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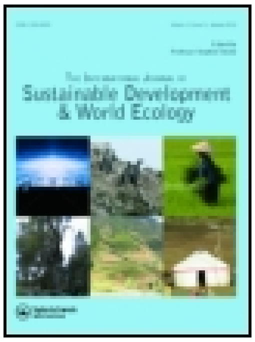

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ABSTRACT

Conversion of Cropland to Forestland Program (CCFP) has greatly impacted China's agricultural sector, and more specifically rural farmers. While changes in living standards as a result of the implementation of the CCFP have been analyzed, little research has been conducted regarding the impacts of such policies on farming operations. As agriculture contributes nearly 10% of national GDP, it is important to analyze the implications of policies on a national industry. An input-oriented data envelopment analysis (DEA) model was used to examine the technical efficiency of farming operations following implementation of the CCFP, using survey data from farmers in Jiangxi, Shaanxi, and Sichuan provinces. Additionally, the impact of factors such as urbanization, age and education, and land fragmentation was examined with respect to farming operational efficiency. Scale inefficiency was found to have the greatest effect on overall inefficiency in farming operations in comparison to pure technical inefficiency, which was largely influenced by the presence and degree of land fragmentation of land holdings. Findings can be used to inform national land-use policies facilitating land fragmentation in China and address gaps in existing broader level studies that utilize non-parametric approaches to examine the technical efficiency of Chinese farmers affected by the CCFP.

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China; data envelopment analysis; forest policy; forest land-use; technical efficiency

1. Introduction

In recent decades, multiple environmental land-use policies have been implemented in China. The largest in scale and investment has been the Conversion of Cropland to Forestland Programme (CCFP), also known as the Grain-to-Green Program. Implemented in 1999, the CCFP aims to reduce and control soil erosion and land degradation in high-risk areas through the conversion of farmland or desertified fields back to grasslands and forests (Chen et al. 2009a), particularly in the Yangtze and Yellow River basins. The program aimed to increase national forest cover by 14.7 million ha, or by 5%, by the reconversion of farmland to forests, this ambitious program has affected over 32 million households or nearly 17% of the rural population (Wang et al. 2018). The present study builds upon the analysis of the dataset from (Wang et al. 2018) by analyzing the effect of the CCFP on rural operations. This was done through analysis of the technical efficiency of the affected population, a technique that has been used previously to analyze the CCFP (Xuxia and Xiuqing 2002; Yang et al. 2009; Li et al. 2010a). Unlike many previous studies, which have analyzed only the population of interest in a single area, the present study examined data from three Chinese provinces, thereby providing a more comprehensive analysis.

1.1 Current research on the CCFP and the role of technical efficiency

A substantial body of literature exists addressing the positive ecological benefits of increasing forest cover in China (Caldwell et al. 2007; Groom et al. 2010). Afforestation and reforestation have been associated with a reduction in soil erosion area by 4.1 million hectares, or a 4.1% reduction annually (Wang et al. 2008), with a significant reduction occurring in the Yellow and Yangtze River basins (Zhou et al. 2009).

While the overall ecological effects of environmental land-use policies such as the CCFP over the last few decades have been generally positive at the national level (Sun et al. 2015), the CCFP's impact and response at the local level have been mixed. Most previous studies have used income as a proxy for the welfare of individual farmers affected by the CCFP (Wang 2009; Delang and Yuan 2015). One study, however, has found that while the CCFP has been successful in terms of poverty alleviation, the program has failed to provide equal

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distributional benefits to households with the lowest income (Uchida et al. 2005). Liang et al. (2012) further concluded that the CCFP only benefits poor participants if the compensation received from the government is 'greater than the opportunity cost of the retired land (p. 152)'. Previous research has also suggested that the CCFP subsidy compensation system design is too uniform, and should target economically constrained households in order to be more cost-effective in poverty alleviation (Groom et al. 2009). Financial compensation to farmers affected by rural land-use change policies has provided labor flexibility and opportunities for employment and income (Uchida et al. 2009); however, as most farmers are migrating to urban areas (Fang and Dewen 2003), this may contribute to other problems related to overcrowding in urban centers (Friedmann 2007).

Similarly, studies have been conducted regarding the satisfaction of rural farmers to the CCFP. These have found that the program was generally well perceived and was supported by local farmers in Sichuan and Shaanxi (Yan-Qiong et al. 2003; Cao et al. 2009). However, other studies have indicated that farmers in Shaanxi are concerned about the long-term personal costs that might occur as a result of environmental restoration (Cao et al. 2009) and that the goals of the CCFP have not always been clearly understood by farmers (Du 2004). While the majority of farmers understood and were in agreement with the CCFP's overall goal of environmental sustainability, maintaining livelihoods was often of greater concern to locals affected by the programs (Lian et al. 2007).

While there have been a number of studies of the CCFP, little research has been conducted examining the effects of the reforms on farming operations. National land-use policies have affected rural farmers to varying degrees, with most farmers now gaining their income from a mixture of agricultural, forestry, subsidies, and off-site work (Li et al. 2010a). This study, therefore, aimed to observe the operational activities of farmers affected by the CCFP through an analysis of their technical efficiency.

Technical efficiency can be described as the effectiveness with which a set of inputs is utilized to produce an output, and can be modeled through a variety of techniques, such as the Data Envelopment Analysis (DEA) model (Charnes et al. 1978). While both DEA and Stochastic Frontier Analysis (SFA) methods have been used to calculate the technical efficiency of farming operations, DEA models are non-parametric and have gained greater popularity in recent years due to their ability to calculate multiple inputs and outputs with differing units, as well as their lack of a need to specify functional form (Hjalmarsson et al. 1996; Krasachat 2003). As such, the flexibility of DEA models provides an advantage over parametric SFA models.

The impacts of the CCFP on the technical efficiency of farming operations in Ansai, a district of Yan'an prefecture in the province of Shaanxi, have previously been analyzed using the constant returns to scale (CRS) model (Li et al. 2010b). However, this model is only appropriate when the operation can be conducted at an optimized scale (Coelli et al. 2005). Previous studies regarding the impacts of the CCFP on farmers' technical efficiency have all been limited in scope to a single town or county (Xuxia and Xiuqing 2002; Yang et al. 2009; Li et al. 2010b); therefore, this study sought to analyze the impacts of the CCFP at a broader level. More specifically, we utilized an input-oriented DEA model to analyze the technical efficiency of a sample of farmers directly affected by the CCFP with a focus on variable returns to scale (VRS). The farmers were surveyed in 2012 and resided in areas heavily affected by the CCFP.

2. Data and methodology

2.1 Research questionnaire and variables selection

As there are no large-scale rural Chinese agricultural databases available, a subset of data was used from a questionnaire distributed in 2012 to rural households affected by the CCFP (Wang et al. 2018). The questionnaire was distributed to respondents through the joint efforts of local forestry agencies as well as various state government agencies. Survey data collection followed a non-probability purposeful sampling technique (Wang et al. 2018). This was required to restrict the survey to respondents who were targets of the CCFP.

The questionnaire was tailored to investigate the characteristics and responses of these farmers from five aspects, including: (1) understanding of the CCFP; (2) participation in the CCFP; (3) outlook on the effectiveness of the CCFP; (4) opinions and suggestions for the CCFP; (5) characteristics of the sample households. This paper examines the characteristics of the sample households (aspect 5) since it provided information such as income, land holdings, number of household laborers, and capital expenditure; all of which are necessary variables for the DEA analysis. Additionally, individual socio-demographic statistics (i.e. education, age) were also examined to gain further context.

2.2 Sampling procedure

As the dataset employed for this study was a subset of the one used in Wang et al.'s (2018) paper, the sampling procedure was identical up to the point where the subset was created. The initial sample used was taken from the aforementioned study. The sampling procedure employed in Wang et al. (2018) created a sample[1] randomly selecting 50–60 rural households from 32 counties in Jiangxi, Shaanxi, and Sichuan (Wang et al. 2018). For a map and overview of the three provinces, please see Figures 1 and 2.

Figure 1. Selected provinces for the study: Jiangxi, Shaanxi, and Sichuan.

Figure 2. National extent of the CFPP or Grain-to-Green Program (Wang et al. 2013).

A subset of respondents was further selected for this paper by eliminating the rural household respondents from the sample of the aforementioned paper who do not have income from forestry or agricultural activity. A lack of income from either forestry or agricultural activities disqualified the respondents from being used in the DEA model, as it suggests that no farming or forestry operations take place on their land holdings. Additionally, several rural households had questionnaire responses which included too many errors or missing data, as such, they were removed for this subset as well.

After removing all unqualified rural households and ones with incomplete responses, a total of 886 out of the initial 1089 respondents from the initial sample of Wang et al. (2018) remained. Some counties had no respondents who received income from forestry/agricultural activities on their land. As such, during the creation of the subset, all households from those particular counties ended up being removed. Therefore, the final sample used in this model included 886 respondents from 27 counties across the three provinces.[2] A breakdown of the distribution of respondents[3] for each county is included in Figure 3. As shown, due to the large variation in observations between different counties, an analysis at the county level would be difficult; therefore, the analysis of this paper will be confined to the provincial level.

Due to the specific criteria for respondents (i.e. rural farmers in China currently gaining an income from forestry or agricultural activities), limited accessibility, and voluntary responses, results cannot be generalized at the national level. Rather, the purpose of the household sampling was to gain responses from the rural farmers directly impacted by the CCFP in order to gain insight into their characteristics and the impacts of the CCFP on them.

Wang et al. (2018)'s study only analyzed the responses of the households affected by the CCFP but not how their actual farming operations were affected. Therefore, this paper will address the gap by adding insight to how their operations were affected in terms of technical efficiency.

2.3 Statistical analysis

Data analysis was conducted utilizing Stata SE Version 12.0 software, in addition to DEAP Version 2.1 software (Coelli 1996). Further basic exploratory and descriptive analyses were conducted using Microsoft Excel.

2.4 Methodology

The first DEA model was published in 1978 (Charnes et al. 1978), since then there have been many developments, with an improved model being released in 1984 (Banker et al. 1984). DEA models can adopt several forms, all of which have unique characteristics. For this study, each sample farmer was referred to as a single decision-making unit (DMU), evaluated relative to their ratio of inputs to outputs. The DMUs were subject to the same inputs and outputs enabling the analysis of their respective efficiencies (Charnes et al. 1978). All technical efficiency calculations were conducted using DEAP 2.1 (Coelli 1996).

Calculating technical efficiency utilizing the DEA model is advantageous as it does not require specification of a functional form which can introduce potential biases based on the form Krasachat 2003. Technical efficiency is typically calculated using one of the two assumptions, (1) Constant Returns to Scale (CRS) or (2) Variable Returns to Scale (VRS). Under CRS, the assumption is that the DMU is operating at an optimal scale Krasachat 2003. This assumption can be relaxed under VRS where the possibility that the DMU is not operating at an optimal scale can occur, 2003. We will calculate technical efficiency scores under both methods in the present study. Additionally, we utilized an input-oriented model as farmers generally have greater control over inputs, and input-oriented models have been used in farming sector studies across multiple countries (Thiele and Brodersen 1999; Krasachat 2003; Galanopoulos et al. 2006).

Since VRS will always be greater than or equal to CRS due to the relaxing of the assumption that the DMU is operating under optimal scale, scale efficiency can also be calculated (Krasachat 2003). This can be done so by dividing the technical efficiency scores under CRS by the one under VRS, this is expressed below:

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}} \tag{1}$$

where if SE = 1 perfect scale efficiency has been achieved, indicating that a CRS assumption would be appropriate as farming operations[4] would be occurring at an optimized scale (Ding 2003). An SE value < 1 implies that scale inefficiencies exist. This is an important calculation in the present study, as it will allow us to determine the scale efficiencies (or inefficiencies) under the CCFP.

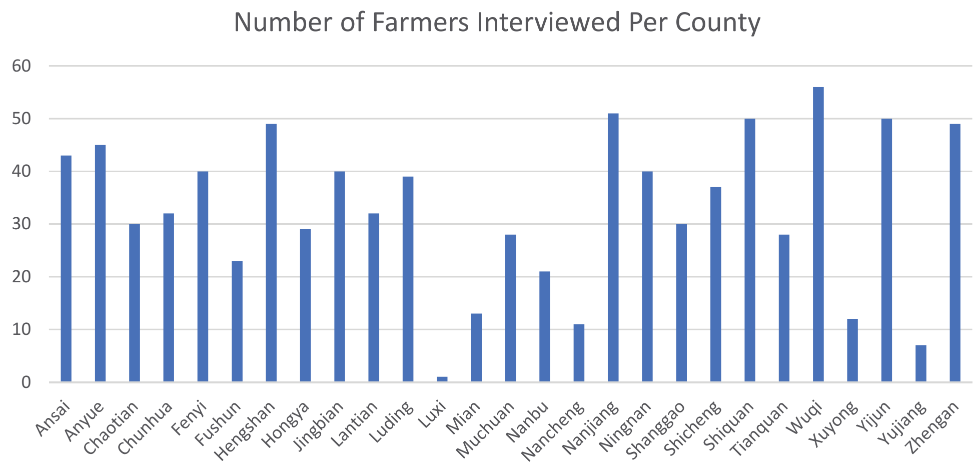

Figure 3. Distribution of sample respondents by county.

Under the condition of input-orientation, this study tested whether a DMU 'under evaluation can reduce its inputs while keeping the outputs at their current levels' (Zhu 2014). Inputs including land, labor, and capital were minimized while holding the output constant.

As such, following the methodology of Charnes et al. (1978), the technical efficiency score calculated from the input-oriented DEA model can be represented most basically as the following:

$$\max h_0 = \frac{\sum_r U_r Y_{rj_0}}{\sum_i V_i X_{ij_0}} \tag{2}$$

$$s.t. \frac{\sum_r U_r Y_{rj}}{\sum_i V_i X_{ij}} \leq 1, For\ Each\ DMU\ j = 1, \ldots, n,$$

$$U_r, V_i \geq 0$$

where h_0 is the technical efficiency score given as the ratio for r outputs represented as Y and i inputs represented as X. Furthermore, outputs are weighted by U and inputs are weighted by V. The constraints force the score to take a value lesser than or equal than 1 such that a technical efficiency score of 1 means the DMU is fully efficient and lies right at the efficiency frontier enveloping the DMUs operating at less than full technical efficiency (Charnes et al. 1978). Additionally, the interpretation of the weights is that they are the values which maximize the technical efficiency score for that particular DMU (Charnes et al. 1978).

Since this paper computes technical efficiency scores using DEAP 2.1 which follows the computational methodology laid out in Charnes et al. (1978), please refer to the aforementioned text for a full mathematical description of the computational method.

Inputs to this model included capital, labor, and land, whereas the output of the function was farmer income. Capital reflects the material costs of crops, seedlings, pesticides, fertilizers, and irrigation. Labour is the total number of laborers listed by each household in the survey subtracted by the number of migratory laborers that are not present to contribute to farming operations. Land is defined as including all holdings held following the implementation of the CCFP. Income reflects the combined income from both agricultural and forestry activities in the year of the survey. All inputs and the output reflect the combined inputs/output from both agricultural and forestry activities as the CCFP has had an effect on the technical efficiency of both activities.

Quantifying the degree of land fragmentation in the sample provinces is an important part of the analysis due to the link between land fragmentation and scale inefficiency (Latruffe and Piet 2013). Multiple measures of land fragmentation exist, such as utilizing the number of plots as a proxy (Fleisher and Liu 1992; Wan & Cheng 2001a), with more land plots reflecting a higher degree of land fragmentation. More recent research has employed the Simpson Index as a method to gauge land fragmentation (Wu et al. 2005; Shuhao et al. 2008; Chen et al. 2009b). Consequently, we utilized both measures to expand and provide a comprehensive analysis.

The Simpson Index (SI) can be calculated as:

$$SI = 1 - \frac{\sum_{i=1}^{N} a_i^2}{\left(\sum_{i=1}^{N} a_i\right)^2} \tag{3}$$

where a_i is the area of an individual land plot. The index ranges from 0 to 1 with higher values reflecting a higher degree of land fragmentation (Wu et al. 2005).

Finally, simple descriptive statistical methods were utilized to examine characteristics such as age, education, as well as inputs of the sample DMUs to gain greater context regarding the differences between the sample DMUs from each province.

2.5 Remote sensing analysis

Remote sensing analysis was also conducted alongside the DEA model to complement its findings.

2.5.1 Dataset

Data products from the global land cover initiative, GlobeLand30, were used to analyze national forest cover change in China during the period of study (2000–2010) for sampled provinces. GlobeLand30 is the first open-access, high-resolution map of the Earth's land cover, and comprises land cover classifications for years 2000–2010, derived from more than 20,000 multi-spectral images from Landsat TM5/ETM+ (Landsat 5 Thematic Mapper [TM5] and Enhanced Thematic Mapper Plus [ETM+]) and the Chinese Environmental Disaster Alleviation Satellite (HJ-1), in addition to auxiliary datasets (Chen et al. 2015). GlobeLand30 data products include images with a 30-m resolution and identify land cover class according to 10 land cover classifications (Table 1) (Chen et al. 2015). The overall accuracy of GlobeLand30 2010 is over 80%, suggesting that it is more accurate than existing automated classification methods (Chen et al. 2015).

2.5.2 Forest change map generation

In order to generate a map of forest cover change, the land classification types were reclassified and recoded. First, a water-related classification was created, combining pre-existing land classes 'waterbodies' and 'permanent snow, ice sheet, and glacier'. Post-reclassification, the remaining nine land classification types were recoded to reflect this (Table 1). The land cover change map was calculated by generating the differences between GlobeLand30 2000&2010 land cover

Table 1. Definitions of the 10 land cover types in GlobeLand30 data products and their recoded values (Chen et al. 2015).

Land cover type	Definition
Cropland	Land used for agriculture and horticulutre, including paddy fields, irrigrated and dry farmland, orchards, etc.
Forest	Land with tree cover >30%, including deciduous and confierous forests, and sparse woodland with 10–30% tree cover
Grassland	Lands with >10% grass cover
Shrubland	Land with shrub cover >30%, including both deciduous and evergreen shrubs, and desert steppe with shrub cover >10%
Wetland	Land covered with wetland plants and waterbodies, including inland marsh, lake marsh, river floodplain, forest/shrub wetland, peat bogs, mangrove and salt marsh
Waterbodies	Waterbodies in land area, including rivers, lakes, resevoirs, etc.
Tundra	Land covered by lichen, moss, and hardy perennial herbs and shrubs in the polar regions, including shrub tundra, herbaceous tundra, wet tundra, barren tundra
Artifical cover	Land modified by human activities, including habitation, industrial and mining areas, transportation facilitaites, and interior urban green zones and waterbodies, etc.
Bare land	Land with vegetation cover <10%, including desert, sandy fields, and bare rock
Permanent snow, ice sheet, and glacier	Land covered by permanent snow, glacier, and ice caps

classifications. In the derived change map, pixels associated with each land class conversion were attributed to the respective land cover type, enabling an analysis of the net change, gain, and loss of forest cover, as well as the respective transitions and trends between land classes during the study period.

2.5.3 Forest change map analysis

Forest change analysis was then conducted at various scales. Zonal statistics were used to summarize forest change events at the national, provincial, and county levels. Calculated metrics included the percentage net forest change, forest gain, forest loss, and the associated land cover type from which the conversion occurred. The area of each class was calculated as follows:

$$S_c = \text{pixel}_{\text{area}} * \sum_{i=0}^{N-1} p_{c_i}$$

where S_c is the change of area in class '*c*' in year '*i*' *within* a certain region. The pixel size of the change map is represented by $\text{pixel}_{\text{area}}$.

The rate of change of land cover class, *c*, was calculated as:

$$R_c = \frac{S_c}{S_{forest\_2000}}$$

where $S_{\text{forest\_2000}}$ is the total forested area in the year 2000 within a certain region. These metrics were added as new attributes of corresponding political boundary files. Land-use conversions and net forest change were mapped at the county level after analyses using ArcMap 10.3.1 from the ESRI software suite.

For a full visual overview of the methodology and analysis process please see Figure 4.

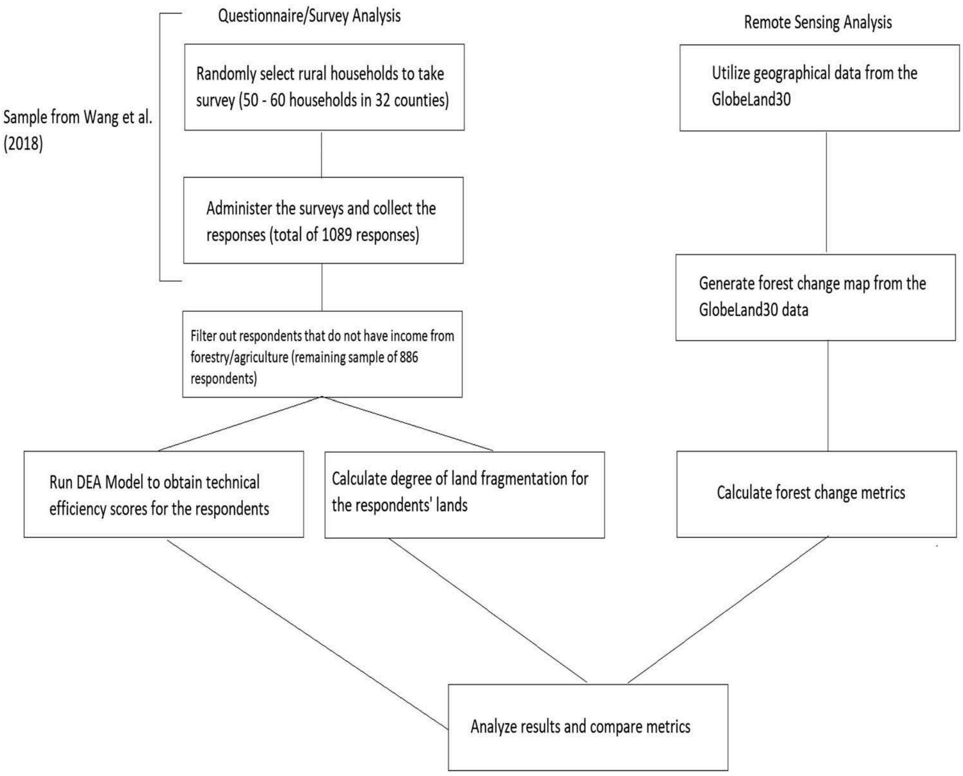

Figure 4. Flowchart of the methodology and analysis process.

3. Results and discussion

3.1 Technical efficiency (TE) scores

The results of the DEA model analysis in terms of TE scores for the entire sample[5] and by province are provided in Table 2:

The mean TE score for the entire sample (i.e. including responses from all three surveyed provinces) under VRS measured 0.90. The mean CRS TE score for the sample was 0.55. The mean scale efficiency (SE) score, derived from these two scores, was 0.61 (Table 2).

VRS TE scores can be considered as pure technical efficiency (PTE) scores, whereas CRS TE scores can be considered as the overall technical efficiency (OTE). The relative inefficiencies can be obtained from the OTE, PTE, and SE values. In measuring both efficiency and inefficiency, OTE can be decomposed into pure technical and scale efficiency and OTIE into pure technical and scale inefficiency (Krasachat 2003; Kumar and Gulati 2008). These values indicate that most of the inefficiency can be eliminated through addressing inefficiencies from improper scaling and utilizing best practices. In addition, inefficiencies in scale are much greater than those from purely technical inefficiencies. Nearly every farmer in the sample demonstrated increasing returns to scale (IRS), wherein only 3 farmers out of 886 reported decreasing returns to scale (DRS) – potentially indicating the need to enlarge household land holdings in terms of area (Wan and Cheng, 2001b).

The results indicate that farmer from Shaanxi and Sichuan on average demonstrate greater PTE following implementation of the CCFP compared to those in Jiangxi (Table 2). The lowest ratio of optimally efficient farmers to farmers that were not optimally efficient (VRS TE score less than 1) exists in Jiangxi (VRS TE score of 1, producing at the optimal production frontier) (Table 3). Shaanxi exhibited the greatest ratio of optimally efficient farmers to inefficient farmers (Table 3).

As PTE proxies as an index for management performance (Charnes et al. 1978; Kumar and Gulati 2008), it can be deduced that the sample group collectively demonstrated good management practices as most inefficiencies are unrelated to management performance. However, relative to Sichuan and Shaanxi, management performance in Jiangxi was low.

3.2 Breakdown of inputs and role of urbanization

The level of inputs (land, capital, and labor) by province can also be examined to further add context and insights into the TE scores. In observing the mean inputs for the provinces, Jiangxi had noticeably higher inputs for every aspect relative to the other provinces, followed by Shaanxi (Table 4).

The survey included data for agricultural and forestry land holdings both prior- and post-implementation of the CCFP. On average, farmers in Shaanxi and Sichuan experienced minor decreases in land holdings following CCFP implementation. In contrast, farmers in Jiangxi gained on average an additional 0.38 ha of land (Table 5).

The data indicate that the sampled farmers in Jiangxi were operating with greater inputs than their counterparts in Shaanxi and Sichuan (Table 4). On average, these farmers also gained more land for productive use because of the CCFP (Table 5). It is possible that farmers in Jiangxi were not able to utilize all their inputs effectively, thereby lowering their PTE.

The changes in agriculture/forestry land experienced by the sampled farmers are also reflective of the level of urbanization and other land-use changes. As the Chinese National Bureau of Statistics (NBS) only has data for land-use change since 2004, urbanization rates from 2004–2011 were assessed for the selected provinces along with land used for state construction projects (since these would have required provincial land in order to build infrastructure, thereby taking land away from the potential productive land base). As shown at the provincial level, from 2004–2011 Jiangxi experienced the lowest urbanization rate based on measures of urban population density increase, in addition to having the lowest proportion of land used for state construction projects (Table 6). In contrast, Sichuan exhibited the highest urbanization rate and proportion

Table 2. TE scores by province.

Sample	Mean OTE	Mean OTIE	Mean PTE	Mean PTIE	Mean SE	Mean SIE
All	0.55	0.45	0.90	0.10	0.61	0.39
Jiangxi	0.54	0.46	0.87	0.13	0.63	0.37
Shaanxi	0.57	0.43	0.90	0.10	0.64	0.36
Sichuan	0.53	0.47	0.91	0.09	0.58	0.42

Table 3. Ratios of optimally and non-optimally efficient farmers.

Province	Ratio of optimally efficient farmers to non-optimally efficient farmers
Jiangxi	0.4458
Shaanxi	0.4912
Sichuan	0.4507

Table 4. Breakdown of mean inputs by province.

Province	Mean land (ha)	Mean capital (USD)	Mean labour (persons)
Jiangxi	2.53	765.91	1.92
Shaanxi	1.72	446.22	1.85
Sichuan	1.02	383.37	1.67

Table 5. Breakdown of mean land obtained from the period of the CFPP.

Province	Mean land obtained during the period of the CFPP (ha)
Jiangxi	0.3833
Shaanxi	− 0.0207
Sichuan	− 0.0033

Table 6. Urbanization statistics by province (National Bureau of Statistics of China 2014).

Province	Urban population density increase 2004–2011 (%)	Land used for state construction projects increase 2004–2011 (%)
Jiangxi	71.02%	−29.27%
Shaanxi	159.06%	41.67%
Sichuan	1,054.36%	227.27%

of provincial land used for state construction, measuring greater than 6 and 5 times more than the increases observed in Shaanxi, respectively (Table 6). A greater increase in urbanization and urban expansion rates may explain why sample households in Shaanxi and Sichuan, on average, reported a loss of farmland for agriculture and forestry (Table 5). As such, urbanization may have played a role in the higher inputs for farmers in Jiangxi relative to farmers in Shaanxi and Sichuan.

Despite higher inputs and an increase in land holdings post-implementation of the CCFP in Jiangxi relative to Sichuan and Shaanxi, the PTE of Jiangxi was still the lowest of the sampled provinces. This should emphasize the importance of managing inputs effectively, as even after an increase in land holdings and funds (perhaps from government subsidies), other sampled provinces exhibited greater PTE values (Table 2). This finding suggests the need for further study into the distribution of inputs in relation to technical efficiency to ensure that gains in inputs from land-use policies can be effectively employed and incorporated into farming operations.

3.3 Breakdown of individual farmer characteristics

While provincial-level averages may provide general insight into the technical efficiency of farming operations following the implementation of national policies and programs, the individual characteristics of the farmers that were surveyed may play a role in the outcome of the DEA model. Personal features of respondents such as age and education were recorded in the questionnaires and may provide more sophisticated insights into technical efficiency. In the survey, age was recorded as a categorical value ranging from less than 24 years old to greater than 65 years old. Famers' age has been shown to have an inverse effect on their efficiency in a multitude of countries (Llewelyn and Williams 1996; Seyoum et al. 1998). A decrease in farming operational efficiency with increasing age may be explained by the general willingness of younger farmers to adopt newer, more efficient technologies.

Jiangxi exhibited the lowest proportion of young farmers, with only 32.5% of farmers between the ages of less than 24 and 44 (i.e. age categories 1–3) and nearly 67.5% of the sample population being 45 or older (i.e. age categories 4–6) (Figure 5). Both Shaanxi and Sichuan had a higher proportion of young farmers (<45 years), representing 44.6% and 45.9% of their sampled population, respectively (Figure 5). The higher proportion of older farmers may have contributed to a lower technical efficiency value in Jiangxi (Table 2), as this subset of the population is typically less involved in technology and may find it harder to adapt to the shift from agricultural to forestry activities.

The potential influence of education on technical efficiency is less well known than age effects. Intuitively, education should increase the general efficiency of farmers, as no or lower levels of education imply fewer skills and/or lower adaptability. However, this is only true up to a certain threshold (Moock 1981). In the questionnaire, respondents provided their level of education based on six categories, ranging from no education to a graduate degree or higher. The largest proportion of respondents from Sichuan had relatively little education, with roughly 45.9% of respondents

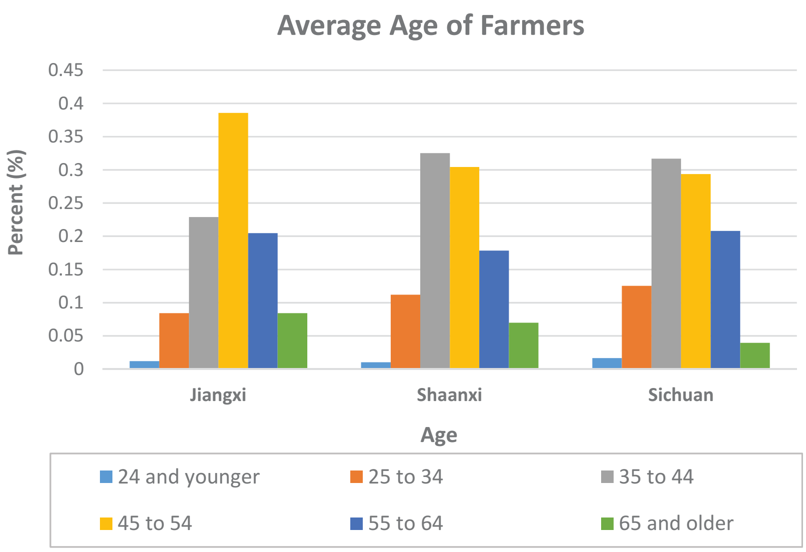

Figure 5. Age distribution of the sampled farmers in each province.

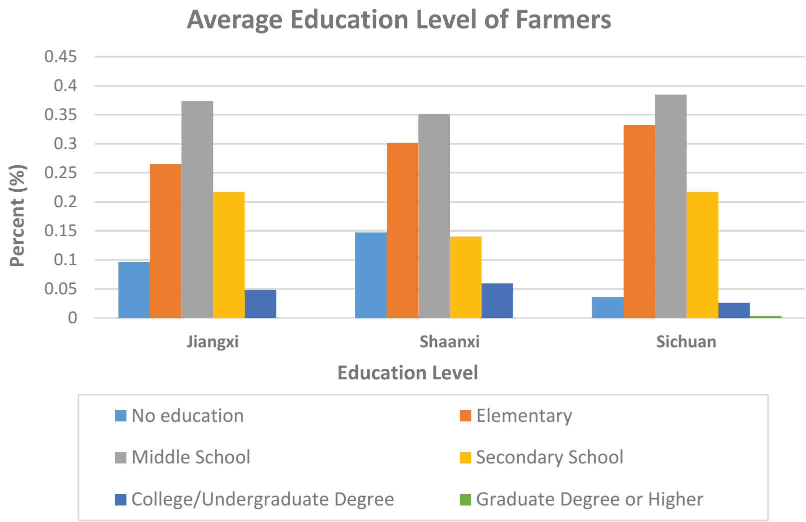

Figure 6. Education distribution of the sampled farmers.

identifying themselves as having the lowest three levels of education (Figure 6). In contrast, Jiangxi exhibited the smallest proportion of farmers with low levels of education and contained the highest proportion of educated farmers (Figure 6). The overall efficiency of provinces, however, was not related to the dominant levels of education amongst rural farmers. Jiangxi had the highest proportion of educated farmers (Figure 6) but exhibited the lowest overall efficiency values of the three provinces (Table 2). It is therefore impossible to draw any conclusions about the effects of education level on the efficiency of farming operations.

3.4 Role of land fragmentation

Land fragmentation contributes to scale inefficiency (Latruffe and Piet 2013), and should, therefore, be considered an important part of the analysis of operational efficiency. Some studies suggest that land fragmentation may not negatively impact productivity in paddy farming regions such as Malaysia and the Philippines (Niroula and Thapa 2005). However, land fragmentation in China has been found to have a negative impact on technical efficiency (Wan & Cheng 2001a; Wu et al. 2005).

Land fragmentation measured as both the number of land plots as well as the calculated Simpson's Index (SI) by province is shown in Table 7.

In both measures of land fragmentation, Sichuan had noticeably higher land fragmentation than the other two provinces which coincide with its greater scale inefficiency compared to the other two provinces (Table 2). In terms of using SI as the measure, Jiangxi and Shaanxi are fairly similar while Sichuan had noticeably higher land fragmentation. In terms of using the mean number of land plots both Jiangxi and Sichuan are noticeably higher than Sichuan.

Table 7. Land fragmentation measures for each province.

Province	Mean SI	Mean number of land plots
Jiangxi	0.54	6.25
Shaanxi	0.56	3.38
Sichuan	0.68	9.13

As such, land fragmentation seems to have some effect on the scale inefficiency of the province, which supports existing research like Chen et al. (2009b). Chen et al. (2009b suggested that eliminating land fragmentation would result in greater efficiency gains for Chinese farmers. Conceptually, this makes sense as divided or distant land plots should make it more difficult for farmers to operate efficiently.

Following the implementation of the CCFP, the primary inefficiencies of the sample farming households resulted from SIE rather than PTIE (Table 2). The potential efficiency gains from eliminating or reducing land fragmentation should support efforts for land consolidation in some areas by the state. Fragmented land holdings and insecurity of land use rights may also decrease the incentive for rural farmers to manage their lands sustainably (Dai et al. 2013). The operations of farmers have a large impact on rural ecology and livelihoods and, as such, fragmented land holdings can be detrimental to long-term environmental and economic viability.

3.5 Role of net forest cover change

Observing provincial level net forest cover change from 2000–2010 provided further insights into the technical efficiency and impacts of the CCFP.

During this period, Sichuan experienced a dramatic increase in forest cover with an increase of 13.96% (Table 8). In the same period, the national average forest cover increase was only 0.96%. While Sichuan experienced the greatest increase in net forest cover

Table 8. Provincial net forest cover change from 2000 to 2010 (GlobeLand30).

Province	Net forest change (%)
Jiangxi	0.40%
Shaanxi	0.95%
Sichuan	13.96%

(Figure 7), it also had the greatest degree of land fragmentation (Table 7), the highest rate of urbanization (Table 6), the least amount of inputs (Table 4), and the lowest SE and OTE (Table 2) of the three provinces. However, farmers in Sichuan had the largest number of land plots (Table 7) and displayed the highest PTE (Table 2) amongst all provinces, which may have contributed to the large increase in provincial forest cover. From 2000–2010, Shaanxi had a net forest gain of 0.95% (Table 8), similar to the national average. Farmers in Shaanxi had the lowest number of land plots (Table 7) but had the highest ratio of optimally efficient farmers (Table 3) and the greatest overall total efficiency and scale efficiency (Table 2). Jiangxi, on the other hand, experienced the lowest comparative net forest cover change (0.4%) (Table 8), despite the greatest amount of inputs (Table 3) and lowest land fragmentation (Table 7).

Of the provinces included in this study, Sichuan had the greatest land fragmentation, the greatest scale inefficiencies, and the highest net forest increase. This is significant because it shows that despite the successful reforestation, noticeable operational problems can still be present. This is an important policy consideration as success in the main objective of a program should not overshadow the problems faced by locals in delivering the main objective. This is a major problem with the implementation of top-down policies.

4. Conclusions

This study utilized an input-oriented DEA model to examine farming operations following the implementation of the CCFP. It did so by observing the technical efficiency of affected farmers in Jiangxi, Shaanxi, and Sichuan. Factors such as urbanization, age and education level, and land fragmentation were examined in relation to the technical efficiency of farming operations. The presence of inputs such as land, capital, and labor in addition to urbanization did not seem to affect pure technical efficiency values in this study. Farmers in Jiangxi had the greatest amount of inputs and gained the largest amount of land following the implementation of the CCFP, but still had the lowest PTE. While the level of education did not seem to affect efficiency levels, age seems to play some role, with older farmers generally being less efficient. The greatest pure technical inefficiencies were observed in Jiangxi, possibly due to the age of farmers or their inability to manage inputs efficiently.

Scale inefficiency seems to be a great contributor to overall inefficiency in farming operations in comparison to pure technical inefficiency. This was largely influenced by the presence and degree of land fragmentation in farmers' land holdings. This finding supports current research regarding national land-use change policies that facilitate land fragmentation in China. For a more sophisticated understanding of the

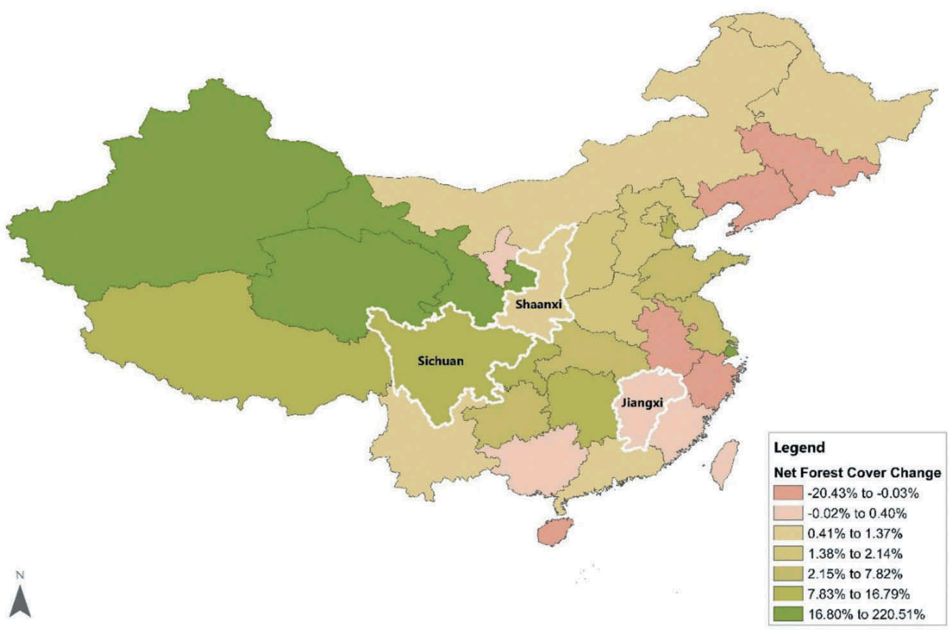

Figure 7. Provincial level percent net forest increase from 2000–2010 (GlobeLand30).

implications for policy adjustments, further research should be conducted on the links between large-scale initiatives such as the CCFP and the efficiency or welfare of farmers at a broader level. In addition, future studies need to cover the entire area covered by the CCFP. Greater oversight and capacity building to aid in the transition of older laborers from agricultural land practices to forest management should be addressed in future initiatives to increase efficiency and adaptability. Additionally, while this study utilized a DEA model specifically for its flexibility and lack of a need for specification of a functional form, more research is needed that compares DEA and SFA methods for analyzing farmers affected by the CCFP.

Notes

1. For a full description of how that sample of rural households was created please see (Wang et al. 2018).
2. The original sample in Wang et al. (2018) had 1089 households from 32 counties in the 3 provinces.
3. These respondents are either households with multiple people or of only a single person. For simplicity, the use of the term 'farmer' later on in this paper will be used to describe these respondents regardless of whether they are a multi-person household or a single person household.
4. By farming operations, we are referring to any activity that results in the growth of one or both of either (i) crops that are able to generate income for the household or (ii) trees that fulfill the criteria of reforestation as per the CCFP which subsequently allow the household to receive compensation for this activity.
5. From this point forward 'sample' will refer to the sample specifically used for the present study which is the subsection of Wang et al. (2018)'s sample.

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Disclosure statement

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