Diversification or specialisation? Farmers' cropping strategy and economic performance under climate change in China

Mingze Wu, Yueji Zhu and Qi Yang
Management School, Hainan University, Haikou, China

Abstract

Purpose – Farmers' adaptation strategies in agricultural production are required to minimise the negative impact of climate change on a nation's food production in developing countries. Based on the panel data of the provincial level in China from 2000 to 2017, this study aims to analyse the changing climate over recent years and farmers' adaptation strategy in terms of cropping in agricultural production.

Design/methodology/approach – This study uses Simpson's diversity index (SDI) to measure the degree of crop diversity planted by farmers and evaluate the influence of climate change on farmers' cropping strategy using the fixed-effect model. Further, the authors estimate the impact of farmers' cropping strategy on their economic performances in two aspects including yields and technical efficiency of crops.

Findings – The empirical results show that the overall climate appears a warming trend. Different from farmers in some other countries, Chinese farmers tend to adopt a more specialised cropping strategy which can significantly improve the technical efficiency and yields of crops in agriculture. In addition, as a moderating role, the specialised cropping can help farmers to alleviate the negative impact of climate change on technical efficiency of their crops.

Originality/value – First, previous studies showed that the changing climate influenced farmers' adaptation strategies, while most studies focussed on multiple adaptation strategies from the farm-level perspective rather than cropping strategy from the nation-level perspective. Second, the present study investigates how the cropping strategy affects the economic performance (in terms of the technical efficiency and crop yields) of agricultural production. Third, the stochastic frontier analysis method is used to estimate the technical efficiency. Fourth, this study explores the moderating effect between farmers' cropping strategy and technical efficiency by introducing an interaction item of SDI and accumulated temperature.

Keywords Climate change, Farmers' adaptation strategies, Technical efficiency, Cropping

Paper type Research paper

1. Introduction

Climate change seldom stems from agricultural activities but may severely impact agricultural development in a negative way especially in developing countries. In these

© Mingze Wu, Yueji Zhu and Qi Yang. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and noncommercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licences/by/4.0/legalcode>

The authors acknowledge the funding provided by the National Natural Science Foundation of China and Hainan Provincial Natural Science Foundation of China. The authors also would like to thank the anonymous reviewers for their valuable comments.

Funding: This research was supported by the National Natural Science Foundation of China (No. 71863006), Hainan Provincial Natural Science Foundation of China (No. 720RC581).

regions, agriculture is usually regarded as the supporting sector for an economy to fight against hunger and poverty. In the past decades, water shortages, soil drought, flooding and extreme weather events due to climate change have become great risks to agricultural production in many developing countries. The unusual climate might lead to decreased production of the world's major food crops. From 1981 to 2002, the global production of wheat, corn and barley decreased by 40 million tons annually due to rising temperatures (Brondizio and Moran, 2008). However, few smallholder farmers have enough capacity to bear the losses caused by climate change. Due to insufficient funds, poor infrastructure and lagged agricultural technologies, smallholders in developing countries generally have limited choices of strategies to alleviate the impact of climate change on agricultural production.

As a developing country with a large population, China put food security at the top priority due to scarce resources per capita in agricultural production. In the past few decades, China has given a sound answer to the question "who will feed China". China's total grain output has increased from 110 million tons in 1961 to 615 million tons in 2019 (FAO, 2021). In 2020, the number reached a record high, exceeding 669 million tons (Ministry of Agriculture and Rural Affairs of the People's Republic of China, 2020). Thus, the population under hunger and poverty is dramatically declined in China over these years. However, China's food supply may be affected by a number of new challenges. For example, China's cultivated land area is decreasing in recent years, and the reserve land resources are seriously insufficient. More importantly, the feasibility of crop varieties and agricultural technologies is increasingly restricted by the changing climate conditions (Chen *et al.*, 2018). The average annual surface temperature in China has increased significantly by about 0.8 degrees Celsius in the past hundred years, which is basically consistent with the change of average global temperature over the same period of 0.74°C (IPCC, 2014). The temperature rise in China is particularly significant in recent decades. It has changed the spatial-temporal distribution of climate resources in China. The temperature increase in the northern region is higher than the southern, while the degree of sunlight decrease in the southern region is greater than northern, and the precipitation difference may continue to increase to cause "South waterlogging and north drought" (Song *et al.*, 2018). Some researchers considered that climate change had a significant impact on China's agricultural production. For example, the production of China's major crops such as wheat, rice and corn are predicted to fall by around 37% by the second half of the 21st century, if adaptation strategies for combating climate change could not be taken (National Assessment Report on Climate Change, 2007). Global warming might result in the increase of crop diseases and insect pests, and the decline in quality of cultivated land. Regardless of technological progress, the risk of food security could be increasing (Chen *et al.*, 2020). Chinese authorities have launched corresponding policies China's National Climate Change Program (2007) to help smallholder farmers adapt to changing climate, ensure their livelihoods and stabilise the food supply in domestic market. Different adaptation strategies are demanded to increase farmers' resilience and improve the food security in China.

Adaptation strategies are a series of measures taken by groups or individuals to reduce the adverse effects of climate change (Steve, 1995). It is increasingly realised that the negative impact of climate change on agriculture can be minimised by a comprehensive approach encompassing progress in agricultural science, meteorology and information communication and traditional adaptation practices that farmers use before and after the shock. Farmers' adaptation strategies can be simply divided into two categories, namely, changing production practices and adjusting financial management. The first category includes adopting new crop varieties, changing agricultural production time and intercropping, etc.; the second category includes diversifying income sources and purchasing agricultural insurance (Ochoa *et al.*, 2019). The farmers in central Vietnam have lost 20% of their annual income due to extreme weather events caused by climate change. To mitigate these losses, farmers have adopted the first type of adaptation strategies,

such as changing crop varieties, switching to new crops, adjusting farming calendars, monitoring weather forecasts and intercropping (Trinh *et al.*, 2018). Fallowing farmland or crop rotation is also an effective way to reduce the risk of climate change in agriculture (Mottaleb *et al.*, 2019). Elizabeth *et al.* (2008) argued that farmers' adaptation strategy is more determined by short-term climate change of extreme weather events than long-term climate change of average temperature and precipitation conditions. Among the adaptation strategies, crop diversification is one of the important pre-measures to improve the resistance of crops under climate change such as insufficient rainfall and rising temperature (Birthal and Hazrana, 2019). Crop diversification increases the input of production mix to some crops or varieties that are less-vulnerable to climatic shocks, but diversified crops may lead to less revenue per unit of the land area compared to specialised production of one crop on a larger scale. Agricultural technologies can be more likely taken in the context of crop specialisation. However, farmers with fewer crops may be at higher risk of adverse effects of climate change on agricultural production. The risk-averse farmers are more inclined to adopt diversified crop combinations to alleviate the damage of climate impact on crops. If one crop does not perform well under the changing climate, the loss can be compensated by the gains from other crops. In other words, it is uncertain about farmers' choice of crop specialisation or diversification to adapt to climate change.

Scholars have different opinions concerning the impact of different cropping strategies on the economic performance of agricultural production. Some believe that crop diversification has a positive effect on the production efficiency. For example, Nguyen (2017) pointed out that planting different crops could reduce the impact of price fluctuations on farmers' revenues, effectively mitigate natural and market risks of crops, improve soil quality, and thus increase the efficiency of crop cultivation. Niroula and Thapa (2005) argued that crop diversification helped alleviate uncertainties in agricultural production and reduce income fluctuations, especially in rural areas where labour shortage and frequent natural disasters occur. Arslan *et al.* (2017) examined the relationship between planting diversification and technical efficiency in Afghanistan and insisted that farmers adopting diversified planting strategies could enhance technical efficiency. However, others believe that crop diversification may decrease the production efficiency. For example, Llewelyn and Williams (1996) argued that crop diversification was not conducive to the effective allocation of resources and decreased agricultural production efficiency. Generally, specialised cultivation of one crop could enable farmers to adopt more advanced technologies, so that the technical efficiency of production may be improved. Chinese farmer households own far less one hector of land on average. In this context, diversified cropping may cause a problem that few feasible technologies can be applied in these small plots. In contrast, crop specialisation can provide farmers with more choices of agricultural technologies and encourage farmers to invest more on one given crop. So, the production can be improved by using feasible technologies and more other inputs in the farmer's land. However, crop specialisation may make farmers less resistance to the frequent occurrence of extreme climates and may suffer greater economic losses. Therefore, it is necessary to empirically study the impact of Chinese farmers' cropping strategies on the economic performance in agriculture under climate change.

The natural, economic and social environments are varying from province to province in China. These conditions inevitably cause differences in planting structures of crops in different regions (Dai *et al.*, 2015). China's major crops can be roughly classified into three categories, namely, cereals, potatoes and beans. Among them, the total planting area and total output of wheat, rice and corn in cereals account for more than 80% of all food crops (National Bureau of Statistics, 2017). In recent years, the self-sufficiency rate of food in China remains high level, especially the three major crops including rice, wheat and corn, though there are growing population, rising consumption level and changing consumption

structure. For example, the self-sufficiency rates of rice, wheat and corn in China in 2018 were 99.54%, 97.90% and 98.65%, respectively. As the world's largest developing country, China has got the outstanding achievement of "feeding 22% of the world's population by 7% of the world's cultivated land" (You *et al.*, 2011). As temperatures continue to rise and extreme weather events occur frequently, farmers are accordingly adjusting their planting strategies to adapt to climate change (Dai *et al.*, 2015).

This study contributes to the existing studies by exploring the relationship between farmers' cropping strategy and the economic performance in agriculture under climate change. First, previous studies showed that the changing climate influenced farmers' adaptation strategies, while most of them focussed on multiple adaptation strategies from the farm-level perspective rather than specific cropping strategy from the nation-level perspective. The authors attempt to identify the change of cropping strategy under climate change in the main food-producing provinces of China based on the provincial panel data from 2000 to 2017. Second, this study investigates how the cropping strategy affects the economic performance of agricultural production from two aspects of technical efficiency and crop yield. Third, the stochastic frontier analysis (SFA) method is used to estimate the technical efficiency, instead of the data envelopment analysis (DEA) method. The DEA is a nonparametric estimation method and does not require a specific form of estimate function. It is more suitable to evaluate the efficiency of enterprises comprehensively. Agricultural production involves many uncertain factors, which may affect the final output. In this context, the DEA method may overestimate the technical efficiency without considering random errors. The SFA is a parametric method that can effectively control the random errors caused by data problems. Fourth, this study examines the moderating effect between the cropping strategy and the technical efficiency by introducing an interaction item of Simpson's diversity index (SDI) and accumulated temperature (Te). The effect is rarely discussed in previous studies.

The rest of this paper is organised as follows. Section 2 describes the study area and gives an overview of China's major cropping provinces and the data source used in this paper. Section 3 introduces the estimation techniques used to examine the impact of climate change on farmers' cropping strategies and to measure the technical efficiency in a given period of time. Section 4 presents the empirical results and discussion. The conclusions and implications are given in Section 5.

2. Background and data

2.1 Study area

The major crops in China include rice, wheat, corn, sorghum, millet, potatoes and soybeans. China has the longest history of rice cultivation and the highest rice production in the world. Rice is the major cereal crop in southern China, mainly located in the southern part of the Qinling Mountains and Huaihe River and the eastern part of the Qinghai-Tibet Plateau. The northern producing areas of rice are mainly around Yanji city of Jilin Province, Songhua River and Liaohe River. Rice has the highest water needs (700~1,200 mm) among all cereal crops, and it grows in comparatively higher temperature from 28 to 32 Celsius but requires a shorter time of sunlight. In 2017 and 2018, the planting area of rice in China was 30.75 million hectares and 30.19 million hectares and the yield was 212.68 million tons and 212.13 million tons, respectively. Wheat is widely distributed in China, including winter wheat and spring wheat. Spring wheat is mainly distributed in the north of the Great Wall, the west of Minshan Mountain and Daxue mountain. Winter wheat is mainly cultivated in the east of Liupan Mountain and the north of Qinling and Huaihe River. In 2017 and 2018, the planting area of wheat was 24.51 million hectares and 24.27 million hectares and the yield was 134.3

million tons and 131.4 million tons, respectively. As an important food crop and feed source, corn is produced in many areas of China, such as Heilongjiang Province in the northeast and Sichuan Province in the southwest. In 2017 and 2018, the planting area of corn was 42.4 million hectares and 42.13 million hectares and the yield was 259.07 million tons and 257.17 million tons, respectively. Wheat and corn have moderate water requirements of about 400~600 mm. Sorghum, millet and soybeans are mainly distributed in northern China, the planting area of these crops was 13.27 million hectares and the output was 28.5 million tons in 2018. Potatoes are mainly planted in Northeast, Southwest and Northwest regions in China. The planting area of potatoes was 7.18 million hectares and the output was 28.65 million tons in 2018. Among these crops, millet and potato have the lowest water requirement of about 160~200 mm and strong drought tolerance ([China Agricultural Information Network, 2019](#)).

This study selected twelve provinces as representative crop planting areas, including Hebei, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Hubei, Hunan and Sichuan. They are the important provinces for cultivating food crops in China, and the annual output accounts for more than 70% in the country in recent years. These provinces span about 20 latitudes, so there are geographically significant differences in average annual temperature and rainfall. For example, three provinces including Liaoning, Jilin and Heilongjiang, located in the Northeast Plain area, are important grain production bases in China and have the highest adoption rate of machinery in agriculture. There are fertile soil, relatively level land and a mild and humid climate. The disadvantage is high latitude, thus the temperature conditions are not as good as in south China and the main crop is only harvested once a year. Besides rice, wheat and corn, the three northeast provinces are also the largest soybean producing areas. Both Hunan Province in the Dongting Lake Plain area and Hubei Province in the Jiangnan Plain area are located in central China as the subtropical zone. There are hilly lands but outstanding climate conditions that allow a long growing season for crops and multiple harvests in each year. They have comparatively sufficient supply of labour force in agriculture and better production conditions such as irrigation water. The average yield of crops can generally reach 6,000 to 8,250 kg per hectare, so the two provinces are known as China's "rice warehouse". Hebei, Henan, Shandong and part of Jiangsu and Anhui are located in the North China Plain (NCP). These provinces have better economic development and convenient transportation, and the cultivated land area in NCP accounts for about one-fifth of the total cropping area in China. They mainly grow wheat and corn. Most regions in NCP belong to the temperate monsoon climate. There are sufficient sunlight and abundant heat resources, but the precipitation is not enough. This may cause irregular rainfall that are harmful to the crop production. Sichuan Province is located in the hinterland of Southwest China, with complex terrain and abundant mineral and biological resources. It is characterised by the most southern latitude and the lowest altitude. The soil in Sichuan is very fertile with mineral nutrients such as phosphorus and potassium. Inner Mongolia has a high terrain with an average altitude of about 1,000 m. It belongs to the temperate continental monsoon climate, where the sunlight is abundant and the solar energy resources are extremely abundant, but the rainfall is scarce. Thus, it is suitable for planting drought-resistant crops. Both the planting area and yield of potato in Inner Mongolia are ranked first in China.

2.2 Data source

The authors collected panel data of twelve provinces from 2000 to 2017 ([China Meteorological Data Service Centre, 2019](#)). The data of the meteorological stations in the

capital cities is used to represent the climate conditions for twelve provinces. Because the meteorological data in capital cities of Inner Mongolia and Sichuan are not available, the authors use the data of neighbouring cities of the capital cities, instead (Figure 1). Meteorological elements include annual effective accumulated temperature, rainfall and sunlight duration. The effective accumulated temperature is an important indicator that reflects the heat requirements for crop growth. Sunlight is an energy source for photosynthesis of crops and is necessary for chloroplast development and chlorophyll synthesis. It can regulate the activity of some enzymes in agricultural materials. Hence, it has a determinant impact on the growth of crops. The effective accumulated temperature is defined as the sum of the difference between the daily average temperature and the biological zero degree. It is observed that 10°C is generally used as the biological zero degree of the subtropical region. The effective accumulated temperature can be calculated as follows:

$$Te = \sum_{i=1}^n (Ti - 10) \quad (1)$$

where Te is the effective accumulated temperature (°C), Ti is the daily average temperature (°C), Ti is not involved in the calculation when Ti is less than 10°C and n is the number of days in the calculation period.

The crop data were collected from the China National Food Administration, including the planting area and yields of rice, wheat, corn, sorghum, soybeans, millet, potatoes, sweet potatoes and other crops. Other data including agricultural population, gross domestic product (GDP) per capita, capital investment in agricultural machinery and investment in pesticides and fertilisers for each province from 2000 to 2017 were obtained from the National Bureau of Statistics of China.

Figure 1.
Study sites

3. Methodology

3.1 Simpson's diversity index

Crops are growing under different agricultural conditions and water resource is one of the critical factors. This study takes the water requirements of crops as the basis to classify them into three categories, namely, crops with high water needs (H-crops), crops with neutral water needs (N-crops) and those with low water needs (L-crops). Each category contains a different number of main crops. For example, rice and soybeans are H-crops; wheat, corn and sorghum are N-crops, and millet, potatoes and sweet potatoes are L-crops. The authors used SDI to calculate the degree of diversification of the main crops in each province. This technique takes into account the number of crops, as well as their relative proportions in the portfolio. The diversity index can be calculated as below (Birtal and Hazrana, 2019):

$$SDI = 1 - \sum_{i=1}^n P_i^2 \quad (2)$$

In equation (2), P_i is the proportion of crop i 's area out of the total crop area. The index is bounded by zero to one. The value "0" implies farmers only planted one main crop in the province, indicating the highest degree of crop specialisation; The value "1" implies the highest degree of crop diversification in the given province.

3.2 Stochastic frontier analysis

Previous studies have used either a parametric method such as SFA or DEA to estimate the technical efficiency. However, the DEA method attributes deviations from the production frontier to inefficiency, assuming no stochastic errors, and therefore is sensitive to outliers. This restricts its applicability to agricultural studies where production is frequently influenced by unpredictable weather conditions such as floods and droughts (Ma *et al.*, 2018; Koirala *et al.*, 2016). Therefore, this study selected the SFA method to estimate the technical efficiency of crops in each province. The model proposed by Aigner *et al.* (1977) has the following advantages: firstly, it can statistically analyse production activities by constructing a specific production function. It can test the statistical significance of the regression parameters and measure the fitness of the proposed model. Thus, the marginal effects of factors and elastic estimates of parameters can be obtained. Secondly, it can be used to establish a stochastic frontier model, so that the frontier itself is flexible. The estimated results are more likely matched to the reality when using panel data that across a period of time (Fall *et al.*, 2018).

Following Kumbhakar and Lovell (2000) and Axel *et al.* (2017), a single-output stochastic production frontier model can be expressed as follows:

$$Y_{it} = f(X_{it}; \beta) \cdot \exp(v_{it} - u_{it}) \quad (3)$$

where Y_{it} is the output of i -th province in the year t and $f(\cdot)$ is the deterministic output on the boundary of production possibility, indicating the maximum potential output that a certain production factor input can achieve under the given technology. X_{it} is a vector of input factors for i -th province in the year t and β is a vector of parameters. v_{it} is an error term, independently and identically distributed as $N(0, \sigma_v^2)$; u_{it} is a nonnegative one-sided error term, independently and identically distributed, that measures output-oriented TE. This study assumes that u_{it} follows a half-normal or an exponential distribution. TE_{it} is the

output-oriented farm technical efficiency of i -th province in the year t . The stochastic production frontier includes two parts: a deterministic part, $f(X_{it}; \beta)$, that is common to all province, and a province-specific part, $\exp(v_{it} - u_{it})$, that captures random variation in crop output due to factors beyond the control of province and accounts for the measurement error. Thus, output-oriented technical efficiency can be formulated:

$$TE_{it} = \frac{Y_{it}}{f(X_{it}; \beta) \cdot \exp(v_{it})} = \exp(-u_{it}) \quad (4)$$

$TE_{it} \leq 1$ implies that $u_{it} \geq 0$. A value of u_{it} equal to zero represents perfect technical efficiency (i.e. $TE_{it}=1$) while higher values of u_{it} imply lower levels of technical efficiency. u_{it} can be linearly expressed as:

$$u_{it} = \delta_0 + \sum_{i=1}^n \delta_i z_{it} + \omega_{it} \quad (5)$$

where z_{it} is a vector of explanatory variables expected to influence technical efficiency with associated $n + 1$ parameters δ and ω_{it} is a random variable that is defined such that u_{it} is a non-negative truncation of the $N(\delta_i z_{it}, \sigma_u^2)$ distribution. The condition $u_{it} \geq 0$ guarantees that all observations of outputs lie on or beneath the stochastic production frontier. Variance terms in the likelihood function are parameterised by replacing σ_v and σ_u with $\sigma_S^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma_S^2$, where the gamma parameter (γ) lies in the $[0,1]$ interval. Given that the inefficiency effects are stochastic, Battese and Coelli (1995) argue that some explanatory variables can be included in equation (5). Parameters β , δ , σ_S^2 and γ can be consistently estimated by the maximum likelihood method.

When using the SFA to estimate the technical efficiency of agricultural production, it is important to consider the consistency and flexibility of the theory, as well as the correct choice of production function (Sauer *et al.*, 2006). Although the traditional Cobb-Douglas production function has advantages in calculation and explaining phenomena, but it assumes that the production elasticity is constant and the substitution elasticity is 1. This may make the production function inflexible; at the same time, it does not conform to the actual agricultural production process. In contrast, the translog production function is flexible and can better fit the empirical data. This study parameterises $f(\cdot)$ by a translog specification (Ferreira and Fères, 2020):

$$\begin{aligned} \ln Y_{it} = & \alpha_i + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln S_{it} + \beta_4 \ln M_{it} + \frac{1}{2} \beta_{11} \ln^2 K_{it} + \frac{1}{2} \beta_{22} \ln^2 L_{it} \\ & + \frac{1}{2} \beta_{33} \ln^2 S_{it} + \frac{1}{2} \beta_{44} \ln^2 M_{it} + \beta_{12} \ln(K_{it}) \ln(L_{it}) + \beta_{13} \ln(K_{it}) \ln(S_{it}) \\ & + \beta_{14} \ln(K_{it}) \ln(M_{it}) + \beta_{23} \ln(L_{it}) \ln(S_{it}) + \beta_{24} \ln(L_{it}) \ln(M_{it}) + \beta_{34} \ln(S_{it}) \ln(M_{it}) \\ & + v_{it} - u_{it} \end{aligned} \quad (6)$$

In this study, one output variable and four input variables are selected for model estimation. Where Y_{it} is the food production for the i -th province at year t ; α_i is the drift term; K_{it} is the capital investment for the i -th province at year t , represented by the total power of machinery; L_{it} is the manpower input represented by the total number of rural labours; S_{it} is

the land input represented by the total planting area of crops; M_{it} is the intermediate input, including pesticide, chemical fertiliser and diesel oil.

3.3 Linear regression model

The SDI technique is used to measure the degree of crop diversification as farmers' cropping strategies under climate change. Then a linear regression model is constructed to estimate the impact of climate change on farmers' cropping strategies. It can be given as follows:

$$SDI_{i,t+1} = \alpha_i + \beta_1 Climate_{i,t} + \beta_2 X_{i,t} + \mu_{i,t} \quad (7)$$

where $SDI_{i,t+1}$ indicates the crop diversification lag one year; α_i is the drift term; β is the coefficient to be estimated; $Climate_{i,t}$ is a vector of main explanatory variable include $Te_{i,t}$, $Re_{i,t}$, $Se_{i,t}$ and denote the change degree of effective accumulated temperature, rainfall and sunlight duration for i -th province at year t , respectively; $X_{i,t}$ is a vector of control variables (e.g. GDP per capita, agricultural population, food crops area and the proportion of agricultural GDP in the given province); and $u_{i,t}$ is the error term.

To understand whether crop diversification can improve the technical efficiency and yield of crops, the equations can be expressed as:

$$TE_{i,t} = \alpha_i + \beta_1 SDI_{i,t} + \beta_2 \ln(X_{i,t}) + \varepsilon_{i,t} \quad (8)$$

$$\ln(Y_{i,t}) = \alpha_i + \beta_1 SDI_{i,t} + \beta_2 \ln(X_{i,t}) + \eta_{i,t} \quad (9)$$

where $TE_{i,t}$ and $Y_{i,t}$ are the technical efficiency and yield of the crops in the i -th province at year t ; α_i and β are the coefficients to be estimated; $\varepsilon_{i,t}$ and $\eta_{i,t}$ are the error terms.

Climate change may regulate farmers' cropping strategy, thereby affect technical efficiency of crops. Equation (8) can be changed as:

$$TE_{i,t} = \alpha_i + \beta_1 SDI_{i,t} + \beta_2 \ln(Climate_{i,t}) + \beta_3 \ln(X_{i,t}) + \xi_{i,t} \quad (10)$$

To further understand the moderating role of farmers' diversified cropping, interaction terms of climate variables and SDI variable can be added in the equation:

$$TE_{i,t} = \alpha_i + \beta_1 SDI_{i,t} + \beta_2 \ln(Climate_{i,t}) + \beta_3 SDI_{i,t} \ln(Climate_{i,t}) + \beta_4 \ln(X_{i,t}) + \xi_{i,t} \quad (11)$$

The multicollinearity problem may occur when introducing interaction terms in the equation. The original data are processed to be zero-centred to avoid possible multicollinearity in the multiplication of SDI and climate variables.

4. Results and discussion

4.1 Descriptive statistics of the sample

The descriptive statistics of climate change variables are shown in Table 1. The authors divide the sample of 18 years into 3 periods based on the average value of the variables. Because the variation of climate change variables can be more easily captured when each period lasts six years. Table 1 shows that the accumulated temperature appeared an obvious

upward trend from the first period to the second, and slightly decreased in the third period. It may have been affected by extreme weather events such as cold waves and rainstorms, but the overall climate still has a warming trend. The average rainfall in the period of 2012 to 2017 increased by about 75 mm compared with the previous period, and the rainfall increased significantly, indicating the rainstorm events may be frequent. In terms of the sunlight duration, it shows a slight fluctuation trend.

The technical efficiency of each province at each year can be calculated based on equation (4). Descriptive statistics of the variables are shown in Table 2. It can be seen from the table that farmers' crop diversification is decreasing over given three periods. In other words, farmers' strategy to adapt changing climate is more crop specialisation than crop diversification. To make all control variables comparable, the authors take the natural logarithm of the original data. On average, GDP per capita in twelve provinces shows a gradual upward trend, and the income of the residents was gradually increasing during the 18 years. Agricultural population was gradually decreased. It may be caused by the rapid development of cities and migration of rural labours. In particular, the young labours had more job opportunities and could obtain higher income from cities. The planting area of cereal crops shows a slow upward trend, while the proportion of agricultural in total GDP was slowly decreasing and it is much lower than the proportion of industry and services industry.

4.2 Farmers' cropping strategy under climate change

The fixed-effect model can be used to estimate the impact of climate change on the degree of crop diversification of farmers in twelve provinces from 2000 to 2017. The regression results of the model are shown in Table 3.

Model 1 did not take into account the farmers' lagging response to climate change and used the same year data of the climate variables and farmers' crop diversification to estimate the equation (7). Among the climate variables, only the sunlight duration has a significant negative impact on farmers' SDI (p -value < 0.01). Generally, the strategy adopted by farmers often lag behind the weather of the previous year. Thus, Model 2

Year Var	2000~2005		2006~2011		2012~2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Te (°C)	2,333.79	745.21	2,355.57	761.97	2,341.03	764.16
Re (mm)	700.44	402.88	687.64	373.70	762.42	439.28
Se (h)	1,285.55	236.67	1,251.53	226.01	1,271.31	263.94

Table 1.
Descriptive statistics
of climate variables

Year Var	2000~2005		2006~2011		2012~2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Technical efficiency	0.87	0.10	0.88	0.10	0.89	0.09
ln Yield	7.82	0.32	8.01	0.31	8.19	0.32
SDI	0.46	0.13	0.42	0.16	0.39	0.16
ln GDP per capita	9.16	0.38	10.10	0.42	10.79	0.30
ln Agri population	8.25	0.61	7.97	0.54	7.84	0.52
ln Crops area	8.55	0.34	8.64	0.35	8.71	0.35
ln Agri proportion	2.77	0.29	2.51	0.27	2.34	0.28

Table 2.
Descriptive statistics
of main variables

Table 3.
Estimated results of
farmers' cropping
strategy under
climate change

Variable name	Model 1(SDI)	Model 2 (SDI-lag)
<i>Climate variables</i>		
ln Te	-0.050 (0.038)	-
ln Re	-	-0.063* (0.037)
ln Se	0.009 (0.009)	0.014* (0.009)
	-	-
	-0.052*** (0.018)	-0.044*** (0.018)
<i>Control variables</i>		
ln GDP per capita	0.004(0.011)	0.012 (0.011)
ln Agri population	0.060** (0.028)	0.069** (0.028)
ln Crops area	-0.111 *** (0.032)	-0.134*** (0.034)
ln Agri proportion	0.066 *** (0.018)	0.072*** (0.018)
Constant	0.635* (0.329)	0.637* (0.341)
R ²	0.503	0.505
Prob > F	0.000	0.000
Number of obs	216	204
	216	204
	0.000	0.000
	216	204
	0.505	0.513
	0.000	0.000
	204	204

Notes: Standard errors are presented in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

considered the lagging of farmers' cropping strategy by one year. The results show that the two climate variables, including accumulated temperature and sunlight duration, have negative impact on farmers' SDI, while the rainfall has a positive impact. That is to say, with the increase of sunlight duration, the solar radiation gets enhanced. This may cause that the degree of crop diversification is decreasing. Farmers were more likely to choose specialised cultivation to adapt to climate change in these provinces. The growing of crops requires different sunlight duration. Farmers chose crop varieties that are more suitable for the duration and intensity of local sunlight, rather than diversifying crops.

Agricultural population, planting area and the proportion of agriculture are also the factors that affect farmers' specialised cropping. Crop diversification usually requires more input of agricultural labours. However, the agricultural population was declined in the twelve provinces. To facilitate management of crops, farmers may focus on a few crops for cultivation, thereby reducing the degree of crop diversification. The results show that the larger the area of crops owned by farmers, the higher the degree of specialisation. The possible reason is that farmers tend to invest more on a limited number of crops to realise the economy of scale, when they can cultivate larger area of land. Thus, the degree of crop specialisation was enhanced. The results also indicate that the proportion of agriculture out of GDP was positively associated with the degree of crop diversification.

The authors take the Qinling Mountains and the Huaihe River as the geographical dividing line to conduct a comparative analysis between the south and the north of China. The northern provinces include Hebei, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong and Henan; the southern provinces include Jiangsu, Anhui, Hubei, Hunan and Sichuan. Figure 2 shows that L-crops are the most crops in the northern area, accounting for more than 60%; in the southern area, the proportion of L-crops is about 40%. The proportion of H-crops planted in the south is more than 50%, but less than 30% in the north. Compared with the north, the south of China has more abundant rainwater resources, which is more suitable for growing H-crops. For all sampling provinces, the planting area of N-crops has shown a slight upward trend, while the planting area of H-crops and L-crops has decreased, but the decline trend of L-crops was more obvious than that of H-crops. The possible reason is that the intensified climate change has caused the rainfall irregularly distributed across a production year, and some regions experienced natural disasters such as drought more frequently in recent years. Farmers tend to choose to plant N-crops which are comparatively neutral to climate change, so as to reduce the economic losses caused by possible natural disasters.

Some researchers argued that the climate change could severely influence the timing of rainfall and increase the temperature, and thus the irregular rainfall would seriously affect farmers' agricultural activities in a negative way (Amfo and Ali, 2020; Oluwatusin, 2014).

Figure 2.
Change of corps
planted in different
areas

The increase in minimum temperature tends to boost production, while the change in rainfall patterns may have adverse effects (Oyekale, 2012). The excessive rainfall may cause floods and less rainfall may lead to drought in production areas. However, different climatic conditions (e.g. temperature, rainfall and sunlight) favour different crops. For example, rice is highly susceptible to drought, whereas sorghum is tolerant to drought. Farmers can prevent the crop loss due to climatic change by including more suitable crops in their portfolio. Crop diversification is also deemed as one of the farmers’ adaptation strategies to climatic shocks (Ndamani and Watanabe, 2016; Orimogunje *et al.*, 2020).

4.3 Effect of cropping strategy on economic performance

The linear regression model was used to analyse the impact of crop diversification on agricultural technical efficiency and yield of crops. The estimated results are shown in Table 4. The coefficient of SDI shows a negative sign with statistically significance at 1% level, indicating that farmers could improve technical efficiency through specialised cropping. This is consistent with the findings of Llewelyn and Williams (1996). Technical efficiency measures the gap between the actual output of the production unit and the frontier output, reflecting the utilisation of all production factors of the unit. If the crops are less diverse, farmers may allocate resources more efficiently. Also, under crop specialisation in agricultural practices, the proficiency of farmers can be enhanced. These factors lead to the improvement of technical efficiency in agriculture. The coefficient of SDI to yield also shows a negative sign with statistically significance at 1% level, suggesting that specialised cropping could increase the yield of crops. According to the climate conditions, farmers can choose a few varieties of crops that are appropriate for local cultivation and concentrate more on the management of the corps in the production. Also, the fewer crops enable farmers to achieve the economy of scale in agriculture.

The control variables also have significant impacts on agricultural technical efficiency and yield of crops. The coefficients of GDP per capita, agricultural population, planting area and agricultural proportion have the significantly positive signs, indicating that these four factors could increase the agricultural technical efficiency and yield of crops in the study areas. The increase of GDP per capita implies the development of the regional economy, which has strong supporting effect on agriculture sector and provides an economic basis for farmers to adopt better technologies in agricultural production. If farmers could get more income, they may invest more on agricultural inputs to improve the efficiency of production. The yield of crops increases with the decrease of agricultural population. When the agricultural labours were substituted by machineries in production, the yield of crops indeed

Table 4.
Impact of farmers’
cropping strategy on
economic
performance

Variable	Technical efficiency	Yield
SDI	−0.054*** (0.017)	−0.693*** (0.128)
ln GDP per capita	0.018*** (0.003)	0.202*** (0.020)
ln Agri population	0.012 * (0.007)	0.264*** (0.046)
ln Crops area	0.030*** (0.008)	1.087 *** (0.066)
ln Agri proportion	0.017 *** (0.005)	0.223*** (0.037)
Constant	0.331*** (0.081)	−5.789 *** (0.659)
R ²	0.723	0.906
Prob > F	0.000	0.000
Number of obs	216	216

Notes: Standard errors are presented in parentheses. Significance level: ****p* < 0.01, ***p* < 0.05, **p* < 0.1

could be improved. In the same sense, with the larger planting area, farmers had higher tendency to adopt advanced technologies. This enables farmers to realise the effect of the large scale, and the economic performance of crops can be improved. The negative association between labour force and technical efficiency was also identified in previous studies (Haji, 2007).

Our results are different from that given by Ickowitz *et al.* (2019). They deemed that there are complementarities between crops in production so that yields for some crops may increase if they are planted together, such as corn and leguminous crops. Rahman (2009) also insisted that crop diversification is a desired strategy, and it contributes to the agricultural growth in Bangladesh. This implies that there could be a loss in profits and income if farmers were focus on cultivating specialised crops under climate change. Crop diversification has been recognised as a principal adaptation strategy to cope with climate change (Khanal and Mishra, 2017; Richard, 2018; Asfaw *et al.*, 2018; Elena *et al.*, 2020). Asfaw *et al.* (2018) argued that crop diversification exerted a positive and significant welfare impacts when farmers were facing climatic problems. In contrast, some researchers (Llewelyn and Williams, 1996) found that crop diversification significantly inhibited the technical efficiency in production, which is more consistent to our findings.

4.4 Moderating effect

Table 5 reports that the Te among climate variables has a significantly negative impact on technical efficiency of crops. The moderating effect occurs when the relationship between the dependent and independent variable is affected by another independent variable (David *et al.*, 2012). Thus, insignificant climate variables can be removed and annual effective accumulated temperature is remained as the explanatory variable in the model. At the same time, an interaction term of SDI and Te is added in the estimation model. So, the equation (11) can be formulated as:

$$TE_{i,t} = \beta_0 + \beta_1 SDI_{i,t} + \beta_2 \ln(Te_{i,t}) + \beta_5 SDI_{i,t} \ln(Te_{i,t}) + \theta_{i,t} \quad (12)$$

The explanatory variables and moderating variable can be centralised to make them comparable at the same scale, and the regression results are shown in Table 6. The coefficients of SDI and accumulated temperature present significant and negative signs,

Variable	Technical efficiency			
SDI	−0.054*** (0.017)	—	—	—
Te	—	−0.016* (0.009)	—	—
Re	—	—	−0.002 (0.002)	—
Se	—	—	—	0.003 (0.005)
ln GDP per capita	0.018*** (0.003)	0.016*** (0.003)	0.018*** (0.003)	0.018*** (0.003)
ln Agri population	0.012* (0.007)	0.006 (0.007)	0.009 (0.007)	0.009 (0.007)
ln Crops area	0.030*** (0.008)	0.038*** (0.008)	0.036*** (0.008)	0.035*** (0.008)
ln Agri proportion	0.017*** (0.005)	0.013*** (0.004)	0.013*** (0.004)	0.014*** (0.005)
Constant	0.331*** (0.081)	0.437*** (0.115)	0.301*** (0.082)	0.265*** (0.091)
R^2	0.723	0.714	0.710	0.710
Prob > F	0.000	0.000	0.000	0.000
Number of obs	216	216	216	216

Notes: Standard errors are presented in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5.
Estimated results of
equation (10)

Table 6.
Estimated results of
moderating effect of
farmers' cropping
strategy

while the coefficient of the interaction term is positive and statistically significant, indicating that farmers' cropping strategy moderates the impact of accumulated temperature on the technical efficiency. Next, the authors estimate the marginal effect of accumulated temperature on technical efficiency under different degrees of crop specialisation (1-SDI) of farmers. The results are shown in Figure 3. The estimated results show that when the degree of crop specialisation is greater than 0.559, the marginal effect of accumulated temperature on the technical efficiency is decreasing, and the moderating effect is statistically significant; the moderating effect is not statistically significant when the degree of crop specialisation is less than 0.559.

The moderating effect of farmers' cropping strategy is shown in Figure 4. High IV and Low IV, respectively refer to adding and subtracting one standard deviation on the mean value of the explanatory variable *Te*. The square and circle in Figure 4 refer to adding and subtracting one standard deviation on the mean value of the moderating variable, respectively. It can be clearly seen that the impact of increasing accumulated temperature on

Variable	Technical efficiency
c.SDI	-0.188*** (0.019)
c.Te	-0.029** (0.014)
C.SDI#C.Te	0.083** (0.036)
Constant	0.879*** (0.001)
R ²	0.419
Prob > χ^2	0.000
Number of obs	216

Notes: Standard errors are presented in parentheses. Significance level: ****p* < 0.01, ***p* < 0.05, **p* < 0.1

Figure 3.
Marginal effect of
accumulated
temperature on
technical efficiency

Figure 4.
Moderating effect of
farmers' cropping
strategy

the technical efficiency is stronger in the case of higher crop specialisation than in the case of lower crop specialisation (1-SDI). This means the former may lead to a more dramatic decline in technical efficiency of crops when the accumulated temperature rises. Anyhow, the technical efficiency still remains higher than that of farmers who adopted less specialised cropping. Therefore, farmers tend to adopt specialisation strategies to alleviate the possible damage to technical efficiency of crops caused by the warming climate.

5. Conclusion

The changing climate severely threatens the sustainable development of agriculture and livelihoods of smallholder farmers in developing countries. China holds the largest population of smallholder farmers and distinct natural resource endowment in different regions. It became the biggest challenge for them to adapt to climate change and secure the food supply in the country. This study attempts to evaluate farmers' cropping strategy and the economic performance under climate change based on the panel data of 12 provinces. This study reveals that specialised cropping is farmers' important strategy to improve the resistance of crops to climatic shocks. Northern farmers in China chose to plant more N-crops, while more H-crops were planted in the south. Different from the findings of others' work (Trinh *et al.*, 2018), farmers have adapted to climate change by reducing the diversity of food crops, so as to mitigate the loss of their benefits from climatic shocks. Farmers' crop specialisation could significantly improve the yield and technical efficiency of crops. In addition, crop specialisation had a marginal effect associated with the impact of accumulated temperature on the technical efficiency. Specifically, when the degree of crop specialisation is greater than 0.559, the marginal effect of accumulated temperature on technical efficiency is decreased, and the moderating effect of farmers' cropping strategy is statistically significant.

The study findings have important implications regarding adaptation strategies that can increase agriculture resilience to climate change for smallholder farmers in developing

countries. Firstly, the local government can promote the cooperation among smallholder farmers, as well as different agencies. Agricultural extension stations and farmers' cooperatives can introduce more training and guidance for farmers to actively adopt measures to combat the changing climate. For example, agencies can introduce new varieties of crops that are more drought-resistant and train farmers with the best practices of crop management under some extreme weather events. Secondly, farmers are encouraged to use crop specialisation strategy to mitigate the risk of climate change to the economic performance in agricultural production. Also, they may adjust the timetable for agricultural cultivation or increase inputs such as fertilisers to manage the harvest time accordingly. Furthermore, the local government may provide agricultural subsidies for smallholder farmers to buy insurance so as to alleviate economic loss once they suffer the negative impact in production from the extreme climatic events.

References

- Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977), "Formulation and estimation of stochastic frontier production function models", *Journal of Econometrics*, Vol. 6 No. 1, pp. 21-37.
- Amfo, B. and Ali, E.B. (2020), "Climate change coping and adaptation strategies: how do cocoa farmers in Ghana diversify farm income?", *Forest Policy and Economics*, Vol. 119, p. 102265.
- Arslan, A., Belotti, F. and Lipper, L. (2017), "Smallholder productivity and weather shocks: adoption and impact of widely promoted agricultural practices in Tanzania", *Food Policy*, Vol. 69, pp. 68-81.
- Asfaw, S., Pallante, G. and Palma, A. (2018), "Diversification strategies and adaptation deficit: evidence from rural communities in Niger", *World Development*, Vol. 101 No. 1, pp. 219-234.
- Axel, E., Trung, T.N. and Ulrike, G. (2017), "Production efficiency of rice farms in Thailand and Cambodia: a comparative analysis of Ubon Ratchathani and Stung Treng provinces", *Paddy and Water Environment*, Vol. 15 No. 1, pp. 79-92.
- Battese, G.E. and Coelli, T.J. (1995), "A model for technical inefficiency effects in a stochastic frontier production function for panel data", *Empirical Economics*, Vol. 20 No. 2, pp. 325-332.
- Birthal, P.S. and Hazrana, J. (2019), "Crop diversification and resilience of agriculture to climatic shocks: evidence from India", *Agricultural Systems*, Vol. 173 No. 3, pp. 345-354.
- Brondizio, E.S. and Moran, E.F. (2008), "Human dimensions of climate change: the vulnerability of small farmers in the Amazon", *Philosophical Transactions of the Royal Society B: Biological Sciences*, Vol. 363 No. 1498, pp. 1803-1809.
- Chen, Q., Liu, Y., Ge, Q. and Pan, T. (2018), "Impacts of historic climate variability and land use change on winter wheat climatic productivity in the North China plain during 1980-2010", *Land Use Policy*, Vol. 76, pp. 1-9.
- Chen, C., van Groenigen, K.J., Yang, H., Hungate, B.A., Yang, B., Tian, Y., Chen, J., Dong, W., Huang, S., Deng, A., Jiang, Y. and Zhang, W. (2020), "Global warming and shifts in cropping systems together reduce China's rice production", *Global Food Security*, Vol. 24, p. 100359.
- China Agricultural Information Network (2019), "Crop variety column", available at: www.agri.cn/ (accessed 25 December 2019).
- China Meteorological Data Service Centre (2019), available at: <http://data.cma.cn> (accessed 15 December 2019).
- China's National Climate Change Program (2007), "The central people's government of the people's republic of China", available at: www.gov.cn/gzdt/2007-06/04/content_635590.htm (accessed 10 September 2021).
- Dai, J., Kesternich, M., Löschel, A. and Ziegler, A. (2015), "Extreme weather experiences and climate change beliefs in China: an econometric analysis", *Ecological Economics*, Vol. 116 No. 6, pp. 310-321.

- David, P.M., Stefany, C. and Amanda, N.B. (2012), "Guidelines for the investigation of mediating variables in business research", *Journal of Business and Psychology*, Vol. 27 No. 1, pp. 1-14.
- Elena, B.P., Denis, A.D.C. and Marcelo, J.B. (2020), "Climate variability and crop diversification in Brazil: an ordered probit analysis", *Journal of Cleaner Production*, Vol. 256, p. 120252.
- Elizabeth, B., Temesgen, T.D., Glwadys, A.G. and Claudia, R. (2008), "Adaptation to climate change in Ethiopia and South Africa: options and constraints", *Environmental Science and Policy*, Vol. 12 No. 4, pp. 413-426.
- Fall, F., Akim, A. and Wassongma, H. (2018), "DEA and SFA research on the efficiency of microfinance institutions: a meta-analysis", *World Development*, Vol. 107, pp. 176-188.
- FAO (2021), "FAOSTAT online database", available at: www.fao.org/faostat/en/#country/351 (accessed 9 September 2021).
- Ferreira, M.D.P. and Féres, J.G. (2020), "Farm size and land use efficiency in the Brazilian Amazon", *Land Use Policy*, Vol. 99, p. 104901.
- Haji, J. (2007), "Production efficiency of smallholders' vegetable-dominated mixed farming system in Eastern Ethiopia: a non-parametric approach", *Journal of African Economies*, Vol. 16 No. 1, pp. 1-27.
- Ickowitz, A., Powell, B., Rowland, D., Jones, A. and Sunderland, T. (2019), "Agricultural intensification, dietary diversity, and markets in the global food security narrative", *Global Food Security*, Vol. 20, pp. 9-16.
- IPCC (2014), "Climate change 2014: synthesis report", Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), Geneva.
- Khanal, A.R. and Mishra, A.K. (2017), "Enhancing food security: food crop portfolio choice in response to climatic risk in India", *Global Food Security*, Vol. 12, pp. 22-30.
- Koirala, K.H., Mishra, A. and Mohanty, S. (2016), "Impact of land ownership on productivity and efficiency of rice farmers: the case of the Philippines", *Land Use Policy*, Vol. 50, pp. 371-378.
- Kumbhakar, S.C. and Lovell, C.A.K. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.
- Llewellyn, R.V. and Williams, J.R. (1996), "Nonparametric analysis of technical, pure technical, and scale efficiencies for food crop production in East Java, Indonesia", *Agricultural Economics*, Vol. 15 No. 2, pp. 113-126.
- Ma, W., Renwick, A., Yuan, P. and Ratna, N. (2018), "Agricultural cooperative membership and technical efficiency of apple farmers in China: an analysis accounting for selectivity bias", *Food Policy*, Vol. 81, pp. 122-132.
- Ministry of Agriculture and Rural Affairs of the People's Republic of China (2020), available at: <http://zdscxx.moa.gov.cn:8080/nyb/pc/search.jsp> (accessed 9 September 2021).
- Mottaleb, K.A., Singh, P.K., He, X., Hossain, A., Kruseman, G. and Erenstein, O. (2019), "Alternative use of wheat land to implement a potential wheat holiday as wheat blast control: in search of feasible crops in Bangladesh", *Land Use Policy*, Vol. 82, pp. 1-12.
- National Assessment Report on Climate Change (2007), "Compilation committee for the National Assessment Report on Climate Change", Science Press, Beijing.
- National Bureau of Statistics (2017), available at: www.stats.gov.cn/tjsj/zxfb/201712/t20171208_1561546.html (accessed 27 May 2020).
- Ndamani, F. and Watanabe, T. (2016), "Determinants of farmers' adaptation to climate change: a micro level analysis in Ghana", *Scientia Agricola*, Vol. 73 No. 3, pp. 201-208.
- Nguyen, H.Q. (2017), "Analyzing the economies of crop diversification in rural Vietnam using an input distance function", *Agricultural Systems*, Vol. 153, pp. 148-156.
- Niroula, G.S. and Thapa, G.B. (2005), "Impacts and causes of land fragmentation, and lessons learned from land consolidation in South Asia", *Land Use Policy*, Vol. 22 No. 4, pp. 358-372.

- Ochoa, M.W.S., Härtl, F.H., Paul, C. and Knoke, T. (2019), "Cropping systems are homogenized by off-farm income – empirical evidence from small-scale farming systems in dry forests of Southern Ecuador", *Land Use Policy*, Vol. 82, pp. 204-219.
- Oluwatusin, F.M. (2014), "The perception of and adaptation to climate change among cocoa farm households in Ondo state, Nigeria", *Academic Journal of Interdisciplinary Studies*, Vol. 3 No. 1, p. 147.
- Orimogunje, A.O., Ogundeji, B.A., Ademola, T.I., Balogun, S.T. and Oyeledun, K.O. (2020), "Cocoa farmers' coping strategies for climate change adaptation in Ogun state, Nigeria", *Journal of Scientific Research and Reports*, Vol. 26 No. 2, pp. 44-51.
- Oyekale, A.S. (2012), "Impact of climate change on cocoa agriculture and technical efficiency of cocoa farmers in South-West Nigeria", *Journal of Human Ecology*, Vol. 40 No. 2, pp. 143-148.
- Rahman, S. (2009), "Whether crop diversification is a desired strategy for agricultural growth in Bangladesh?", *Food Policy*, Vol. 34 No. 4, pp. 340-349.
- Richard, K.A. (2018), "Livelihood diversification strategies to climate change among smallholder farmers in Northern Ghana", *Journal of International Development*, Vol. 30 No. 8, pp. 1318-1338.
- Sauer, J., Frohberg, K. and Hockmann, H. (2006), "Stochastic efficiency measurement: the curse of theoretical consistency", *Journal of Applied Economics*, Vol. 9 No. 1, pp. 139-165.
- Song, J., Guo, Y., Wu, P. and Sun, S. (2018), "The agricultural water rebound effect in China", *Ecological Economics*, Vol. 146, pp. 497-506.
- Steve, O. (1995), "The environment as hazard", *Environmental Pollution*, Vol. 90 No. 2, pp. 272-273.
- Trinh, T.Q., Rañola, R.F., Camacho, L.D. and Simelton, E. (2018), "Determinants of farmers' adaptation to climate change in agricultural production in the central region of Vietnam", *Land Use Policy*, Vol. 70, pp. 224-231.
- You, L., Spoor, M., Ulimwengu, J. and Zhang, S. (2011), "Land use change and environmental stress of wheat, rice and corn production in China", *China Economic Review*, Vol. 22 No. 4, pp. 461-473.

About the authors

Mingze Wu is a postgraduate student majored in agricultural management at Hainan University. His work is supervised by Dr. Yueji Zhu.

Yueji Zhu is an Associate Professor in the department of Agri-forestry Economics and Management at Hainan University. He and his team are working in the field of Agricultural and Resource Economics. Yueji Zhu is the corresponding author and can be contacted at: zhuyueji@126.com

Qi Yang is a postgraduate student majored in Agri-forestry Economics and Management at Hainan University. Her work is supervised by Dr. Yueji Zhu.