



# Effect of landscape-scale farmland fragmentation on the ecological efficiency of farmland use: a case study of the Yangtze River Economic Belt, China

Xianhui Hou<sup>1</sup> · Jingming Liu<sup>2</sup> · Daojun Zhang<sup>1</sup> · Minjuan Zhao<sup>1</sup> · Yuqing Yin<sup>1</sup>

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## Abstract

Improving the ecological efficiency of farmland use (EEFU) has become an important part of ensuring food security and solving environmental pollution problems. At present, the Chinese government is actively promoting large-scale farmland transfer to reduce the level of farmer-/plot-scale farmland fragmentation (FF), so it is crucial to clarify the effect of landscape-scale FF on EEFU. This study applies the non-dynamic panel and threshold models in an empirical study of the municipal administrative regions along the Yangtze River Economic Belt (2000, 2005, 2010, and 2015). The results reveal that there is a single threshold for the effects of area, shape, and distance fragmentation on EEFU with farmland area per capita (FAPC) as the threshold variable. The threshold values are 1.548, 1.373, and 1.542, respectively. The effects of area and distance fragmentation on EEFU are initially promoted and then suppressed; however, shape fragmentation always has an inhibitory effect on EEFU. These findings suggest that ignoring the condition of FAPC of different regions and promoting large-scale farmland transfer blindly will give rise to the decline of EEFU. These results are conducive to the sustainable utilization of farmland and the formulation of related policies.

**Keywords** Farmland fragmentation · Ecological efficiency of farmland use · Econometric model · Farmland area per capita · The Yangtze River Economic Belt

## Introduction

As the most populous nation, farmland is under great pressure for supporting social economic development and ensuring food security in China (Deng et al. 2015; Liu 2018). On the one hand,

China underwent rapid urbanization in the past 40 years. The conversion of farmland to construction land has not only become an important guarantee for local government finances (Zhong et al. 2019), but also provides space for urban expansion, especially for high-quality farmland around the city (Wu et al. 2017). On the other hand, farmland is still the main means of production for about 5.516 million China's farmers (Population Investigation Division, National Bureau of Statistics of China 2020). Efficient use of cultivated land resources is an important route for farmers to achieve income growth. Therefore, the Chinese center government always attaches great importance on the utilization and protection of farmland resources (Lu et al. 2018a; Zhang et al. 2019; Jin et al. 2019) and has launched many principal campaigns to maintain the quantity and quality of farmland, e.g., the dynamic balance system of farmland quantity and the basic farmland protection system (Wu et al. 2017). Also, in order to ensure food security and raise farmers' income for rural poverty reduction, the Chinese center government has also implemented a number of agricultural subsidy policies to encourage farmers to actively engage in agricultural production (Huang et al. 2013).

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- ✉ Xianhui Hou  
houxh2017@nwfufu.edu.cn
- ✉ Jingming Liu  
jimmyliu1993@stu.xjtu.edu.cn
- ✉ Minjuan Zhao  
minjuan.zhao@nwsuaf.edu.cn

<sup>1</sup> College of Economics and Management, Northwest A&F University, NO. 3 Taicheng Road, Yangling, Shaanxi 712100, People's Republic of China

<sup>2</sup> School of Public Policy and Administration, Xi'an Jiaotong University, NO. 28 Xianning Road, Xi'an, Shaanxi 710049, People's Republic of China

In recent years, benefited from the large amount of chemical fertilizer input (Yu 2016), China's grain production has shown a sustained growth trend, and the current outputs equaled about one fifth of world corresponding supplies (Liu et al. 2020). From the perspective of farmland use practices, focusing only on economic benefits while ignoring the associated ecological (environmental) problems of farmland use will inevitably cause land degradation and environmental pollution (Balota et al. 2014), such as heavy metal pollution (Zhang et al. 2020), soil compaction (Prokop et al. 2018), greenhouse gas emissions (Lu et al. 2018a), and nonpoint source pollution (Dalu et al. 2018; Ruan et al. 2020). Relevant researches have also pointed out that one-third of the world's farmland is polluted and damaged due to unreasonable utilization (Verheijen et al. 2009; Cao et al. 2020). Thus, balancing the benefits between economic and ecological plays a key role in realizing the sustainable utilization of farmland resources (Hou et al. 2019a).

Ecological efficiency (eco-efficiency), the achievement of the highest possible economic benefits with the least possible input of resources and damage to the environment, has been widely studied by scholars and governments (Schaltegger and Sturm 1990). Eco-efficiency has been applied to urbanization (Bai et al. 2018), agricultural production (Bonfiglio et al. 2017), and energy consumption (Yang et al. 2018). Similarly, in order to quantify the sustainability of farmland use, many scholars have examined and discussed EEFU (Lu et al. 2018a; Ren et al. 2019; Hou et al. 2019a). For example, on the basis of the comprehensive consideration of economic output, nonpoint source pollution, and carbon emissions, Feng et al. (2015) point out that China's EEFU showed a significant downward trend from 1993 to 2013. Sabiha et al. (2017) computed the eco-efficiency of high-yielding farmland in Bangladesh and found that undesirable output or on-farm environmental damage induces an efficiency loss of 20%. In addition, Hou et al. (2019a) focused on the impact of urbanization on EEFU.

At present, the Chinese government is actively promoting large-scale farmland transfer to reduce the level of FF (Xie and Lu 2017). Thus, the impact of FF on farmland use has been a topic of interest for researchers. One view is that FF is the main obstacle to improving agricultural productivity and realizing agricultural modernization (Ali and Deininger 2014; Latruffe and Piet 2014; Sklenicka 2016; Sklenicka et al. 2017; Lu et al. 2018b). In contrast, many studies suggest that FF can enrich the agricultural production structure (Bellon and Taylor 1993), spread the working time of agricultural production across different seasons (Bellon 1996), reduce land ownership-related conflicts (Ntihinyurwa et al. 2019), and increase biodiversity (Thenail and Baudry 2004; Thenail et al. 2009). However, the above research focuses more on farmer-/plot-scale FF and less on the effects of FF on the utilization of farmland at the landscape scale.

In fact, due to the large population and limited farmland resources in rural areas, the tense human-land relationship is the main factor for the farmer-/plot-scale FF in the rural areas of China, which has also been confirmed by many scholars (Liu et al. 2017; Xie and Lu 2017). In recent years, the rapid development of the social economy has significantly changed the relationship between humans and land in China's rural areas, thus increasing FAPC and promoting the transfer of farmland (Long 2014). With the expansion of the farmland management size for farmers, farmer-/plot-scale FF have gradually evolved into landscape-scale FF. Consequently, the effect of landscape-scale FF on the EEFU is also worthy of attention, especially for relevant policy design and decision making in the future (Del Corral et al. 2011; Latruffe and Piet 2014). More importantly, farmland transfer policy implies a hypothesis that landscape-scale FF is beneficial to EEFU. Unfortunately, the effects of landscape-scale FF on EEFU remains unclear. Additionally, the variation of FAPC is a dominant factor for the different type transformation of FF from farmer-/plot-scale to landscape-scale, but few studies have explored the effects of landscape-scale FF on EEFU in combination with changes in FAPC.

In this study, we selected Fragstats 4.2 software and the slack-based measure (SBM) undesirable model to calculate the landscape-scale FF and the EEFU, respectively. Further, according to the threshold model proposed by Hansen (1999), we constructed an analysis model with FAPC as the threshold variable to analyze the impact of FF on EEFU. Prior to this analysis, we used the non-dynamic panel model to perform a comparative analysis to provide a useful reference for relevant policy formulation. Accordingly, the specific contents of this study are as follows: “**Literature review**” systematically summarizes the relationship of different scales of fragmentation and the effect of FF on farmland use. “**Data sources**” describes how landscape-scale FF and EEFU are calculated and explains the construction of threshold and non-dynamic panel models. “**Methodology**” introduces the study area situation and the related data acquisition methods and process. “**Results and discussion**” presents the findings of the empirical analysis and discussion. “**Conclusions**” details research conclusions.

## Literature review

### FF definitions and their interrelationship

Many scholars have defined the concept of FF from different perspectives. For example, Mcpherson (1982) pointed out that FF means that a household's farmland resources are divided into several spatially separated plots. The same or similar concepts have been used in many relevant studies, such as the plot size of each household/farm (Carter and Yao 2002), the

number of plots owned by the household/farm (Xie and Lu 2017), and the average plot size of the household/farm (Niroula and Thapa 2005). In contrast, to measure FF, most studies use the plot size of each household/farm rather than the number of plots operated by the household and the farm's average plot size. Since farmland plot is a basic operational unit, Niroula and Thapa (2007) consider it meaningful to analyze the impact of FF on farmland utilization. Consequently, plot size, shape (single plot or multiple plots), and distance (between the plot and the farm, as well as among the plots), which usually influence the cost of farmland utilization and abnegation of modern technologies, are the most commonly used variables to represent the level of FF (Del Corral et al. 2011; Kawasaki 2010). It can be seen that the FF concepts mentioned above are defined from the perspective of whether the use of farmland is beneficial for farmers, so they are often referred to as farmer-/plot-scale FF. In contrast, some scholars have also proposed some FF indicators at the landscape scale, such as the number, size, and shape of plots; distance of the plots from the farmer's residence; and distance between the plots, which was calculated at the municipality level (Jia and Petrick 2014; Latruffe and Piet 2014).

As we all know, only land suitable for agricultural production can be developed or converted into farmland. Hence, farmland patches have different sizes, shapes, and locations at the landscape scale, which determine the basic conditions of farmland use, as represented by labels (1), (2), and (3) in Fig. 1. However, since China has a large population but not enough farmland, farmers often own several widely dispersed plots of different quality in order to achieve a fair distribution of farmland, as denoted by labels A-1, A-2, and A-3 in Fig. 1 (Tan et al. 2006; Lu et al. 2018b). One patch is usually divided into many plots for different farmers (Sklenicka 2016). Currently, landscape-scale farmland patches could lead to the separation of farmland plots from the border, shape, and spatial distance perspective to some extent, but due to the decentralized farmland management of farmers, the FF caused by the division of farmland patches is more serious (Latruffe and Piet 2014; Guo et al. 2019; Carter and Yao 2002; Ntihinyurwa et al. 2019). With improvements at the social and economic levels, many members of rural populations have moved to cities. The increase in FAPC in rural areas brings the possibility of farmland transfer. Since farmers with high labor productivity have high marginal output, in general, they are always motivated to expand the area of their farmland by leasing or exchanging farmland management rights<sup>1</sup> (Janus et al. 2018). At this time, farmers are more inclined to transfer adjacent farmland to reduce costs and increase income (Guo et al. 2019). For example, in order to expand the farmland area, farmer A exchanged the plot A-2 with the plot C-1 from

farmer C at stage 2 and rented the plot B-1 from farmer B at stage 3 (Fig. 1) In this context, patches (1) will be managed independently by farmer A at stage 3, and thus the condition of farmland patches (1) which will have a direct impact on farmland use activities, i.e., at stages 3 and 4 in Fig. 1. With the increase rate of rural population loss, the area owned by each farmer expanded. However, if the income of some farmland patches is less than the opportunity cost or the operating costs, these farmlands will be marginalized or even abandoned by farmers, as shown in stage 4 in Fig. 1 (Strijker 2005). Li and Li (2019) have also confirmed that a large number of farmlands have been abandoned in mountainous areas where the farmland landscape is very fragmented.

The FF has attracted widespread attentions since it plays an important role in the utilization of farmland. It is important to note that landscape-scale FF can always affect farmland use activities, but the degree of effect varies with the change in the FAPC (Di Falco et al. 2010; Kawasaki 2010; Latruffe and Piet 2014; Xie and Lu 2017). In addition, to facilitate an understanding of fragmentation, this study uses the term “plot”, rather than “patch”, in the following sections.

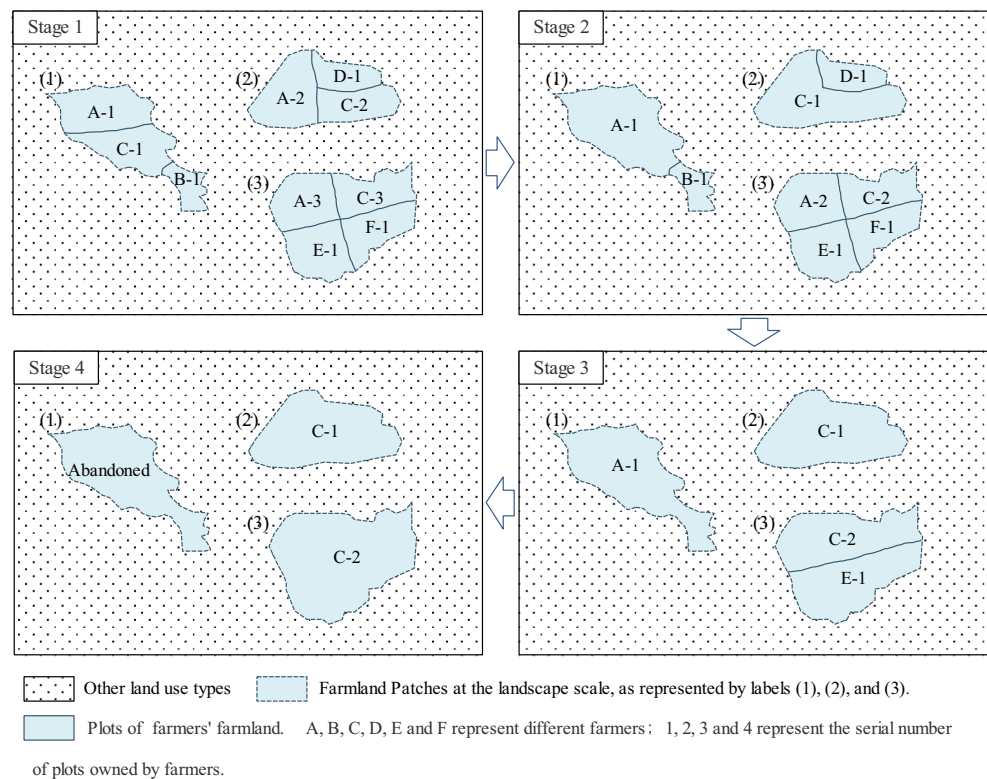
### Effect of FF on farmland utilization

Most studies have considered FF to be an obstacle to farmland utilization (Di Falco et al. 2010; Latruffe and Piet 2014). For example, Kawasaki (2010) investigated the costs and benefits of FF by using panel data obtained from Japanese rice farms and revealed that FF increases production costs and offsets economies of size. Further, FF also increases the time and fuel required to travel between plots and reduce the size of land through the loss or wastage of some areas at their boundaries (Carter and Yao 2002; Ntihinyurwa et al. 2019). Moreover, based on household survey data collected from the Jiangsu province in China, Lu et al. (2018b) confirmed that an increase in the Simpson index per unit resulted in an average increase in costs by 39%, whereas an increase in plot size resulted in an average decrease in costs by 8%. In addition, relevant studies have shown that farmers are not enthusiastic about adopting modern technology and investments in farmland construction when plots are very small or irregularly shaped (Di Falco et al. 2010; Tan et al. 2010). In addition, some scholars reveal that FF will increase the cost of water transportation (Kawasaki 2010; Tan et al. 2010). With the increase in agricultural production costs, FF has become the main cause for a reduction in agricultural labor productivity (Jia and Petrick 2014), agricultural land circulation (Xie and Lu 2017), and the abandonment of farmland (Lu et al. 2018b).

However, some scholars clarify that FF also has many positive effects. On the one hand, FF has undeniably played an important role in agricultural development (Lin 1992). For instance, the Household Responsibility System in China has

<sup>1</sup> In China, farmlands are under the ownership of village collectives, and this ownership cannot be sold to others.

Fig. 1 Process of FF evolution



significantly promoted the development of agriculture and guaranteed a high demand for agricultural products in the development of the national economy (Xu et al. 2019). Following the implementation of land reforms in 1991, the transformation of large farms to highly intensive small-scale farms promoted the rapid development of Bulgarian agriculture (Buckwell and Davidova 1993) and a similar phenomenon also occurred in Central and Eastern European countries (Dijk 2002). As clarified by Di Falco et al. (2010), FF plays an important role in ensuring food security; hence, policy makers should not despise small farmers and consider them burdensome. On the other hand, some scholars have found that FF can enrich the agricultural production structure (Bellon and Taylor 1993), offset labor insufficiency during busy seasons and surplus labor during slack seasons (Bellon 1996), and reduce land ownership-related conflicts (Ntihinyurwa et al. 2019). Moreover, FF reduces agricultural production risks arising from the occurrence of disease, hail, droughts, floods, and other natural disasters and, thereby, ensures food security (Del Corral et al. 2011).

Overall, FF affect many aspects of farmland use activities, especially the relationship between input and output of farmland. It is important to note that the above concept of FF highlights the influence of farmer-scale or plot-scale FF on the input-output of farmland utilization. As EEFU represents the combination relationship of input and output; however, few researches examine how FF affects the EEFU at landscape scale. As noted in “FF definitions and their

interrelationship”, farmland use activities can also be influenced by landscape-scale FF, which will inevitably affect the EEFU. However, previous studies have not provided conclusive evidence on the effect of landscape-scale FF on EEFU. In addition, with the change in the FAPC, the impact of the landscape-scale FF on the EEFU is complex. Therefore, it is likely that there is not a linear relationship between FF and EEFU.

## Data sources

### Study area

The Yangtze River Economic Belt (YREB), which is the area where the main river and the tributaries of the Yangtze flow, encompasses eight provinces and two municipalities (Fig. 2). It has a total area of 2.05 million km<sup>2</sup> and accounts for more than 40% of the country’s population and GDP (Hou et al. 2019a). As one of the country’s three major grain-producing areas, the YREB contributes to China’s food security. Therefore, the rational and complete utilization of all farmland is the basic condition for food security in the YREB. However, in recent years, due to the increase in the cost of land utilization brought about by fragmentation, the phenomenon of abandonment and idle farmland is more serious along the YREB. Moreover, fertilizer, pesticide use, and nonpoint source pollution have increased in the region (Wang et al.



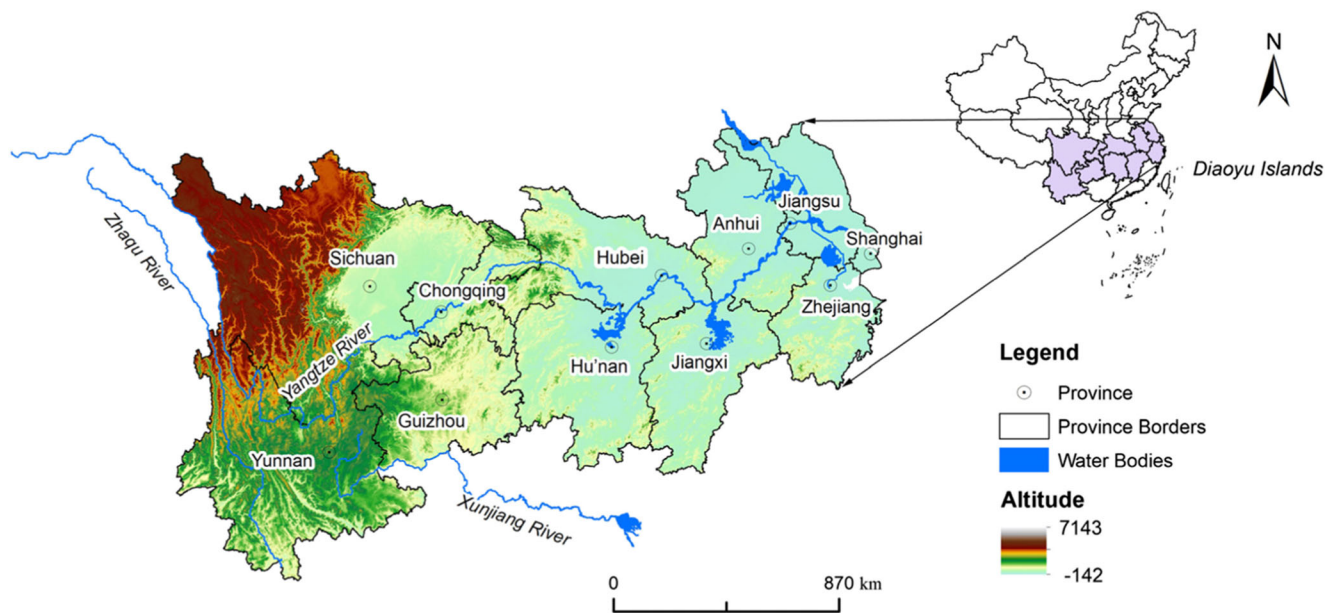


Fig. 2 Location and elevation of the YREB

2018; Jin et al. 2018). Therefore, the analysis of FF’s impact on the EEFU in the YREB has immense practical significance.

**Data sources and processing**

We obtained the data on the region’s farmland (with spatial resolution of  $30 \times 30 \text{ m}^2$  taken by the US Landsat TM/ETM satellite) from the land-use database provided by the Resources and Environment Scientific Data Centre (<http://www.resdc.cn>) (Deng et al. 2015). Using the geographic information system technology, we calculated each municipal district’s farmland area, which is the basic unit of analysis in this study. This study covers 4 years: 2000, 2005, 2010, and 2015. Social and economic statistics (e.g., data on machinery, fertilizers, length of highways, GDP, and the primary industry labor force) were obtained from the *China Regional Economic Statistical Yearbook* (2000, 2005, and 2010). In addition, the number of people engaged in units of the primary industry (guidance department on agricultural technology) was provided by the *China City Statistical Yearbook* (2000, 2005, 2010, and 2015). Since the *China Regional Economic Statistical Yearbook* lacks the relevant data for 2015, this study consulted the statistical yearbooks of each province to obtain the required index data. Regarding the EEFU, we selected labor force, agricultural machinery, and use of fertilizers as the input vector; the loss of nitrogen and phosphorus from fertilizers as undesirable production; and the primary industry’s output value as desirable production. Further, to achieve interregional comparability, we used the input and output per unit area to calculate the EEFU. The formula for the calculation is as follows:  $Z_i = F_i/A_i$ , where  $Z_i$  is the average input or output of farmland use,  $F_i$  is the input of production factors or output

of products,  $A_i$  is the farmland area in the municipal administrative jurisdiction, and the subscript  $i$  represents a municipal administrative district. Moreover, we used the loss coefficient and fertilizer input to calculate the undesirable outputs of farmland use. The concrete calculation formula is  $\text{wastage} = \text{input number of fertilizers} \times \text{loss coefficients}$  (Zhao et al. 2016). To achieve comparable values in different periods, we adjusted the price-related variables to a unified price.

**Methodology**

**Calculation of the farmland fragmentation**

FF can be described from three perspectives: size, shape, and distance fragmentation of plots (Lu et al. 2018b). As a result, this study selects the following three indicators to reflect the landscape-scale FF, and Fragstats 4.2 software is used to calculate the corresponding index value.

**Plot size coefficient of variance**

The plot size coefficient of variance (PScov) reflects the heterogeneity of a region’s farmland area (Zhang et al. 2015). The larger the PScov value, the higher the dispersion degree of the region’s farmland plot area. Further, with an increase in FAPC, the PScov value of plot area can better reflect the influence of plot area on farmland use than the average plot area.

$$MPS = \frac{1}{n} \sum_{i=1}^n a_i \tag{1}$$

$$PSSD = \sqrt{\frac{\sum_{i=1}^n \left[ a_i - \left( \frac{\sum_{i=1}^n a_i}{n} \right) \right]^2}{n}} \left( \frac{1}{100,000} \right) \quad (2)$$

$$PScov = \frac{PSSD}{MPS} \quad (3)$$

where  $n$  is the number of farmland plots in the region,  $a_i$  is the area ( $m^2$ ) of the farmland plot  $i$ ,  $MPS$  is the mean plot area ( $m^2$ ), and  $PSSD$  represents the plot size standard deviation.

### Area-weighted mean shape index

Many studies have pointed out that the shape of farmland plots can affect mechanical input and marginal income, such as Latruffe and Piet (2014), because the irregular shape of farmland not only increases the difficulty of farming but also reduces the utilization efficiency of agricultural machinery. However, by increasing the plot area of farmland, the negative impact of irregular shape will be weakened. Therefore, we selected the area-weighted mean shape index (AWMSI) to reflect the farmland's shape fragmentation level. The larger the AWMSI, the more complex and irregular the plot shape. The specific formula is as follows:

$$AWMSI = \sum_{i=1}^n \left[ \left( \frac{0.25P_i}{\sqrt{a_i}} \right) \left( \frac{a_i}{A} \right) \right] \quad (4)$$

where  $n$  is the number of farmland plots in the region;  $P_i$  and  $a_i$  are the perimeter (m) and area ( $m^2$ ) of farmland plot  $i$ , respectively; and  $A$  is the total area of farmland plots in a region.

### Mean nearest neighbor distance

In general, the distance between farmland plots results in an increase in transportation costs and a reduction in the efficiency of fixed assets (Carter and Yao 2002; Zhou et al. 2019). The mean nearest neighbor (MNN) is the main index used to measure landscape-level plot proximity (Riitters and Costanza 2019). In general, the larger the MNN, the larger the distance between farmland plots. Conversely, the plots of farmland were close to each other and distributed in aggregation. The specific formula is as follows:

$$MNN = \frac{\sum_{j=1}^n d_{\min ij}}{n} \quad (5)$$

where  $d_{\min ij}$  is the closest distance between plots  $i$  and  $j$  and  $n$  denotes the number of plots in the region.

### Calculation of the eco-efficiency of farmland use

Over the years, the Data Envelopment Analysis (DEA) model has become a popular model to measure efficiency (Charles et al. 2019). However, traditional DEA models (e.g., CCR and

BBC models) ignore the input-output slack. Hence, Tone (2002) constructed an SBM of the DEA model. Subsequently, by introducing undesirable outputs into the SBM model, the SBM-undesirable model for eco-efficiency evaluation was constructed (Cooper et al. 2007). The specific operating principles of SBM-undesirable are as follows: the input vector can be expressed as  $x \in R_m$  and the two output vectors as  $y^g \in R^a$  and  $y^k \in R^b$ . According to the actual process of farmland use, all kinds of input and output are greater than or equal to zero, that is,  $X \geq 0$ ,  $Y^g \geq 0$ , and  $Y^k \geq 0$ . Therefore, we can define the production possible set as  $p = \{(x, y^g, y^k) | x \geq X\lambda, y^g \geq Y^g\lambda, y^k \geq Y^k\lambda\}$ ,  $\lambda \in R^n$ ,  $\lambda \geq 0$ . Based on this, The SBM-undesirable model for calculating EEFU can be shown as follows:

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m D_i^- / x_{i0}}{1 + \frac{1}{a+b} \left( \sum_{r=1}^a D_r^g / y_{r0} + \sum_{h=1}^b D_h^k / y_{h0} \right)} \quad (6)$$

$$s.t. x_0 = X\lambda + D^-, y_0^g = Y^g\lambda + D^g, y_0^k = Y^k\lambda + D^k$$

$$D^- \geq 0, D^g \geq 0, D^k \geq 0, \lambda \geq 0$$

where  $D^-$ ,  $D^g$ , and  $D^k$  are the relaxed variables;  $\lambda$  is the weight vector; when  $\rho$  is less than 1, it means that at least one of  $D^-$ ,  $D^g$ , and  $D^k$  is not zero, and there is room for improvement of EEFU.

### Selection of other variables

Besides FF, many factors can affect the process of farmland use and thereby EEFU. Specifically, the proportions of the rural labor force and farmland area determine the allocation of farmland in rural regions, as well as determining the input-output relationship in the process of farmland use (Lin 1992). Many studies suggest that the presence of surplus rural labor force restricts the input of agricultural machinery and, thereby, limits economic benefits (Xie and Lu 2017). Moreover, a large labor force will also inhibit farmland transfer, and further aggravate the degree of farmland fragmentation (Latruffe and Piet 2014; Lu et al. 2018b). Contrarily, industrial development promotes the transfer of the agricultural labor force, and the contribution of the tertiary industry to the gross domestic product (GDP) often indicates the level of industrial development (Cai 2008). Additionally, the acquisition of sufficient market and technological information can promote acquisition of more advanced production technologies and optimization of the input-output relationship for farmland use, whereas the business volume of postal services can reflect the regional level of information communication (Chen et al. 2009). According to location theory, the provision of adequate highway transportation measures can reduce production costs and, thereby, improve the economic benefits of farmland use (Xiao et al. 2015). Furthermore, to improve the output of farmland

use, the Chinese government has established a Special Guidance Department on Agricultural Technology to provide technical guidance on the use of farmland, and the number of people working in this department usually indicates the level of governmental investment (Wang and Li 2014). Since 2006, a series of policies that support and benefit agricultural development has been promulgated in China, including the abolishment of agricultural taxes and provision of an increase in agricultural subsidies. Such policies cannot only solve the issue of insufficient funds in agricultural production but also improve the economic revenues of farmland use (Wang et al. 2018). Hence, in this study, the aforementioned indicators are the control variables, as shown in Table 1.

**Model establishment and estimation**

**Non-dynamic panel model**

**Model establishment** According to the “Literature review”, the EEFU is the result of comprehensive influence of external factors on farmland use. The Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model is classically used to analyze the impact of external factors and human activities on the environment (Ehrlich and Holdren 1971). Therefore, the STIRPAT model can be used as a basic model to analyze the FF’s impact on the EEFU. The specific forms of the STIRPAT model are as follows:

$$I = aP^bA^cT^d e \tag{7}$$

where *I* denotes the environment pressure; *P* is the number of people; *A* denotes the per capita affluence; *T* represents the technology level; *e* is the error term; *a* denotes the model’s fit coefficient; and *b*, *c*, and *d* denote the elastic coefficients of *P*, *A*, and *T*, respectively.

To eliminate heteroscedasticity, this model usually uses natural logarithmic transformation:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \tag{8}$$

Since panel data may have individual effects in large-scale studies, the removal of individual-specific means—a traditional method—is usually required to eliminate individual effects. Along with obtaining the index selection result, we expanded Equation (8) to incorporate the influence factors of the EEFU to examine FF’s impact on the EEFU. The non-dynamic panel model is defined as follows:

$$\ln EEFU_{i,t} = \beta_0 + \beta_1 \ln PS_{cov_{i,t}} + \beta_2 \ln AWMSI_{i,t} + \beta_3 \ln MNN_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \tag{9}$$

where *X* denotes the control variables, including *lnFAPC*, *lnLID*, *lnLHR*, *lnBVPS*, *lnPEPI*, and *FAP*;  $\beta$  is the regression coefficient;  $\varepsilon$  is the scalar value assumed to be identical and independent; and *i* and *t* denote the individual and time, respectively.

**Estimation and test** According to the empirical analysis practice, unit root tests and cointegration test should be performed on panel data to avoid spurious issues (Hou et al. 2019b). However, short panel data usually cannot reflect the time trend and the stationary nature of the sequence; hence, Baltagi (2008) suggests that the non-stationarity of short panel data be ignored. In addition, fixed-effect, random-effect, and mixed-effect models are used to estimate panel data; therefore, *F* test (Baltagi et al. 2007; Wooldridge 2005), Hausman test (Hausman 1978), and LM test (Breusch and Pagan 1980) were used to determine which estimation model we should select. Further, the cross-section correlation, heteroscedasticity, and sequence correlation in the panel data would render ineffective the traditional estimation method based on standard deviation statistical inference (Driscoll and Kraay 1998). Based on this issue, Hoechle (2007) proposed a regression method called the “Driscoll-Kraay standard error” which effectively overcomes the shortcomings of cross-section correlation, heteroscedasticity, and sequence correlation in panel data.

**Table 1** Results of the selection of some variables and their calculation methods

Variable	Interpretation of variable	Calculation method (unit)
FAPC	Farmland area per capita	FAPC = farmland area (km <sup>2</sup> ×10 <sup>-1</sup> )/the number of people employed in the primary industry (10,000 people)
LID	Levels of industrial development	LID = the production value of the tertiary industry (100 million yuan (CNY¥))/gross domestic product (100 million yuan)
LHR	Length of highways in a region	No calculation method (km)
BVPS	Business volume of postal services	No calculation method (100 million yuan)
PEPI	People engaged in units of the primary industry (guidance department on agricultural technology)	No calculation method (10,000 people)
FAP	Favorable agriculture policy	No calculation method (dummy variable)

## Threshold model

According to the method by Hansen (1999), we constructed a threshold model to analyze FF's impact on the EEFU. There may be multiple thresholds; however, multiple thresholds and a single threshold are set in the same manner. Therefore, we used a single-threshold model to explain the model establishment process. This single-threshold model is defined as follows:

$$\ln EEFU_{i,t} = \beta_0 + \beta_1 tdv \cdot I(\ln FAPC \leq \theta) + \beta_2 tdv \cdot I(\ln FAPC > \theta) + \varphi X_{i,t} + \varepsilon_{i,t} \quad (10)$$

where  $I(\cdot)$  is the indicator function which usually takes a value of 0 or 1;  $tdv$  represents the threshold dependent variable and denotes  $\ln PS_{cov_{i,t}}$ ,  $\ln AWMSI_{i,t}$ , and  $\ln MNN_{i,t}$ , respectively;  $\ln FAPC$  is the threshold variable;  $\theta$  is the threshold value that should be estimated; and  $\varepsilon_{i,t}$  is assumed to be independent and identical. The other variables have the same concepts as those defined in Equation (9). When one among  $\ln PS_{cov_{i,t}}$ ,  $\ln AWMSI_{i,t}$ , and  $\ln MNN_{i,t}$  is selected as the threshold dependent variable, the remaining variables will be added to the control variables. Moreover, single, double, and triple thresholds are, in turn, identified by a self-sampling process. For threshold effect test and significance test of threshold value, refer to the study by Hansen (1999).

## Results and discussion

### Analysis of the regression results of non-dynamic panel data

In Table 2, (1), (2), and (3) represent the estimation results of the mixed-, fixed-, and random-effect models, respectively. Further, the  $F$  test result rejected the original hypothesis  $H_0$ : all  $u_i = 0$ , indicating that the fixed-effect model is superior to the mixed-effect model. Simultaneously, according to the Hausman test results,  $p < 0.01$ . Accordingly, we rejected the original hypothesis that there is no difference between the random- and fixed-effect models. The fixed-effect model is more suitable than the random-effect model for estimating FF's impact on the EEFU. However, the Pesaran test (Pesaran et al. 2004), Wooldridge test (Wooldridge 2005), and modified Wald tests (Greene 2000) revealed that the corresponding  $p$  values were less than 0.01, indicating that panel data could not exclude the possibility of cross-section correlation, heteroscedasticity, and sequence correlation. Therefore, we used the fixed-effect Driscoll-Kraay model's standard error to estimate the

regression coefficient, and Table 3 depicts the results of this estimate.

Among the control variables,  $\ln FAPC$ ,  $\ln LHR$ ,  $\ln LID$ , and  $FAP$  have a significant effect on the  $\ln EEFU$ . Conversely,  $\ln BVPS$  and  $\ln PEPI$  have a significant negative effect on  $\ln EEFU$ . It can thus be concluded that continuing to reduce the rural population, improve rural traffic conditions, and increase favorable agriculture policy will play an important role in improving the EEFU. This is similar to the results of other studies (Xie and Lu 2017; Hou et al. 2019a). Specifically, rural population transfer and favorable agriculture policy promote the substitution of agricultural machinery for rural labor, thus reducing the cost of farmland use. The improvement of traffic conditions is conducive to the cultivation of cash crops, thus raising incomes. In contrast, the effect of the development of the tertiary industry on the EEFU is quite constrained, as industrial development has caused a large number of young laborers to leave the countryside, leaving behind the elderly. Contrary to expectations,  $\ln BVPS$  has a negative effect on  $\ln EEFU$ . This could be because farmers pay more attention to economic benefits and ignore the negative environmental benefits brought by farmland use, which is also the root cause of a large number of chemical fertilizers and pesticides lost in the process of farmland use in China. In addition, according to the negative effects of  $\ln PEPI$  on  $\ln EEFU$ , although it is only at 10% significance, we speculate that guidance department on agricultural technology still focuses on the economic rather than ecological benefits of farmland use. Further, three types of FF were observed to have no significant impact on the EEFU, for which there may be two reasons: first, landscape-level FF does not affect farmland use activities; hence, FF's impact on the EEFU is not significant. Second, there is a nonlinear relationship between the FF and the EEFU. So, it is necessary to use threshold model to test the impact of landscape-scale FF on the EEFU.

### Analysis of the threshold regression result

Table 3 reports that the  $p$  statistic of the  $F$  test is less than 0.01; accordingly, we rejected the original hypothesis that there is no threshold effect. According to the  $F$  statistics and 95% confidence interval, there is a single threshold for the impacts of the three types of FF (size, shape, and distance) on the EEFU. In this case, we used a single-threshold model for the regression analysis.

Table 4 reports the regression results with  $\ln PS_{cov}$ ,  $\ln AWMSI$ , and  $\ln MNN$  as the threshold-dependent variables, respectively. We found that  $\ln PS_{cov}$  and  $\ln MNN$  have similar effects on  $\ln EEFU$ . When  $\ln FAPC$  does not exceed the threshold value (1.548 and 1.542), size and distance fragmentation promote EEFU improvement. On the contrary, they will inhibit EEFU improvement. Specifically, when  $\ln FAPC$  is lower than threshold value, spatially dispersed and different-scale



**Table 2** Results of non-dynamic panel regression

Variables	(1) OLS robust	(2) FE robust	(3) RE robust	(4) Driscoll–Kraay
<i>lnPScov</i>	−0.0260 (0.1001)	0.5492 (0.2713)	−0.0473 (0.1213)	0.5492 (0.1629)
<i>lnAWMSI</i>	0.1031 (0.1175)	0.1079 (0.1573)	0.1489 (0.1319)	0.1079 (0.1435)
<i>lnMNN</i>	0.6552*** (0.1752)	0.2847 (0.2097)	0.6302*** (0.2064)	0.2847 (0.1591)
<i>lnFAPC</i>	0.3192*** (0.0847)	0.4122** (0.0901)	0.3342*** (0.1020)	0.4122** (0.0848)
<i>lnLID</i>	−0.2030 (0.2037)	0.1543* (0.1420)	−0.1166 (0.1986)	0.1543* (0.1372)
<i>lnLHR</i>	−0.0668 (0.0756)	0.5337*** (0.0158)	0.0003 (0.0627)	0.5337*** (0.0126)
<i>lnBVPS</i>	0.0853 (0.0590)	−0.4564** (0.0280)	0.0305 (0.0737)	−0.4564** (0.0284)
<i>lnPEPI</i>	−0.0442 (0.0340)	−0.0218* (0.0452)	−0.0437 (0.0378)	−0.0218* (0.0452)
<i>FAP</i>	0.3694*** (0.0738)	0.5842** (0.0277)	0.3868*** (0.0659)	0.5842*** (0.0245)
<i>cons</i>	−5.1048*** (1.3256)	−10.6038*** (2.6321)	−5.3146*** (1.3649)	−10.6038*** (1.8467)
<i>F test</i>	$F(125, 369) = 1.84$ Prob > $F = 0.0000$		—	—
<i>Hausman test</i>	—	$\text{Chi}^2(9) = 63.64$ Prob> $\text{Chi}^2 = 0.0000$		—
<i>Pesaran test</i>	Pesaran’s test of cross-sectional independence = 38.457, Pr = 0.0000			—
<i>Wooldridge test</i>	$F(1, 125) = 28.162$ , Prob > $F = 0.0000$			—
<i>Modified Wald test</i>	$\text{Chi}^2(126) = 421.31$ Prob > $\text{Chi}^2 = 0.0000$			—

Note: \*\*\*, \*\*, and \* indicate that variables are statistically significant at 1%, 5%, and 10%, respectively. The values in parentheses reflect the standard error in columns (1), (2), and (3) and the Driscoll-Kraay standard error in (4)

farmland plot can satisfy the requirements of farmers’ agricultural production activities. In fact, landscape-scale FF does not have a direct impact on the EEFU at this time. On the contrary, landscape-scale FF creates conditions for the farmer-/plot-scale FF’s positive effect on EEFU. For example, a small plot reduces fertilizer input and its undesirable output and may also reduce the cost of farmland use because there is no need to manage different space of the plot (as stages 1 or 2 in Fig. 1)

(Sklenicka 2016). However, in the context of social economy development, the increase of FAPC also increases the plot size managed by farmers, thus increasing the effect of landscape-FF on farmers’ farmland use activities (as stages 3 or 4 in Fig. 1).

Unlike the two aforementioned types of FF, *lnAWMSI* has a negative effect on *lnEEFU*, irrespective of whether the *lnFAPC* crosses the threshold value (1.373). The possible

**Table 3** Testing for the threshold effects and threshold value estimation

Threshold-dependent variable	Number of thresholds	F-statistics	Threshold values	95% confidence interval
<i>lnPScov</i>	Single threshold	6.976***	1.548	[−0.261, 0.983]
	Double threshold	10.647	1.018	[0.667, 1.519]
			0.490	[0.281, 0.748]
<i>lnAWMSI</i>	Triple threshold	0.000	0.758	[0.662, 0.868]
	Single threshold	5.346**	1.373	[−1.261, 1.983]
	Double threshold	4.689*	1.549	[1.274, 1.983]
<i>lnMNN</i>			0.834	[0.153, 1.196]
	Triple threshold	0.000	1.128	[1.016, 1.288]
	Single threshold	6.215**	1.542	[−0.317, 1.983]
	Double threshold	8.422	1.121	[0.587, 1.697]
			0.483	[−0.504, 0.748]
	Triple threshold	0.000	0.758	[0.667, 0.868]

Note: \*\*\*, \*\*, and \* indicate that variables are statistically significant at 1%, 5%, and 10%, respectively. Each bootstrap sample was repeated 300 times, and the minimum sample estimate is 50 samples

reason is shape fragmentation restricts the input of agricultural machinery, increases the cost, and reduces the economic benefits of farmland use. Comparing the regression coefficient, we find that when the  $\ln FAPC$  does not exceed the threshold value, the regression coefficient of shape fragmentation is only  $-0.0677$ . In contrast, the regression coefficient becomes  $-0.4501$ . In addition, the significance level of regression coefficient also changed greatly, from 5 to 10%. It is also confirmed that with the increase of FAPC, the effect of landscape-scale FF on farmland use is increasingly prominent.

The regression coefficients of other control variables were only mildly altered compared with the regression outcomes of the non-dynamic panel and threshold models; however, the significance level did not change, which demonstrates that the threshold model's assessment findings are robust (Hansen 1999). Thus, we have reason to believe that the results of panel threshold model are more credible. This confirms our initial hypothesis that there is a nonlinear relationship between landscape-scale FF and EEFU. The above research results have strong policy implications regarding the economic and ecological benefits of farmland use. When farmers only consider economic benefits, the promotion of large-scale farmland transfer is not conducive to solving the ecological and environmental problems of farmland use. In response, in regions that exceed the threshold value, the local government should not only actively promote large-scale farmland transfer, it should also give play to the positive effects of policies such as improved traffic conditions, labor transfer, and agricultural subsidies so as to offset the negative effects of landscape-scale FF on the EEFU. On the contrary, for regions in which FAPC is lower than the threshold value, the transfer of farmland should not be promoted on a large scale, but should properly guide farmers' chemical fertilizer reduction actions so as to solve the ecological and

environmental problems of cultivated land use in combination with the positive role of other policies.

## Conclusions

With the rapid development of the social economy, ecological (environmental) problems caused by farmland use are becoming increasingly prominent. Therefore, promoting a balance between economic and ecological benefits is key to realizing the sustainable utilization of farmland. At present, in the context of the promotion of large-scale farmland transfer to reduce the level of farmer-/plot-scale FF, the impact of landscape-scale FF on the EEFU remains unclear. Therefore, in this study, non-dynamic panel and threshold effect models were applied to conduct an empirical analysis based on panel datasets of the YREB's municipal administrative regions in the years 2000, 2005, 2010, and 2015.

The study concludes that there is a nonlinear relationship between landscape-scale FF and EEFU under the constraint of  $\ln FAPC$ , in which the threshold values of area, shape, and distance fragmentation are 1.548, 1.373, and 1.542, respectively. Landscape-scale FF is not always conducive to the balance of economic and ecological benefits of farmland use. Promoting large-scale farmland transfer blindly will cause the intensification of eco-environmental problems in the utilization of farmland. In contrast, combining the FAPC of different regions, the implementation of farmland transfer policy in some areas alone becomes a feasible measure to alleviate the eco-environmental impacts of farmland use. At the same time, exerting the positive effect of the shrinking rural population, improving rural traffic conditions, and increasing favorable agriculture policy have remarkable effects on improving EEFU.

**Table 4** Regression results of the threshold model

Threshold-dependent variable	$\ln PScov$	$\ln AWMSI$	$\ln MNN$
$\ln PScov$	—	0.2545 (0.41)	0.4829 (0.81)
$\ln AWMSI$	0.1415 (0.21)	—	0.1397 (0.21)
$\ln MNN$	0.1055 (0.14)	0.3254 (0.43)	—
$\ln FAPC$	0.4286** (2.03)	0.3370** (1.58)	0.4226** (2.01)
$\ln LID$	0.1553* (0.88)	0.1254* (0.71)	0.1511* (0.85)
$\ln LHR$	0.5343*** (1.30)	0.5229*** (4.21)	0.5306*** (4.27)
$\ln BVPS$	-0.4257*** (-4.20)	-0.4692*** (-4.67)	-0.4208*** (-4.13)
$\ln PEPI$	-0.0278* (-0.40)	0.0085* (0.12)	-0.0284* (-0.41)
$FAP$	0.5473*** (4.32)	0.5117*** (3.54)	0.5522*** (4.35)
$\beta_1$	0.4975** (0.83)	-0.0677** (-1.37)	0.1183** (0.15)
$\beta_2$	-0.0260** (-1.18)	-0.4501* (0.65)	-0.0352*** (-1.27)
$con$	-9.3980** (-1.86)	-9.5710** (-1.89)	-9.3475** (-1.86)

Notes: \*\*\*, \*\*, and \* indicate that variables are statistically significant at 1%, 5%, and 10%, respectively. The values in the parentheses denote that the corresponding Z statistic and  $\beta_1$  and  $\beta_2$  are the regression coefficients of the threshold-dependent variable and threshold variable cross terms

Undeniably, using artificial measures to change the landscape-scale FF is also a measure to reduce the negative effect of landscape-scale FF on EEFU. However, the reclamation of farmland usually leads to the reduction and fragmentation of other types of landscapes (e.g., forest and grass), while the withdrawal of farmland from agricultural production may not be conducive to food security. Therefore, we do not recommend that the impact of landscape-scale FF on EEFU be reduced by changing the landscape characteristics of farmland.

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**Data availability** All data generated or analyzed during this study are included in this published article.

## Declarations

**Ethics approval and consent to participate** Not applicable.

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