Prior studies have focused on the identification and driving forces of cropland abandonment, but few have

392    explored the potential impact of this phenomenon on food security (Tian et al., 2021). Cropland is a vital basis

393    for food production, and ensuring a specific amount of high-quality cropland crucial to maintaining food security.

394    Although the Chinese government has issued policies such as Compensation for Cropland Occupation,

395    Protection of Prime Cropland, and Construction of High-standard Prime Cropland, cropland abandonment still

396    poses a serious threat to food security due to natural and socio-economic factors (Zhang et al., 2023). We found

397    that an average annual food loss of 7.94 billion kilograms, equivalent to the total amount of food (wheat, paddy

398    and rice) imported each year. Hence, government departments should develop reclamation policies according

399    to the pattern and driving force of abandoned cropland and improve farmers' engagement in agricultural

400    production, for example, by improving the basic conditions and facilities of cropland, and adjusting the cropland

401    layout. Furthermore, the primary reason for abandonment is closely related to residents' income; therefore, it is

402    possible to adjust the land planting structure and increase the agricultural output value of cropland. Potential

403    strategies may also include innovating the sales and distribution mechanisms of agricultural products, bolstering

404    the marketing of locally distinctive farm products, and resolving issues related to single-market channels and

405    poor circulation. By boosting farmers' income and enhancing the overall efficiency of cropland use, farmers'

406    enthusiasm for agricultural production can be revitalized.

407    We found that cropland abandonment mostly occurred in SWR, LPR, IMGWR and NER regions, which are

408    affected by fragmentation of cropland resources, low precipitation and large labor exodus. In contrast, the

409    HHHR and MLYTR regions are rich in cropland resources and have a suitable natural climate, which facilitates

410    large-scale crop production. Moreover, with the development of urbanization, the utilization rate of agricultural

411    machinery and fertilizers has increased, enhancing the level of farmland intensification and compensating to

412    some extent for the food loss due to the reduction of cropland (Hu et al., 2020; Wang et al., 2021). Therefore,

413    to ensure food security, local governments should not only strictly implement the cropland protection system,

414    but also strengthen the quality of cropland to improve the intensive use of cropland (Lin and Huang, 2019).

415    The acquisition of highly precise spatial distribution data for grain production is pivotal for estimating national-

416    scale grain loss. In this study, we used statistical data from provincial units to estimate the amount of grain loss,

417    which is important for cropland conservation. However, the method cannot be accurate to pixel units, which

418    inevitably leads to errors in the results. In view of this, we combined remote sensing and statistical data to

419    recalculate the amount of grain loss in 2001 and 2010, so as to verify the reasonableness of the results. It is

420    worth noting that the remote sensing data mainly refer to the potential crop yield and multiple cropping index

421    of farmland in each image element, while the statistical data refer to the ratio of grain to crop sown area. Fig. 8

422    demonstrates that the trends of potential crop yield loss and grain loss for each province are largely congruent.

423    The correlation between the two time periods is 0.94 and 0.88, respectively, demonstrating that despite minor

424    mismatches with the statistical data, they do not alter our conclusions.
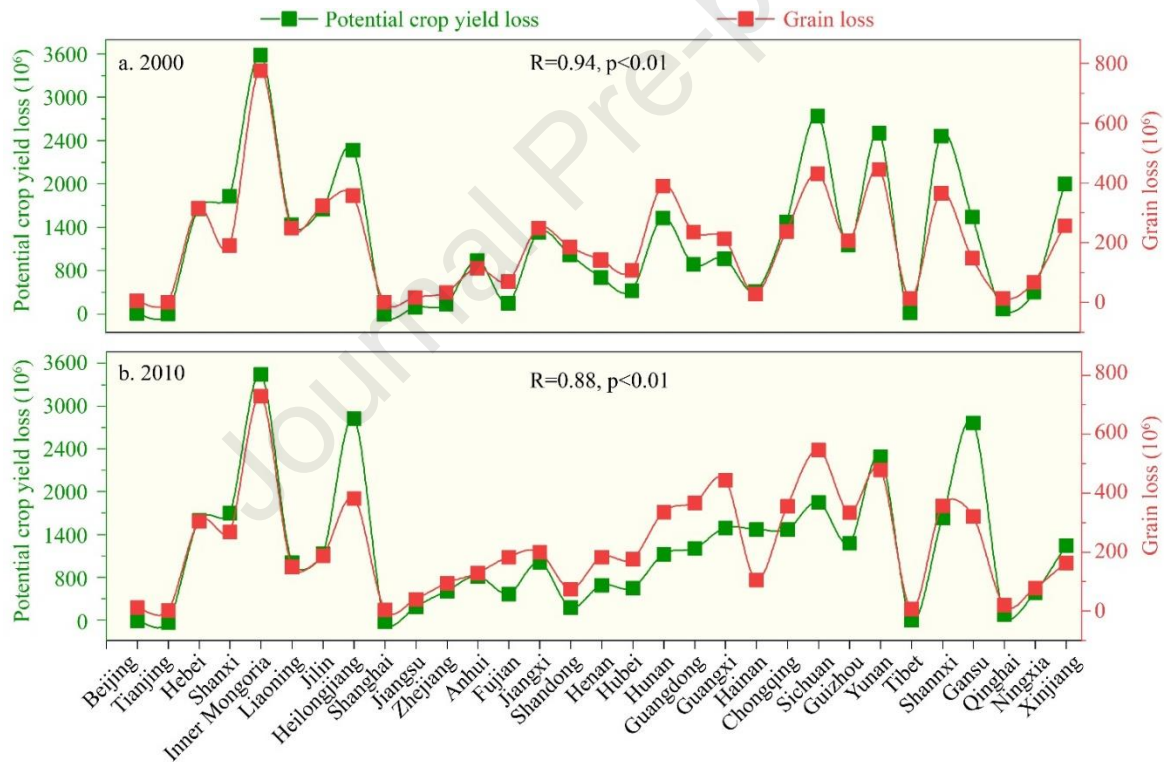


**Fig. 8** Comparative analysis of potential crop yield loss and grain loss.

### 4.4 Limitations and future directions

428    This study has several limitations. First, we considered individual pixels as complete land units and assessed

429    only the major land cover changes for each pixel. However, due to the limitation of Landsat image resolution

430   (30 m), we did not consider the fluctuation of land cover area within a single pixel, leading to errors in the

431   assessment of abandonment results. Second, this study failed to reveal the driving factors of abandonment in

432   detail. Cropland abandonment is influenced by natural, demographic, socioeconomic, policy, land rent, and

433   labor cost factors. Despite we combined various types of factors and used machine learning algorithms to

434   explain the relative and marginal effects of each factor on abandonment, which is of great value in understanding

435   the drivers of cropland abandonment. Studies have shown that the income level of rural residents often

436   determines whether they abandon their land. However, we did not collect statistical survey data on agricultural

437   subsidies and farming costs. Finally, this study lacks a more accurate model for assessing food yield losses.

438   Although we combined statistical data and used the provincial scale to roughly assess the grain yield loss caused

439   by the abandonment of cropland, it is difficult to accurately assess the final result due to the different

440   characteristics of each region. In the future, we will use higher resolution images and sub-pixel analysis methods

441   to better understand the changes in cropland within each pixel, thus improving the granularity and accuracy of

442   the assessment. In addition, combining long time series statistics and remote sensing data to more scientifically

443   assess the impact of abandonment on food security and provide data support for the formulation of arable land

444   protection policies.

## 5. Conclusion

446   This study used continuous long-term land-cover data from 1990 to 2019 to investigate the spatiotemporal

447   patterns and regional differences in cropland abandonment. Furthermore, we explored their drivers using the

448   BRT method by combining natural factors, landscape patterns, population, and socioeconomic data. Overall,

449   this study fills the gap in the high-resolution, large-scale and long-term pattern of China's cropland

450   abandonment and enriches the content of the driving forces of abandonment.

451   Our findings indicate that, on average, China experiences an annual cropland abandonment of $2.34 \times 10^4$ , with

452   the majority of these abandonments concentrated in the inland regions, e.g., SWR and IMGWR. This

453   phenomenon is because of the poor level of economic development and natural conditions. Moreover, cropland

454   abandonment is distributed near the Hu line. However, due to the interference of natural, landscape, population,

455   and socioeconomic factors, cropland abandonment east of the Hu line is much more than in the west, with a

456   difference of approximately 54%. Interestingly, AI was the primary driving force affecting cropland

457 abandonment, different from previous studies, and a significant spatial heterogeneity occurred across

458 agricultural regions. Moreover, as the AI of cropland landscape pattern increases, it is negatively correlated with

459 the abandonment rate.

460 This study grasps the overall abandonment pattern and driving force, and provides practical implications for

461 guiding cropland reclamation. Overall, a large amount of cropland has been abandoned all year round, posing

462 hidden threats to national food security and directly hindering the implementation of rural revitalization plans.

463 Moreover, we found that the annual food loss due to the cropland abandonment is about 7.94 billion kilograms,

464 which can feed 19.85 million people. Hence, government departments should develop reclamation policies

465 according to the pattern and driving force of abandoned cropland and improve farmers' engagement in

466 agricultural production.

## Acknowledgments

## Supplementary data

472 Supplemental information can be found attached.

473

474 References

475 Alcantara, C., Kuemmerle, T., Baumann, M., Bragina, E.V., Griffiths, P., Hostert, P., Knorn, J., Müller, D., Prishchepov,

476     A.V., and Schierhorn, F*., et al.* (2013). Mapping the extent of abandoned farmland in Central and Eastern Europe using

477     MODIS time series satellite data. *Environmental Research Letters*, *8*(3), 35035. http://doi.org/10.1088/1748-

478     9326/8/3/035035.

479 Arnaez, J., Lasanta, T., Errea, M.P., and Ortigosa, L. (2011). Land abandonment, landscape evolution, and soil erosion in

480     a Spanish Mediterranean mountain region: The case of Camero Viejo. *Land Degradation & Development*, *22*(6), 537-

481     550. http://doi.org/10.1002/ldr.1032.

482 Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., Prishchepov, A.V., Kruhlov, I.,

483     and Hostert, P. (2011). Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. *Land Use*

484     *Policy*, *28*(3), 552-562. http://doi.org/10.1016/j.landusepol.2010.11.003.

485 Box, G.E., and Jenkins, G.M. (1976). Time series analysis, control, and forecasting. *San Francisco, CA: Holden Day*,

486     *3226*(3228), 10.

487 Bren, D.A.C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K., Haberl, H., Creutzig, F., and Seto, K.C. (2017).

488     Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences*,

489     114(34), 8939-8944. http://doi.org/10.1073/pnas.1606036114.

490 Chen, L., Meadows, M.E., Liu, Y., Lin, Y. (2022). Examining pathways linking rural labour outflows to the abandonment

491     of arable land in China. *Population, Space and Place*. 28, e2519. https://doi.org/10.1002/psp.2519.

492 Chen, H., Tan, Y., Xiao, W., He, T., Xu, S., Meng, F., Li, X., Xiong, W. (2023). Assessment of continuity and efficiency

493     of complemented cropland use in China for the past 20 years: A perspective of cropland abandonment. Journal of

494     Cleaner Production. 388, 135987. https://doi.org/10.1016/j.jclepro.2023.135987.

495 Dara, A., Baumann, M., Kuemmerle, T., Pflugmacher, D., Rabe, A., Griffiths, P., Hölzel, N., Kamp, J., Freitag,

496     M., and Hostert, P. (2018). Mapping the timing of cropland abandonment and recultivation in northern

497     Kazakhstan using annual Landsat time series. *Remote Sensing of Environment*, *213*49-60.

498     http://doi.org/10.1016/j.rse.2018.05.005.

499 Deng, X., Huang, J., Rozelle, S., Zhang, J., and Li, Z. (2015). Impact of urbanization on cultivated land changes in China.

500     *Land Use Policy*, *45*1-7. http://doi.org/10.1016/j.landusepol.2015.01.007.

501 Díaz, G.I., Nahuelhual, L., Echeverría, C., and Marín, S. (2011). Drivers of land abandonment in Southern Chile and

502     implications for landscape planning. *Landscape and Urban Planning*, *99*(3), 207-217.

503     http://doi.org/10.1016/j.landurbplan.2010.11.005.

504  Elith, J., Leathwick, J.R., and Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*,

505      *77*(4), 802-813. http://doi.org/10.1111/j.1365-2656.2008.01390.x.

506  Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., and Hostert, P. (2015). Mapping farmland

507      abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sensing of Environment*,

508      *163*312-325. http://doi.org/10.1016/j.rse.2015.03.028.

509  Gibson, G.R., Campbell, J.B., and Zipper, C.E. (2015). Sociopolitical influences on cropland area change in Iraq, 2001–

510      2012. *Applied Geography*, *62*339-346. https://doi.org/10.1016/j.apgeog.2015.05.007.

511  Han, Z., and Song, W. (2019). Spatiotemporal variations in cropland abandonment in the Guizhou–Guangxi karst

512      mountain area, China. *Journal of Cleaner Production*, *238*117888. http://doi.org/10.1016/j.jclepro.2019.117888.

513  Han, Z., and Song, W. (2020). Abandoned cropland: Patterns and determinants within the Guangxi Karst Mountainous

514      Area, China. *Applied Geography*, *122*102245. https://doi.org/10.1016/j.apgeog.2020.102245.

515  Hastie, T., Tibshirani, R., Friedman, J.H., and Friedman, J.H. (2009). The elements of statistical learning: data mining,

516      inference, and prediction, Vol 2 (Springer).

517  He, C., Liu, Z., Xu, M., Ma, Q., and Dou, Y. (2017). Urban expansion brought stress to food security in China: Evidence

518      from decreased cropland net primary productivity. *Science of the Total Environment*, *576*660-670.

519      http://doi.org/10.1016/j.scitotenv.2016.10.107.

520  He, Y., Xie, H., and Peng, C. (2020). Analyzing the behavioural mechanism of farmland abandonment in the hilly

521      mountainous areas in China from the perspective of farming household diversity. *Land Use Policy*, *99*104826.

522      http://doi.org/10.1016/j.landusepol.2020.104826.

523  Hou, D., Meng, F., and Prishchepov, A.V. (2021). How is urbanization shaping agricultural land-use? Unraveling the nexus

524      between farmland abandonment and urbanization in China. *Landscape and Urban Planning*, *214*104170.

525      http://doi.org/10.1016/j.landurbplan.2021.104170.

526  Hu, Q., Xiang, M., Chen, D., Zhou, J., Wu, W., Song, Q. (2020). Global cropland intensification surpassed expansion

527      between 2000 and 2010: A spatio-temporal analysis based on GlobeLand30. *Science of the Total Environment*. 746,

528      141035. https://doi.org/10.1016/j.scitotenv.2020.141035.

529  Huang, Z., Du, X., and Castillo, C.S.Z. (2019). How does urbanization affect farmland protection? Evidence from China.

530      *Resources, Conservation and Recycling*, *145*139-147. https://doi.org/10.1016/j.resconrec.2018.12.023.

531  Keenleyside, C., Tucker, G., and McConville, A., eds. (2010). Farmland Abandonment in the EU: an Assessment of Trends

532      and Prospects.

533  Kong, X. (2014). China must protect high-quality arable land. *Nature*, *506*(7486), 7. http://doi.org/10.1038/506007a.

534 Lai, Z., Chen, M., and Liu, T. (2020). Changes in and prospects for cultivated land use since the reform and opening up in

535    China. *Land Use Policy*, 97104781. http://doi.org/10.1016/j.landusepol.2020.104781.

536 Levers, C., Schneider, M., Prishchepov, A.V., Estel, S., and Kuemmerle, T. (2018). Spatial variation in determinants of

537    agricultural land abandonment in Europe. *Science of the Total Environment*, 64495-111.

538    http://doi.org/10.1016/j.scitotenv.2018.06.326.

539 Li, L., Pan, Y., Zheng, R., and Liu, X. (2022). Understanding the spatiotemporal patterns of seasonal, annual, and

540    consecutive farmland abandonment in China with time-series MODIS images during the period 2005－2019. *Land*

541    *Degradation & Development*, *33*(10), 1608-1625. http://doi.org/10.1002/ldr.4233.

542 Li, S., and Li, X. (2017). Global understanding of farmland abandonment: A review and prospects. *Journal of Geographical*

543    *Sciences*, *27*(9), 1123-1150. http://doi.org/10.1007/s11442-017-1426-0.

544 Li, S., Li, X., Sun, L., Cao, G., Fischer, G., and Tramberend, S. (2018). An estimation of the extent of cropland abandonment

545    in mountainous regions of China. *Land Degradation & Development*, *29*(5), 1327-1342.

546    http://doi.org/10.1002/ldr.2924.

547 Li, Y., Zhou, T., Jiang, G., Li, G., Zhou, D., and Luo, Y. (2021). Spatial pattern and mechanisms of farmland abandonment

548    in Agricultural and Pastoral Areas of Qingzang Plateau. *Geography and Sustainability*, *2*(3), 139-150.

549    http://doi.org/10.1016/j.geosus.2021.06.003.

550 Liang, X., Li, Y., and Zhou, Y. (2020). Study on the abandonment of sloping farmland in Fengjie County, Three Gorges

551    Reservoir Area, a mountainous area in China. *Land Use Policy*, 97104760.

552    http://doi.org/10.1016/j.landusepol.2020.104760.

553 Lin, M., Huang, Q. (2019). Exploring the relationship between agricultural intensification and changes in cropland areas

554    in the US. *Agriculture, Ecosystems & Environment*. 274, 33-40. https://doi.org/10.1016/j.agee.2018.12.019.

555 Liu, X., Shi, L., Qian, H., Sun, S., Wu, P., Zhao, X., Engel, B.A., Wang, Y. (2020). New problems of food security in

556    Northwest China: A sustainability perspective. *Land Degradation & Development*. 31, 975-989.

557    https://doi.org/10.1002/ldr.3498.

558 Liu, X., Wang, Y., Li, Y., Liu, F., Shen, J., Wang, J., Xiao, R., Wu, J. (2017). Changes in arable land in response to

559    township urbanization in a Chinese low hilly region: Scale effects and spatial interactions. *Applied Geography*. 88, 24-

560    37. https://doi.org/10.1016/j.apgeog.2017.08.019.

561 Liu, X., Zheng, J., Yu, L., Hao, P., Chen, B., Xin, Q., Fu, H., Gong, P. (2021). Annual dynamic dataset of global cropping

562    intensity from 2001 to 2019. *Scientific Data*. 8, 283. https://doi.org/10.1038/s41597-021-01065-9.

563    Löw, F., Fliemann, E., Abdullaev, I., Conrad, C., and Lamers, J.P.A. (2015). Mapping abandoned agricultural land in Kyzyl-

564    Orda, Kazakhstan using satellite remote sensing. *Applied Geography*, *62*377-390.

565    https://doi.org/10.1016/j.apgeog.2015.05.009.

566    Löw, F., Prishchepov, A. V., Waldner, F., Dubovyk, O., Akramkhanov, A., Biradar, C., Lamers, J. P. A. (2018). Mapping

567    Cropland Abandonment in the Aral Sea Basin with MODIS Time Series. *Remote Sensing*. 10(2), 159.

568    http://doi.org/10.3390/rs10020159

569    Meyfroidt, P., Schierhorn, F., Prishchepov, A.V., Müller, D., and Kuemmerle, T. (2016). Drivers, constraints and trade-

570    offs associated with recultivating abandoned cropland in Russia, Ukraine and Kazakhstan. *Global Environmental*

571    *Change*, *37*1-15. http://doi.org/10.1016/j.gloenvcha.2016.01.003.

572    Morell-Monzó, S., Estornell, J., and Sebastiá-Frasquet, M. (2020). Comparison of Sentinel-2 and High-Resolution Imagery

573    for Mapping Land Abandonment in Fragmented Areas. *Remote Sensing*, *12*(12). http://doi.org/10.3390/rs12122062.

574    Movahedi, R., Jawanmardi, S., Azadi, H., Goli, I., Viira, A., and Witlox, F. (2021). Why do farmers abandon agricultural

575    lands? The case of Western Iran. *Land Use Policy*, *108*105588. http://doi.org/10.1016/j.landusepol.2021.105588.

576    Müller, D., Kuemmerle, T., Rusu, M., and Griffiths, P. (2009). Lost in transition: determinants of post-socialist cropland

577    abandonment in Romania. *Journal of Land Use Science*, *4*(1-2), 109-129. http://doi.org/10.1080/17474230802645881.

578    Müller, D., Leitão, P.J., and Sikor, T. (2013). Comparing the determinants of cropland abandonment in Albania and

579    Romania using boosted regression trees. *Agricultural Systems*, *117*66-77. http://doi.org/10.1016/j.agsy.2012.12.010.

580    Ojha, R.B., Atreya, K., Kristiansen, P., Devkota, D., and Wilson, B. (2022). A systematic review and gap analysis of drivers,

581    impacts, and restoration options for abandoned croplands in Nepal. *Land Use Policy*, *120*106237.

582    http://doi.org/10.1016/j.landusepol.2022.106237.

583    Olsen, V.M., Fensholt, R., Olofsson, P., Bonifacio, R., Butsic, V., Druce, D., Ray, D., and Prishchepov, A.V. (2021). The

584    impact of conflict-driven cropland abandonment on food insecurity in South Sudan revealed using satellite remote

585    sensing. *Nature Food*, *2*(12), 990-996. http://doi.org/10.1038/s43016-021-00417-3.

586    Osei-Owusu, A.K., Kastner, T., de Ruiter, H., Thomsen, M., and Caro, D. (2019). The global cropland footprint of

587    Denmark's food supply 2000−2013. *Global Environmental Change*, *58*101978.

588    http://doi.org/10.1016/j.gloenvcha.2019.101978.

589    Price, B., Kienast, F., Seidl, I., Ginzler, C., Verburg, P.H., and Bolliger, J. (2015). Future landscapes of Switzerland: Risk

590    areas for urbanisation and land abandonment. *Applied Geography*, *57*32-41.

591    http://doi.org/10.1016/j.apgeog.2014.12.009.

592  Qiu, B., Li, H., Tang, Z., Chen, C., Berry, J. (2020). How cropland losses shaped by unbalanced urbanization process?

593      *Land Use Policy*. 96, 104715. https://doi.org/10.1016/j.landusepol.2020.104715.

594  Qiu, B., Yang, X., Tang, Z., Chen, C., Li, H., and Berry, J. (2020). Urban expansion or poor productivity: Explaining

595      regional differences in cropland abandonment in China during the early 21st century. *Land Degradation &*

596      *Development*, *31*(17), 2540-2551. http://doi.org/10.1002/ldr.3617.

597  Salmerón, R., García, C.B., and García, J. (2018). Variance Inflation Factor and Condition Number in multiple linear

598      regression. *Journal of Statistical Computation and Simulation*, *88*(12), 2365-2384.

599      http://doi.org/10.1080/00949655.2018.1463376.

600  Seppelt, R., Klotz, S., Peiter, E., and Volk, M. (2022). Agriculture and food security under a changing climate: An

601      underestimated challenge. *iScience*,105551. http://doi.org/10.1016/j.isci.2022.105551.

602  Sheng, J., Han, X., Zhou, H. (2017). Spatially varying patterns of afforestation/reforestation and socio-economic factors in

603      China: a geographically weighted regression approach. *Journal of Cleaner Production*. 153, 362-371.

604      https://doi.org/10.1016/j.jclepro.2016.06.055.

605  Shi, T., Li, X., Xin, L., Xu, X. (2018). The spatial distribution of farmland abandonment and its influential factors at the

606      township level: A case study in the mountainous area of China. *Land Use Policy*. 70, 510-520.

607      https://doi.org/10.1016/j.landusepol.2017.10.039.

608  Smaliychuk, A., Müller, D., Prishchepov, A.V., Levers, C., Kruhlov, I., and Kuemmerle, T. (2016). Recultivation of

609      abandoned agricultural lands in Ukraine: Patterns and drivers. *Global Environmental Change*, *38*70-81.

610      http://doi.org/10.1016/j.gloenvcha.2016.02.009.

611  Stefanski, J., Chaskovskyy, O., and Waske, B. (2014). Mapping and monitoring of land use changes in post-Soviet western

612      Ukraine using remote sensing data. *Applied Geography*, *55*155-164. https://doi.org/10.1016/j.apgeog.2014.08.003.

613  Tian, Z., Ji, Y., Xu, H., Qiu, H., Sun, L., Zhong, H., and Liu, J. (2021). The potential contribution of growing rapeseed in

614      winter fallow fields across Yangtze River Basin to energy and food security in China. *Resources, Conservation and*

615      *Recycling*, *164*105159. https://doi.org/10.1016/j.resconrec.2020.105159.

616  Tilman, D., Balzer, C., Hill, J., and Befort, B.L. (2011). Global food demand and the sustainable intensification of

617      agriculture. *Proceedings of the National Academy of Sciences*, *108*(50), 20260-20264.

618      http://doi.org/10.1073/pnas.1116437108.

619  Wang, C., Gao, Q., Wang, X., and Yu, M. (2016). Spatially differentiated trends in urbanization, agricultural land

620      abandonment and reclamation, and woodland recovery in Northern China. *Scientific Reports*, *6*(1).

621      http://doi.org/10.1038/srep37658.

622 Wang, S., Bai, X., Zhang, X., Reis, S., Chen, D., Xu, J., Gu, B. (2021). Urbanization can benefit agricultural production
623     with large-scale farming in China. *Nature Food*. 2, 183-191. http://doi.org/10.1038/s43016-021-00228-6.

624 Xu, D., Deng, X., Guo, S., and Liu, S. (2019). Labor migration and farmland abandonment in rural China: Empirical results
625     and policy implications. *Journal of Environmental Management*, *232*738-750.
626     http://doi.org/10.1016/j.jenvman.2018.11.136.

627 Xu, D., Deng, X., Huang, K., Liu, Y., Yong, Z., and Liu, S. (2019). Relationships between labor migration and cropland
628     abandonment in rural China from the perspective of village types. *Land Use Policy*, *88*104164.
629     http://doi.org/10.1016/j.landusepol.2019.104164.

630 Xu, H., Qu, Q., Chen, Y., Liu, G., and Xue, S. (2021). Responses of soil enzyme activity and soil organic carbon stability
631     over time after cropland abandonment in different vegetation zones of the Loess Plateau of China. *Catena*, *196*104812.
632     http://doi.org/10.1016/j.catena.2020.104812.

633 Yan, J., Yang, Z., Li, Z., Li, X., Xin, L., and Sun, L. (2016). Drivers of cropland abandonment in mountainous areas: A
634     household decision model on farming scale in Southwest China. *Land Use Policy*, *57*459-469.
635     http://doi.org/10.1016/j.landusepol.2016.06.014.

636 Yang, J., and Huang, X. (2021). The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth
637     System Science Data*, *13*(8), 3907-3925. http://doi.org/10.5194/essd-13-3907-2021.

638 Yang, M., Gao, X., Zhao, X., Wu, P. (2021). Scale effect and spatially explicit drivers of interactions between ecosystem
639     services — A case study from the Loess Plateau. *Science of the Total Environment*. 785, 147389.
640     https://doi.org/10.1016/j.scitotenv.2021.147389

641 Yonar, H., Yonar, A., Tekindal, M.A., and Tekindal, M. (2020). Modeling and Forecasting for the number of cases of the
642     COVID-19 pandemic with the Curve Estimation Models, the Box-Jenkins and Exponential Smoothing Methods. *EJMO*,
643     *4*(2), 160-165. http://doi.org/10.14744/ejmo.2020.28273.

644 Zhang, C., Dong, J., and Ge, Q. (2022). Quantifying the accuracies of six 30-m cropland datasets over China: A comparison
645     and evaluation analysis. *Computers and Electronics in Agriculture*, *197*106946.
646     http://doi.org/10.1016/j.compag.2022.106946.

647 Zhang, H., Zhang, J., Song, J. (2022). Analysis of the threshold effect of agricultural industrial agglomeration and industrial
648     structure upgrading on sustainable agricultural development in China. *Journal of Cleaner Production*. 341, 130818.
649     https://doi.org/10.1016/j.jclepro.2022.130818.

650 Zhang, L., Xiao, J., Li, J., Wang, K., Lei, L., Guo, H. (2012). The 2010 spring drought reduced primary productivity in
651     southwestern China. *Environmental Research Letters*. 7, 45706. https://doi.org/10.1088/1748-9326/7/4/045706.

652     Zhang, M., Li, G., He, T., Zhai, G., Guo, A., Chen, H., and Wu, C. (2023). Reveal the severe spatial and temporal patterns

653          of abandoned cropland in China over the past 30 years. *Science of the Total Environment*, *857*159591.

654          http://doi.org/10.1016/j.scitotenv.2022.159591.

655     Zhang, Y., Li, X., and Song, W. (2014). Determinants of cropland abandonment at the parcel, household and village levels

656          in mountain areas of China: A multi-level analysis. *Land Use Policy*, *41*186-192.

657          http://doi.org/10.1016/j.landusepol.2014.05.011.

658     Zhou, B., Aggarwal, R., Wu, J., and Lv, L. (2021). Urbanization-associated farmland loss: A macro-micro comparative

659          study in China. *Land Use Policy*, *101*105228. http://doi.org/10.1016/j.landusepol.2020.105228.

660     Zhu, X., Xiao, G., Zhang, D., and Guo, L. (2021). Mapping abandoned farmland in China using time series MODIS NDVI.

661          *Science of the Total Environment*, *755*142651. http://doi.org/10.1016/j.scitotenv.2020.142651.