Can climate change influence agricultural GTFP in arid and semi-arid regions of Northwest China? Postprint

Authors: FENG,Jian, ZHAO,Lingdi, ZHANG,Yibo, SUN,Lingxiao, YU,Xiang, YU,Yang, ZHAO, Lingdi, YU,Yang

Date: 2020-11-25T00:00:00+00:00

Abstract

There are eight provinces and autonomous regions (Gansu Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Inner Mongolia Autonomous Region, Tibet Autonomous Region, Qinghai Province, Shanxi Province, and Shaanxi Province) in Northwest China, most areas of which are located in arid and semi-arid regions (northwest of the 400 mm precipitation line), accounting for 58.74% of the country's land area and sustaining approximately 7.84$\times10^{6}$ people. Because of drought conditions and fragile ecology, these regions cannot develop agriculture at the expense of the environment. Given the challenges of global warming, the green total factor productivity (GTFP), taking CO_2 emissions as an undesirable output, is an effective index for measuring the sustainability of agricultural development. Agricultural GTFP can be influenced by both internal production factors (labor force, machinery, land, agricultural plastic film, diesel, pesticide, and fertilizer) and external climate factors (temperature, precipitation, and sunshine duration). In this study, we used the Super-slacks-based measure (Super-SBM) model to measure agricultural GTFP during the period 2000–2016 at the regional level. Our results show that the average agricultural GTFP of most provinces and autonomous regions in arid and semi-arid regions underwent a fluctuating increase during the study period (2000–2016), and the fluctuation was caused by the production factors (input and output factors). To improve agricultural GTFP, Shaanxi, Shanxi, and Gansu should reduce agricultural labor force input; Shaanxi, Inner Mongolia, Gansu, and Shanxi should decrease machinery input; Shaanxi, Inner Mongolia, Xinjiang, and Shanxi should reduce fertilizer input; Shaanxi, Xinjiang, Gansu, and Ningxia should reduce diesel input; Xinjiang and Gansu should decrease plastic film input; and Gansu, Shanxi, and Inner Mongolia should cut pesticide input. Desirable output agricultural earnings should be increased in Qinghai

and Tibet, and undesirable output (CO_2 emissions) should be reduced in Inner Mongolia, Xinjiang, Gansu, and Shaanxi. Agricultural GTFP is influenced not only by internal production factors but also by external climate factors. To determine the influence of climate factors on GTFP in these provinces and autonomous regions, we used a Geographical Detector (Geodetector) model to analyze the influence of climate factors (temperature, precipitation, and sunshine duration) and identify the relationships between different climate factors and GTFP. We found that temperature played a significant role in the spatial heterogeneity of GTFP among provinces and autonomous regions in arid and semi-arid regions. For Xinjiang, Inner Mongolia, and Tibet, a suitable average annual temperature would be in the range of 7°C–9°C; for Gansu, Shanxi, and Ningxia, it would be 11°C–13°C; and for Shaanxi, it would be 15°C–17°C. Stable climatic conditions and more efficient production are prerequisites for the development of sustainable agriculture. Hence, in the agricultural production process, reducing the redundancy of input factors is the best way to reduce CO_2 emissions and to maintain temperatures, thereby improving the agricultural GTFP. The significance of this study is that it explores the impact of both internal production factors and external climatic factors on the development of sustainable agriculture in arid and semi-arid regions, identifying an effective way forward for the arid and semi-arid regions of Northwest China.

Full Text

Preamble

Can Climate Change Influence Agricultural GTFP in Arid and Semi-Arid Regions of Northwest China?

FENG Jian[1], ZHAO Lingdi[1,2], *ZHANG Yibo*[3], *SUN Lingxiao*[4], *YU Xiang*[4], *YU Yang*[4,5]

[1]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: Northwest China encompasses eight provinces and autonomous regions (Gansu Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Inner Mongolia Autonomous Region, Tibet Autonomous Region, Qinghai Province, Shanxi Province, and Shaanxi Province), most of which are located in arid and semi-arid regions (northwest of the 400 mm precipitation line). These areas account for 58.74% of the country's land area and sustain approximately 7.84$×10^{6}$ people. Due to drought conditions and fragile ecology, these regions cannot develop agriculture at the expense of the environment. Given the challenges of global warming, green total factor productivity (GTFP)—taking CO_2 emissions as an undesirable output—serves as an effective index for measuring the sustainability of agricultural development. Agricultural GTFP can be influenced by both internal production factors (labor force, machinery, land, agricultural plastic film, diesel, pesticide, and fertilizer) and external climate factors (temperature, precipitation, and sunshine duration).

In this study, we used the Super-Slacks-Based Measure (Super-SBM) model to measure agricultural GTFP at the regional level during 2000–2016. Our results show that the average agricultural GTFP in most provinces and autonomous regions in arid and semi-arid regions underwent a fluctuating increase during the study period, with fluctuations caused by production factors (input and output factors). To improve agricultural GTFP, Shaanxi, Shanxi, and Gansu should reduce agricultural labor force input; Shaanxi, Inner Mongolia, Gansu, and Shanxi should decrease machinery input; Shaanxi, Inner Mongolia, Xinjiang, and Shanxi should reduce fertilizer input; Shaanxi, Xinjiang, Gansu, and Ningxia should reduce diesel input; Xinjiang and Gansu should decrease plastic film input; and Gansu, Shanxi, and Inner Mongolia should cut pesticide input. Desirable output (agricultural earnings) should be increased in Qinghai and Tibet, while undesirable output (CO_2 emissions) should be reduced in Inner Mongolia, Xinjiang, Gansu, and Shaanxi.

Agricultural GTFP is influenced not only by internal production factors but also by external climate factors. To determine the influence of climate factors on GTFP in these provinces and autonomous regions, we used a Geographical Detector (Geodetector) model to analyze the influence of climate factors (temperature, precipitation, and sunshine duration) and identify the relationships between different climate factors and GTFP. We found that temperature played a significant role in the spatial heterogeneity of GTFP among provinces and autonomous regions in arid and semi-arid regions. For Xinjiang, Inner Mongolia, and Tibet, a suitable average annual temperature would be in the range of 7°C–9°C; for Gansu, Shanxi, and Ningxia, it would be 11°C–13°C; and for Shaanxi, it would be 15°C–17°C. Stable climatic conditions and more efficient production are prerequisites for the development of sustainable agriculture.

Hence, in the agricultural production process, reducing the redundancy of input factors is the best way to reduce CO_2 emissions and maintain temperatures, thereby improving agricultural GTFP. The significance of this study is that it explores the impact of both internal production factors and external climatic factors on the development of sustainable agriculture in arid and semi-arid regions, identifying an effective way forward for the arid and semi-arid regions of Northwest China.

Keywords: climate change; agricultural GTFP; Super-slacks-based measure (Super-SBM) model; Geodetector; CO_2 emissions; arid regions; semi-arid regions

∗Corresponding author: ZHAO Lingdi (E-mail: lingdizhao512@163.com); YU Yang (E-mail: yuyang@ms.xjb.ac.cn)

Received 2019-02-06; revised 2019-09-16; accepted 2019-10-15 http://jal.xjegi.com; www.springer.com/40333

1 Introduction

In a narrow sense, agriculture refers to crop farming that provides humans with essential products, including food, vegetables, animal feed, cooking oil, medicines, fibers, and wood. As China has the largest population in the world, agriculture—which influences livelihoods—is particularly significant there (Feng et al., 2005; Gollin et al., 2007; Nigussie et al., 2017). The arid and semi-arid regions in China occupy about 58.74% of the national land area and sustain a population of approximately 7.84×10^{6}. Because of the fragile ecological environment, these regions cannot sacrifice the environment to develop agriculture, making it important for them to develop sustainable practices.

Green total factor productivity (GTFP) is an index for evaluating the sustainability of development by comparing effective input and output factors. Numerous studies have used GTFP to assess sustainable development across different regions and sectors (Feng et al., 2015; Song et al., 2015; Fuinhas et al., 2016; Makijenko et al., 2016; Song et al., 2016; Wang et al., 2016; Liobikiene et al., 2017; Huang et al., 2018). In agricultural research, many scholars have measured agricultural productivity based on input and output factors (Van Ittersum et al., 2003; Peters et al., 2007). Wu (1995) used a frontier production framework to evaluate the increase of total factor productivity (TFP) in China and found growth of 50%–60% in the agricultural sector. Chen et al. (2009) suggested that agricultural productivity growth was higher in coastal regions and lower in central and western regions, attributing the lower productivity in western regions to lower marginal productivity of land, labor force, capital, and fertilizer input. Tian and Yu (2012) observed that the TFP of China's agricultural sector grew by 2% per year during 1950–2009. Other researchers have suggested that input and output factors during agricultural production processes can influence productivity (MacDonald et al., 2000; Olesen and Bindi, 2002; Liu et al., 2005).

Crop harvests in arid and semi-arid regions are particularly affected by climate. Aridification can limit crop yields, which greatly affects agricultural development (Turner, 2004; Saleska et al., 2007). Over the past 50 years, temperatures have increased significantly in arid and semi-arid regions of Northwest China, whereas precipitation has generally decreased, meaning these regions have experienced severe and long-lasting droughts (Dai, 2011; Ponce et al., 2013; Xiao et al., 2016). Furthermore, only 30%–40% of precipitation is available for crops (Boyer and Westgate, 2004; Zhang, 2008). Precipitation is erratic, and crop harvests tend to be irregular (Lobell et al., 2008; He et al., 2012; Hu et al., 2014). Global warming also affects crop production directly. As Piao et al. (2010) noted, global warming caused a slight decrease in Chinese crop production, with the magnitude of reduction varying between regions. Warming within an appropriate range (0.5°C–2.0°C) is beneficial for photosynthesis and crop growth, while temperature extremes reduce crop productivity and degrade quality (Xiao et al., 2016). However, temperatures in arid and semi-arid regions have risen by approximately 1.4°C–3.0°C over the past 30 years, which not only influences crop growth directly but also threatens water resource use by making these areas more vulnerable to drought (Sheffield and Wood, 2008; Wang et al., 2011; Ren et al., 2012; Trenberth et al., 2014; Leng et al., 2015; Lei et al., 2016). This forms a vicious spiral that threatens sustainable agricultural development in these regions.

As agricultural research has developed, both governments and scholars have recognized the importance of comprehensive assessments that combine climate and production (input and output) factors to make complete and systematic evaluations of agricultural production. Such an approach can provide an integrated evaluation that enables policymakers to make appropriate decisions (Lee and Tollenaar, 2007; Mueller et al., 2009). Deng et al. (2017) introduced the estimation system of agricultural productivity (ESAP) framework to evaluate productivity by considering photosynthetic, photothermal, climatic, and land values in agricultural processes. Although assessment research in sustainable agricultural development has progressed since 2010, analyses of Chinese arid and semi-arid regions remain scarce.

Our study aims to quantify GTFP changes in the agricultural sector between 2000 and 2016 and determine the influence of climate factors in arid and semi-arid regions of Northwest China. We considered climate change factors as external factors and production (input and output) factors as internal factors. To evaluate the sustainability of development, we used the Super-slacks-based measure (Super-SBM) model to calculate agricultural GTFP with input and output factors for different regions. We also utilized the Geographical Detector (Geodetector) model to calculate the influence of different climate factors and explore which factors play a more important role in influencing agricultural GTFP in arid and semi-arid regions of Northwest China.

2.1 Study Area

We used an agricultural panel dataset of arid and semi-arid regions in Northwest China for the period 2000–2016. These arid and semi-arid regions consist mainly of eight provinces and autonomous regions (Gansu Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Inner Mongolia Autonomous Region, Tibet Autonomous Region, Qinghai Province, Shanxi Province, and Shaanxi Province) located at 31°90′–53°23′N and 73°40′–126°04′E. Based on the Chinese classification standard for wet and dry areas, researchers divided arid and semi-arid regions by the 200 mm equipluve (Kunlun Mountains-Tangshan Mountains-Inner Mongolian Plateau), while the 400 mm equipluve (Tibet Plateau-Loess Plateau-Da Hinggan Ling) serves as the demarcation line between semi-arid and semi-humid regions (Zhang et al., 2016). According to this standard, we divided all provinces and autonomous regions under study into arid and semi-arid regions based on average annual precipitation and geographical location. Thus, the arid regions include three provinces and autonomous regions (Gansu, Ningxia, and Xinjiang), and the semi-arid regions cover five provinces and autonomous regions (Inner Mongolia, Tibet, Qinghai, Shanxi, and Shaanxi).

Most areas of semi-arid regions are located between the 200 and 400 mm precipitation lines. The soil erosion problem in these areas is serious, and the agricultural ecological environment is fragile. The main type of vegetation is grassland. Because of the rainless climate, the yield of dry farming is unstable. With extensive cultivation and small yields, the farming economy is underdeveloped compared to that of humid and semi-humid regions in China. Most areas of the arid regions are located northwest of the 200 mm precipitation line. Owing to long-term drought conditions, most land resources are desert. The processes of desertification and salinization have made most areas unsuitable for agricultural development, with only a few areas supporting dry farming and oasis agriculture. Given the harsh climatic conditions, shortage of water resources, and fragile ecological environment, the studied arid and semi-arid regions need to account for climate characteristics when exploring appropriate and sustainable development paths for agriculture.

2.2 Agricultural Data Collection

Following the studies of Chen et al. (2008), Ito (2010), and Kerstens et al. (2018), we regarded labor force, machinery, land, agricultural plastic film, diesel, pesticide, and fertilizer as input factors. Desirable output was calculated by the value of agricultural yield, and undesirable output was measured by standard CO_2 emissions during the production process. In line with previous studies, labor force was measured by the number of agricultural labors, machinery by the total power of agricultural machinery, and land by the total sown area. Plastic film, diesel, pesticide, and fertilizer were directly represented by the amounts used in the agricultural production process. Agricultural yield is represented by gross output value calculated using 2000 prices, and standard CO_2 emissions are the emission coefficients of input factors.

Since China became the world's largest emitter of greenhouse gases in 2008, sustainable agricultural development with regard to greenhouse gas emissions has been a focus of national attention (Liu et al., 2013, 2016). Greenhouse gas emissions play an important role in climate change and are a by-product of crop cultivation. The main sources of agricultural emissions are the use of diesel, pesticide, chemical fertilizer, and plastic film, as well as irrigation and plowing processes. To account for the greenhouse effect, we converted greenhouse gases to standard CO_2 emissions. Following Liu et al. (2018), we calculated CO_2 emissions based on emission coefficients during the cultivation process. The carbon emission coefficients of main carbon sources are shown in Table 1 .

Table 1 CO_2 emission coefficients during the cultivation process

Source of carbon	Fertilizer (kg CE/kg)	Pesticide (kg CE/kg)	Plastic film (kg CE/kg)	Diesel (kg CE/kg)	Irrigation (kg/km^2)	Plowing (kg/km^2)	Reference source
Emission coefficient	Oak Ridge National Laboratory (ORNL), United States	Institute of Resource, Ecosystem and Environment of Agriculture of Nanjing Agricultural University (IREEA), China	Intergovernmental Panel on Climate Change (IPCC), United Nations	China Agricultural University (CAU), China	Duan et al. (2011), China		

Note: "kg CE" stands for kilogram of coal equivalent (energy intensity).

Except for CO_2 emissions, data for other input and output factors were collected from the China Rural Statistical Yearbook (NBSC, 2001–2017a), and all monetary variables were deflated to the price level of the year 2000. Regional climate factors discussed below are represented by temperature, precipitation, and sunshine duration data for capital cities, taken from the 2000 to 2016 editions of China Statistical Yearbook (NBSC, 2001–2017b). Due to the authenticity and credibility of these sources, many agricultural studies have used data from them (Xu et al., 2015; Rigoberto et al., 2017; Shen et al., 2018; Wang et al., 2019; Zhang et al., 2019).

2.3 Super-SBM Model

Many studies have used Data Envelopment Analysis (DEA) methods to analyze GTFP in the agricultural sector (e.g., Heidari et al., 2012; Blancard and Martin, 2014; Pang et al., 2016). As they have no predefined production function, DEA models allow creation of a production frontier with the best input-output ratio through optimized linear programming results. In radial DEA models, inefficiency measurement includes only proportional reduction and enlargement of all inputs and outputs. Because of this limitation, the distance between the inefficient decision-making unit (DMU) and the most effective target contains slack improvement, which cannot be presented in radial DEA efficiency measurement. Unlike radial DEA models, slacks-based measure (SBM) models excel at directly dealing with input and output slacks to eliminate both radial and oriented deviation. Undesirable outputs are unavoidable in any production process, and it is necessary to account for them in efficiency evaluation models (Seiford and Zhu, 2002). Among possible methods for processing undesirable outputs, SBM stands out because it fits the production process perfectly.

However, when evaluating DMU efficiency using traditional SBM models, multiple DMU efficiency values often equal 1, especially under conditions of multiple input and output indicators, making it impossible to further distinguish efficiency values between effective DMUs. To resolve this difficulty, Andersen and Petersen (1993) proposed the Super Efficiency model, and Tone (2002) proposed the Super-SBM model. Following Cheng (2014), the Super-SBM model with undesirable output is described as follows:

Constraint conditions:

$$
\begin{aligned}
&\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{ik} - s_i^- \quad (i = 1, 2, \dots, m) \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rk} + s_r^+ \quad (r = 1, 2, \dots, q_1) \\
&\sum_{j=1}^{n} \lambda_j b_{tj} \le b_{tk} - s_t^- \quad (t = 1, 2, \dots, q_2) \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0, \quad s_i^- \ge 0, \quad s_r^+ \ge 0, \quad s_t^- \ge 0
\end{aligned}
$$

We suppose there are n DMUs (DMU , j=1,2,…,n), each representing a province or autonomous region of China. Each DMU utilizes m inputs x (i=1,2,…,m) to produce q_1 desirable outputs y (r=1,2,…,q_1) and discharge q_2 undesirable outputs b (t=1,2,…,q_2). DMU is the province or autonomous region being measured, x represents its input factors, y its desirable outputs, and b its undesirable outputs. In the equations, s.t. means “subject to,” and λ (j=1,2,…,n) is the nonnegative intensity variable associated with each DMU for combining inputs and outputs. s^-, s^+, and s^- represent slack variables denoting excess inputs, shortage of desirable outputs, and excess undesirable outputs, respectively. The numerator and denominator of the target function evaluate the average distance from actual inputs and outputs to production frontiers. If \$ \$1, it indicates that a production unit is efficient.

2.4 Geodetector

Climate change can influence crop productivity (Yao et al., 2011). In this study, we used the Geographical Detector (Geodetector) model to analyze the influence of climate change on agricultural GTFP. Geodetector is a model for measuring spatial stratified heterogeneity (SSH) that consists of a factor detector, interaction detector, risk detector, and ecological detector. Jin et al. (2018) claimed that light, temperature, and water conditions are the main factors influencing agricultural productivity, so we investigated the factor, interaction, ecological, and risk influences of temperature, precipitation, and sunshine duration on GTFP.

The basic assumption of Geodetector is that the study region can be divided into several sub-regions. If the sum of variances of sub-regions is smaller than total variance of the region, spatial differentiation exists. If spatial distributions of two variables tend to agree, there is statistical correlation between them. Geodetector uses the q statistic to measure spatial differentiation, detect explanatory factors, and analyze interaction between variables (Wang et al., 2010).

2.4.1 Factor Detector

The factor detector can detect the extent to which a certain factor x explains the spatial differentiation of variable y. We used the q value to explain this degree. Factor x can be divided into h (h=1,2,…,L, where L is total number of strata) parts; likewise, we divided variable y . σ^2 and σ^2 are variances of y in strata h and in the whole region, respectively, while Y and Y are average y of strata h and of the whole region, respectively. The q statistic expression is as follows:

$$q = 1 - \frac{SSW}{SST} = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where SSW and SST are sum of squares within strata h and total sum of squares of y , respectively; N and N are units of y in strata h and total y , respectively. The q values range from 0 to 1. The larger the q value, the greater the explanatory power of x to y. If q=1, it indicates x completely explains the spatial distribution of y; if q=0, it indicates x has no relationship with y. The q value means x can explain 100×q% of y.

A simple transformation of the q statistic satisfies a non-central F distribution (Wang et al., 2016):

$$F = \frac{(N - L)}{L - 1} \cdot \frac{q}{1 - q} \sim F(L - 1, N - L, \lambda)$$

where λ is a non-central parameter.

2.4.2 Interaction Detector

The interaction detector identifies interaction relationships between different factors and evaluates their combined effect to determine whether any pair of factors working together will increase or decrease explanatory power of the dependent variable y (or whether influences are independent). The evaluation method first calculates q values of two factors x_1 and x_2 for y separately to obtain $q(x_1)$ and $q(x_2)$. Second, the q value of their interaction is calculated (two strata superimposed to form a new polygonal distribution) to obtain $q(x_1\ x_2)$. Finally, $q(x_1)$, $q(x_2)$, and $q(x_1\ x_2)$ are compared to find the interaction relationship. If $q(x_1\ x_2) < \min(q(x_1), q(x_2))$, the combined effect decreases explanatory power. If $\min(q(x_1), q(x_2)) < q(x_1\ x_2) < \max(q(x_1), q(x_2))$, the effects are mutually exclusive and both decrease explanatory power of y nonlinearly. If $q(x_1\ x_2) > \max(q(x_1), q(x_2))$, the combined effect enhances explanatory power. If $q(x_1\ x_2) = q(x_1) + q(x_2)$, the factors are independent; if $q(x_1\ x_2) > q(x_1) + q(x_2)$, the combined effect enhances explanatory power nonlinearly.

2.4.3 Risk Detector

The risk detector finds significant differences in mean values between sub-regions and tests them with the t statistic:

$$t = \frac{\bar{Y}_h - \bar{Y}_k}{\sqrt{\frac{Var_h}{n_h} + \frac{Var_k}{n_k}}}$$

where Ȳ is the average value of samples y in strata h; Ȳ represents the average value of y (k=1,2,…,L); n and n are sample sizes of sub-regions h and k; Var denotes variance; and the t statistic approximately follows Student's t distribution with degrees of freedom calculated as:

$$df = \frac{(Var_h/n_h + Var_k/n_k)^2}{(Var_h/n_h)^2/(n_h - 1) + (Var_k/n_k)^2/(n_k - 1)}$$

The null hypothesis H_0 is expressed as: Ȳ = Ȳ . If H_0 is rejected at confidence level α, there is significant difference in mean value of y between sub-regions.

2.4.4 Ecological Detector

The ecological detector compares whether effects of any two factors on spatial distribution of y are significantly different, measuring the difference with the F statistic:

$$F = \frac{N_{x_1} \cdot (L_{x_1} - 1) \cdot SSW_{x_2}}{N_{x_2} \cdot (L_{x_2} - 1) \cdot SSW_{x_1}}$$

where N $_1$ and N $_2$ are sample sizes of factors x_1 and x_2; SSW $_1$ and SSW $_2$ are sums of intra-strata variances; and L_1 and L_2 represent numbers of strata for x_1 and x_2. The null hypothesis H_0 is: SSW $_1$ = SSW $_2$. If H_0 is rejected at significance level α, there is significant difference in effect of the two factors on spatial distribution of GTFP. When using Geodetector, if the independent variable is numerical, it must be discretized. In this study, we discretized dependent variables by equal division.

3.1 Descriptive Statistics for Input and Output Factors (Super-SBM Model)

Before using the Super-SBM model to measure GTFP, we conducted basic statistical analysis of input and output factors. Results are presented in Table 2 . Mean and standard deviation values show obvious variations in input and output factors between arid and semi-arid regions across different years. To establish sources of variation, we calculated average values and growth rates for agricultural input and output factors, presented in Tables 3 and 4. Together with Table 3 , these results show that all input and output factors in Ningxia, Tibet, and Qinghai were below average, whereas values in Inner Mongolia were above average. For Gansu, fertilizer and diesel input factors were below average; for Xinjiang, only labor force input was below average. For Shanxi, diesel and plastic film inputs were below average, as were plastic film and pesticide inputs in Shaanxi. With these exceptions, all input and output factors for these regions were above average. Gaps in input and output levels between Ningxia, Tibet, Qinghai, and other regions were very large, representing one main source of standard deviation (see Table 2), along with time differences (see Table 4).

Table 4 shows growth rates of input and output factors from 2000 to 2016. In these arid and semi-arid regions, all input factors except labor force and land input increased. For labor force input, Xinjiang and Tibet experienced positive growth while other regions had negative growth. Xinjiang had the highest growth rate (35.68%), while Shaanxi had the greatest decrease (–38.48%). For land input, Shanxi, Qinghai, and Shaanxi had negative growth while other regions had positive growth. Shaanxi had the greatest decrease (–6.74%), whereas Xinjiang had the highest increase (80.69%). All regions showed increasing trends in machinery, fertilizer, diesel, plastic film, and pesticide inputs. For machinery input, Tibet experienced the highest increase (454.67%) and Shanxi the lowest (2.53%). For fertilizer input, Xinjiang had the highest increase (215.91%) and Qinghai the lowest (22.22%). For diesel input, Tibet increased 785.71% (the highest) and Qinghai only 8.47% (the lowest). For plastic film input, Tibet's increase rate was highest (1700.00%) and Shaanxi's lowest (72.73%). For pesticide input, Gansu increased most (513.16%) and Qinghai least (0.00%). Except for Tibet's yield, all output factors increased. The desirable output (yield) rate in Ningxia rose by 232.79%, while Tibet showed a decrease of –13.65%. Xinjiang had the highest increase in undesirable output (CO_2 emissions) (148.84%), while Shanxi's increase was lowest (18.53%).

In summary, data for sown areas and output values in these arid and semi-arid regions showed increases, indicating expansion of agricultural production scale. Labor force input in arid and semi-arid regions decreased by 10.65% and 31.45%, respectively, while machinery input increased by 120.06% and 86.80%, implying growing mechanization replacing labor. Land input increased in all arid regions but decreased in all semi-arid regions except Inner Mongolia. Use of other inputs—including fertilizer, diesel, plastic film, and pesticide—increased substantially, especially plastic film (203.18% and 123.60% in arid and semi-arid regions) and pesticide (274.07% and 97.50%). Growth rates for desirable output (agricultural earnings) were similar in arid (145.89%) and semi-arid (146.86%) regions, with all provinces showing positive growth except Tibet. Undesirable output (CO_2 emissions) increased greatly (107.69% in arid regions and 53.12% in semi-arid regions), representing a matter of great importance given climate change effects.

3.2 Dynamic Changes in GTFP

Application of the Super-SBM model allowed us to determine gaps in agricultural sustainable development between arid and semi-arid regions by estimating their GTFP. Figure 1 [Figure 1: see original paper] shows regional agriculture GTFP results for 2000–2016. Except for Xinjiang and Tibet, all regions showed similar variation patterns: fluctuating increase from 2000 to 2006, decrease in 2007, then another fluctuating increase from 2008 to 2016. Xinjiang and Tibet started at higher GTFP levels than other regions; Xinjiang maintained its high level while Tibet's dropped sharply. Shanxi and Qinghai had the lowest GTFP levels in 2000. Ningxia, Shaanxi, and Shanxi increased gradually, while other regions increased with fluctuations.

Dynamic changes of input and output slacks in arid and semi-arid regions during 2000–2016 are shown in Figure 2 [Figure 2: see original paper]. In arid regions, GTFP of almost all provinces fluctuated due to input and undesirable output slacks. Xinjiang's GTFP remained comparatively high due to low input and output inefficiency. Sharp declines were mainly due to redundant diesel, land, and plastic film inputs in 2001, and land, fertilizer, and plastic film in 2007–2008. Substantial increases resulted mainly from decreased slacks in diesel, land, and plastic film in 2006, and land, fertilizer, and plastic film in 2015. Undesirable CO_2 output was also important in both increases and decreases. For Ningxia, GTFP dropped in 2007 due to diesel and fertilizer input slacks, while the sharp 2015 increase resulted from decreased diesel and fertilizer slacks. Gansu's GTFP decreased in 2007 mainly due to redundant machinery, fertilizer, pesticide, diesel, and CO_2 output, and again in 2011 due to redundant machinery, plastic film, pesticide, and CO_2 output. The sharp 2016 increase resulted from reduced redundancy in machinery, fertilizer, pesticide, diesel, plastic film, and CO_2 output.

In semi-arid regions, GTFP levels in Qinghai and Tibet were mainly influenced by insufficient desirable output, while GTFP in other provinces fluctuated due to input and undesirable output slacks. Inner Mongolia's GTFP decrease was greater in 2003 and 2007; reductions in fertilizer, pesticide, diesel, and plastic film inputs drove the 2003 increase, while reductions in fertilizer and diesel inputs and CO_2 output were main factors in 2007. In Shanxi and Shaanxi, various agricultural inputs including fertilizer and diesel were redundant in 2007, lowering GTFP. Shanxi's 2009 GTFP increase can be attributed to decreased fertilizer, plastic film, pesticide, and diesel inputs and redundant CO_2 output; in Shaanxi, machinery slack reduction was responsible. Shanxi's 2016 GTFP increase resulted from decreased machinery input; Shaanxi's 2009 increase came from reduced diesel redundancy, while its 2016 increase resulted from reduced machinery, fertilizer, and diesel redundancy. Tibet's GTFP was initially strong with almost no redundant inputs, but insufficient desirable output lowered GTFP. Qinghai's low agricultural input and output levels accounted for its lower GTFP.

In summary, except for Tibet and Qinghai, input and CO_2 output redundancy are main reasons for GTFP decreases. Reducing redundancy is therefore key to increasing GTFP in all arid and semi-arid regions, requiring consideration of each province's specific situation. Compared to other regions, Tibet and Qinghai have little input redundancy, so insufficient agricultural earnings are the main reason for their low GTFP. In these cases, selecting arable crops with higher economic value would be an effective improvement method.

3.3 Influence of Climate Factors on Agricultural GTFP (Factor Detector)

Table 5 shows q values for each climate risk factor. Values for temperature, precipitation, and sunshine duration are 0.2442, 0.0173, and 0.0203, respectively. This means temperature can explain 24.42% of GTFP, while precipitation and sunshine duration explain 1.73% and 2.03%, respectively. All P-values exceed 0.95, meaning results are significant at 95% confidence level. Therefore, all three climate factors influence GTFP, with temperature's effect greater than sunshine duration and precipitation.

Table 5 Spatial heterogeneity of agricultural GTFP caused by climate factors

Statistic	q statistic	P-value
Temperature	0.2442	>0.95
Precipitation	0.0173	>0.95
Sunshine duration	0.0203	>0.95

3.4 Comparison of Influence from Climate Factors on Agricultural GTFP (Ecological Detector)

As shown in Table 6 , if the difference for one climate factor in the first column exceeds that of a factor in the first row, the result is Y, otherwise N. Results show differences in GTFP between temperature groups exceed those for sunshine duration and precipitation, while precipitation differences are smaller than for sunshine duration. Thus, different temperatures cause more GTFP variation than different sunshine durations, which in turn cause more variation than different precipitation levels.

Table 6 Comparison of climate factor influences on agricultural GTFP

	Temperature	Precipitation	Sunshine duration
Temperature		Y	Y
Precipitation	N		N
Sunshine duration	N	Y	

Note: If the difference for one climate factor in the first column is bigger than a factor in the first row, the result is Y, otherwise N.

3.5 Interaction Influence of Climate Factors on Agricultural GTFP (Interaction Detector)

Results for the interaction detector are given in Tables 7 and 8. According to Table 7 , values of q(T), q(P), q(S), q(T P), q(T S), and q(P S) are 0.2442, 0.0173, 0.0203, 0.3004, 0.2981, and 0.0550, respectively. Since q(T P) > q(T) and q(T P) > q(P), combining temperature and precipitation enhances their explanatory power for GTFP. Similarly, q(T S) > q(T) and q(T S) > q(S) shows temperature and sunshine duration combination enhances explanation; and q(P S) > q(P) and q(P S) > q(S) shows precipitation and sunshine duration combination enhances explanation. As graphical representations in Table 8 show, each combination of two factors enhances GTFP explanation nonlinearly.

Table 7 Interaction influence of climate factors on agricultural GTFP

	Temperature	Precipitation	Sunshine duration
Temperature	0.2442	0.3004	0.2981
Precipitation	0.3004	0.0173	0.0550
Sunshine duration	0.2981	0.0550	0.0203

Table 8 Interaction types of climate factors

Climate factor	Graphical representation	Interaction
Temperature Precipitation		Enhances, nonlinear
Temperature Sunshine duration		Enhances, nonlinear
Precipitation Sunshine duration		Enhances, nonlinear

Note: , min($q(x_1)$, $q(x_2)$); , max($q(x_1)$, $q(x_2)$); , $q(x_1)$+$q(x_2)$; , $q(x_1\ x_2)$.

3.6 Risk Detector

The risk detector presents average GTFP for each temperature, precipitation, and sunshine duration group and identifies whether GTFP of each group in a row differs significantly from a group in a column (Y for yes, N for no). Results are shown in Table 9 . GTFP in temperature range 5°C–7°C differs significantly from others (7°C–9°C, 9°C–11°C, 11°C–13°C, 13°C–15°C, and 15°C–17°C). When temperature increases to 11°C–13°C, GTFP reaches its highest point among six temperature groups. GTFP in range 7°C–9°C also differs significantly from 9°C–11°C; when temperature increases to 9°C–11°C, GTFP declines. However, GTFP at 9°C–11°C differs from 11°C–13°C and 15°C–17°C, and average GTFP increases with temperature. Regions with annual mean temperatures around 7°C–9°C, 11°C–13°C, and 15°C–17°C can achieve higher GTFP, mainly because plantation structures differ and crops have different optimal growth temperatures. Higher GTFP at 7°C–9°C appears in some years in Xinjiang, Inner Mongolia, and Tibet; at 11°C–13°C in some years in Gansu, Shanxi, and Ningxia; and at 15°C–17°C in Shaanxi only. This aligns with expectations that favorable annual average temperature for GTFP in arid and semi-arid regions is 11°C–13°C, with higher or lower temperatures decreasing agricultural GTFP. No significant GTFP differences exist between precipitation or sunshine duration groups, indicating these factors do not significantly influence GTFP in arid and semi-arid regions. Overall, suitable annual average temperatures for higher GTFP are 7°C–9°C in Xinjiang, Inner Mongolia, and Tibet; 11°C–13°C in Gansu, Shanxi, and Ningxia; and 15°C–17°C in Shaanxi. Higher or lower temperatures reduce GTFP, consistent with Xiao et al. (2016).

In summary, both internal production factors (input and output) and external climate factors influence GTFP in arid and semi-arid regions. Lower redundancy of input factors (labor force, machinery, land, plastic film, diesel, pesticide, fertilizer) and undesirable output (CO_2 emissions), plus greater desirable output (agricultural earnings), lead to higher GTFP. Among three main climate factors (temperature, precipitation, sunshine duration), temperature plays the most important role in influencing GTFP changes, but combining any two factors enhances their influence. Different provinces and autonomous regions have optimal temperatures for achieving higher GTFP, with other temperatures reducing GTFP.

4 Discussion

In arid and semi-arid regions of Northwest China, GTFP fluctuations are influenced by both slacks in internal production factors and external climate factors. Regional differences in these factors are main reasons for significant spatial GTFP differences, similar to Liu et al. (2015). Consistent with our findings, scholars believe GTFP is influenced not only by internal production factors but also that climate change may cause declines and concomitant fluctuations (Kravchenko and Bullock, 2000; Tao et al., 2006). Spatial distribution of agricultural productivity generally accords with production factors and is seriously influenced by climate change.

To improve GTFP in these regions, both internal production and external climate factors must be considered. Because distributions of production and climate factors differ across provinces, regional differences should be noted and adjusted: agricultural labor force should be reduced in Shaanxi, Shanxi, and Gansu; machinery input decreased in Shanxi, Inner Mongolia, Gansu, and Shanxi; fertilizer input reduced in Shaanxi, Inner Mongolia, Xinjiang, and Shanxi; diesel input reduced in Shaanxi, Xinjiang, Gansu, and Ningxia; plastic film input decreased in Xinjiang and Gansu; pesticide input cut in Gansu, Shanxi, and Inner Mongolia; agricultural earnings improved in Qinghai and Tibet; and CO_2 emissions reduced in Inner Mongolia, Xinjiang, Gansu, and Shaanxi.

Suitable annual average temperatures are 7°C–9°C for Xinjiang, Inner Mongolia, and Tibet; 11°C–13°C for Gansu, Shanxi, and Ningxia; and 15°C–17°C for Shaanxi. Lower input factor redundancy can lead to higher GTFP. For most provinces, input redundancy is the main reason for GTFP decreases. To improve GTFP, suitable input factor management should be implemented. Lower undesirable output (CO_2 emissions) redundancy also raises GTFP, and for most provinces, CO_2 output redundancy is a principal reason for GTFP decreases. Input factors such as fertilizer, plastic film, diesel, and pesticide are main CO_2 emission sources, so improving traditional inputs (e.g., formula fertilization) and expanding clean alternatives (e.g., solar energy, natural gas) are effective reduction methods (Fischer et al., 2010). Reducing input redundancy during production is also necessary to decrease CO_2 emissions and improve GTFP. Finally, increasing desirable output (agricultural earnings) can raise GTFP, particularly in Qinghai and Tibet where earnings insufficiency is the main reason for low GTFP. Selecting higher-value crops would be effective.

Both internal production and external climate factors influence GTFP. Among three climate factors (temperature, precipitation, sunshine duration), temperature plays the most important role. Different provinces have different optimal temperatures for higher GTFP. However, as a large agricultural country, China's rapid agricultural mechanization development and excessive fertilizer, diesel, plastic film, and pesticide use have caused considerable CO_2 emissions. Plastic film, which maximizes rainwater utilization and helps control temperature, is important in arid and semi-arid regions (Li and Gong, 2002; Li and Wang et al., 2011; Zhou et al., 2012; Gan et al., 2013; Zhao et al., 2014), but is also a major CO_2 emission source.

Agriculture in arid and semi-arid regions is at an important transformation stage from traditional to modern forms (Xu et al., 2017). Regional GTFP differences remain large, and input factors are unbalanced. As Ma and Feng (2013) noted, changing production methods to reduce chemical fertilizer use and energy consumption is important. Equipment and fertilization efficiency also need improvement. Given the fragile agricultural environment, more efficient use of production factors including fertilizer, pesticide, diesel, and plastic film should be considered to promote sustainable agriculture.

5 Conclusions

Sustainable agriculture development in arid and semi-arid regions of Northwest China plays an important role in meeting global warming challenges. An appropriate means of achieving sustainable development is improving GTFP and managing CO_2 emissions more effectively. Sustainable agricultural development is influenced by both internal production and external climate factors. For most provinces, reducing input redundancy can directly increase GTFP by reducing CO_2 emissions. Different measures are needed: reducing agricultural labor force in Shaanxi, Shanxi, and Gansu; decreasing machine input in Shanxi, Inner Mongolia, Gansu, and Shanxi; cutting fertilizer input in Shaanxi, Inner Mongolia, Xinjiang, and Shanxi; reducing diesel input in Shaanxi, Xinjiang, Gansu, and Ningxia; decreasing plastic film input in Xinjiang and Gansu; cutting pesticide input in Gansu, Shanxi, and Inner Mongolia; improving agricultural earnings in Qinghai and Tibet; and reducing CO_2 emissions in Inner Mongolia, Xinjiang, Gansu, and Shaanxi.

Among external climate factors, temperature is the main cause of regional GTFP differences. Optimal annual average temperatures are 7°C–9°C in Xinjiang, Inner Mongolia, and Tibet; 11°C–13°C in Gansu, Shanxi, and Ningxia; and 15°C–17°C in Shaanxi. CO_2 emissions are a major cause of temperature changes, and input factors such as machinery, land, plastic film, diesel, pesticide, and fertilizer are significant CO_2 emission sources. Stable climatic conditions and production factor improvements are prerequisites for sustainable agriculture. In agricultural production, reducing input factor redundancy is the best way to reduce CO_2 emissions and maintain crop temperatures, thereby improving agricultural GTFP.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (71974176, 71473233), the Chinese Academy of Sciences (CAS) "Light of West China" Program (2018-XBQNXZ-B-017), the High Level Talent Introduction Project of Xinjiang Uygur Autonomous Region (Y942171), and the "High Talents Program of Xinjiang Institute of Ecology and Geography, CAS" (Y871171).

References

Andersen P, Petersen N C. 1993. A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39(10): 1261–1264.

Blancard S, Martin E. 2014. Energy efficiency measurement in agriculture with imprecise energy content information. *Energy Policy*, 66: 198–208.

Chen P C, Yu M M, Chang C C, et al. 2008. Total factor productivity growth in China's agricultural sector. *China Economic Review*, 19(4): 580–593.

Chen Z, Huffman W E, Rozelle S. 2009. Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review*, 20(2): 153–161.

Cheng G. 2014. *Data Envelopment Analysis: Methods and MaxDEA Software*. Beijing: Intellectual Property Right Press, 180–189. (in Chinese)

Dai A G. 2011. Drought under global warming: a review. *Climate Change*, 2(1): 45–65.

Deng X Z, Gibson J, Wang P. 2017. Management of trade-offs between cultivated land conversions and land productivity in Shandong Province. *Journal of Cleaner Production*, 142: 767–774.

Duan H P, Zhang Y, Zhao J B, et al. 2011. Carbon footprint analysis of farm land ecosystem in China. *Journal of Soil and Water Conservation*, 25(5): 203–208. (in Chinese)

Feng C P, Chu F, Ding J J, et al. 2015. Carbon Emissions Abatement (CEA) allocation and compensation schemes based on DEA. *Omega-International Journal of Management Science*, 53: 78–89.

Feng Z M, Yang Y Z, Zhang Y Q, et al. 2005. Grain-for-green policy and its impacts on grain supply in West China. *Land Use Policy*, 22(4): 301–312.

Fischer G, Winiwarter W, Ermolieva T, et al. 2010. Integrated modeling framework for assessment and mitigation of nitrogen pollution from agriculture: concept and case study for China. *Agriculture, Ecosystems & Environment*, 136(1–2): 116–124.

Fuinhas J A, Marques A C, Almeida P, et al. 2016. Two centuries of economic growth: international evidence on deepness and steepness. *Transformations in Business & Economics*, 15(3): 192–206.

Gan Y T, Kadambot H M S, Turner N C, et al. 2013. Ridge-furrow mulching systems—an innovative technique for boosting crop productivity in semiarid rain-fed environments. *Advances in Agronomy*, 118: 429–476.

Gollin D, Parente S L, Rogerson R. 2007. The food problem and the evolution of international income levels. *Journal of Monetary Economics*, 54(4): 1230–1255.

He F, Wang K, Li X L, et al. 2012. Effects of ridge and furrow rainfall harvesting system on soil hydrothermal condition and yields of *Elymus Sibiricus* L. in arid and semiarid regions. *Transactions of the Chinese Society of Agricultural Engineering*, 28(12): 122–126. (in Chinese)

Heidari M D, Omid M, Mohammadi A. 2012. Measuring productive efficiency of horticultural greenhouses in Iran: a data envelopment analysis approach. *Expert Systems with Applications*, 39(1): 1040–1045.

Hu Q, Pan F F, Pan X B, et al. 2014. Effects of a ridge-furrow micro-field rainwater-harvesting system on potato yield in a semi-arid region. *Field Crops Research*, 166(9): 92–101.

Huang C, Santibanez-Gonzalez E D, Song M. 2018. Interstate pollution spillover and setting environmental standards. *Journal of Cleaner Production*, 170: 1544–1553.

Ito J. 2010. Inter-regional difference of agricultural productivity in China: distinction between biochemical and machinery technology. *China Economic Review*, 21(3): 394–410.

Jin G, Li Z H, Deng X Z, et al. 2018. An analysis of spatiotemporal patterns in Chinese agricultural productivity between 2004 and 2014. *Ecological Indicators*, 2019: 591–600.

Kerstens K, Shen Z, Ignace V D W. 2018. Comparing Luenberger and Luenberger-Hicks-Moorsteen productivity indicators: how well is total factor productivity approximated? *International Journal of Production Economics*, 195: 311–318.

Kravchenko A N, Bullock D G. 2000. Correlation of corn and soybean grain yield with topography and soil properties. *Agronomy Journal*, 92(1): 75–83.

Lee E A, Tollenaar M. 2007. Physiological basis of successful breeding strategies for maize grain yields. *Crop Science*, 47(Suppl.): S202–S215.

Lei Y D, Zhang H L, Chen F, et al. 2016. How rural land use management facilitates drought risk adaptation in a changing climate—a case study in arid Northern China. *Science of the Total Environment*, 550: 192–199.

Leng G Y, Tang Q H, Rayburg S. 2015. Climate change impacts on meteorological, agricultural and hydrological droughts in China. *Global and Planetary Change*, 126: 23–34.

Li X Y, Gong J D. 2002. Effect of different ridge:furrow ratios and supplement irrigation on crop production in ridge and furrow rainfall harvesting system with mulches. *Agricultural Water Management*, 54(3): 243–254.

Liobikiene G, Mandravickaite J, Krepstuliene D, et al. 2017. Lithuanian achievements in terms of CO_2 emissions based on production side in the context of the EU-27. *Technological and Economic Development of Economy*, 23(3): 483–503.

Liu J Y, Xu X L, Zhuang D F, et al. 2005. Impacts of LUCC processes on potential land productivity in China in the 1990s. *Science in China Series D: Earth Sciences*, 48(8): 1259–1269.

Liu T, Liu H, Qi Y J. 2015. Construction land expansion and cultivated land protection in urbanizing China: insights from national land surveys, 1996–2006. *Habitat International*, 46: 13–22.

Liu Y, Zhang J B, Zhang L. 2018. Analysis of carbon emission efficiency of rice in China under different rice planting patterns based on the DEA-SBM model. *Journal of China Agricultural University*, 23(6): 177–186. (in Chinese)

Liu Z, Guan D B, Crawford-Brown D, et al. 2013. Energy policy: a low-carbon road map for China. *Nature*, 500(7461): 143–145.

Liu Z, Davis S J, Feng K S, et al. 2016. Targeted opportunities to address the climate-trade dilemma in China. *Nature Climate Change*, 6(2): 201–206.

Lobell D B, Burke M B, Tebaldi C, et al. 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319(5863): 607–610.

Ma S Z, Feng H. 2013. Will the decline of efficiency in China's agriculture come to an end? An analysis based on opening and convergence. *China Economic Review*, 27: 179–190.

MacDonald D, Crabtree J R, Wiesinger G, et al. 2000. Agricultural abandonment in mountain areas of Europe: environmental consequences and policy response. *Journal of Environmental Management*, 59(1): 47–69.

Makijenko J, Burlakovs J, Brizga J, et al. 2016. Energy efficiency and behavioral patterns in Latvia. *Management of Environmental Quality*, 27(6): 695–707.

Mueller L, Kay B D, Hu C S, et al. 2009. Visual assessment of soil structure: evaluation of methodologies on sites in Canada, China and Germany: part I: comparing visual methods and linking them with soil physical data and grain yield of cereals. *Soil & Tillage Research*, 103(1): 178–187.

NBSC (National Bureau of Statistics of China). 2001–2017a. *China Rural Statistical Yearbook 2000–2016*. Beijing: China Statistics Press. (in Chinese)

NBSC (National Bureau of Statistics of China). 2001–2017b. *China Statistical Yearbook 2000–2016*. Beijing: China Statistics Press. (in Chinese)

Nigussie Z, Tsunekawa A, Haregeweyn N, et al. 2017. Factors influencing small-scale farmers' adoption of sustainable land management technologies in north-western Ethiopia. *Land Use Policy*, 67: 57–64.

Olesen J E, Bindi M. 2002. Consequences of climate change for European agricultural productivity, land use and policy. *European Journal of Agronomy*, 16(4): 239–262.

Pang J X, Chen X P, Zhang Z L, et al. 2016. Measuring eco-efficiency of agriculture in China. *Sustainability*, 8(4): 1–15.

Peters C J, Wilkins J L, Fick G W. 2007. Testing a complete-diet model for estimating the land resource requirements of food consumption and agricultural carrying capacity: the New York State example. *Renewable Agriculture and Food Systems*, 22(2): 145–153.

Piao S L, Ciais P, Huang Y, et al. 2010. The impacts of climate change on water resources and agriculture in China. *Nature*, 467(7311): 43–51.

Ponce C, Guillermo E, Moran M S, et al. 2013. Ecosystem resilience despite large-scale altered hydroclimatic condition. *Nature*, 470(1): 1–4.

Ren W, Tian H Q, Tao B, et al. 2012. China's crop productivity and soil carbon storage as influenced by multifactor global change. *Global Change Biology*, 18(9): 2945–2957.

Rigoberto A L, Xi H, Eleonora D F. 2017. What drives China's new agricultural subsidies? *World Development*, 93: 279–292.

Saleska S R, Didan K, Huete A R, et al. 2007. Amazon forests green-up during 2005 drought. *Science*, 318(5850): 612–612.

Seiford L M, Zhu J. 2002. Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142: 16–20.

Sheffield J, Wood E F. 2008. Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Climate Dynamics*, 31(1): 79–105.

Shen Z Y, Baležentis T, Chen X L, et al. 2018. Green growth and structural change in Chinese agricultural sector during 1997–2014. *China Economic Review*, 51: 83–96.

Song M L, Wang S H, Cen L. 2015. Comprehensive efficiency evaluation of coal enterprises from production and pollution treatment process. *Journal of Cleaner Production*, 104: 374–379.

Song M L, Zheng W P, Wang Z Y. 2016. Environmental efficiency and energy consumption of highway transportation systems in China. *International Journal of Production Economics*, 181: 441–449.

Tao F L, Yokozawa M, Xu Y L, et al. 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agricultural and Forest Meteorology*, 138(1–4): 82–92.

Tian X, Yu X H. 2012. The enigmas of TFP in China: a meta-analysis. *China Economic Review*, 23(2): 396–414.

Tone K. 2002. A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, 143(1): 32–41.

Trenberth K E, Dai A G, Schrier G V D, et al. 2014. Global warming and changes in drought. *Nature Climate Change*, 4(1): 17–22.

Turner N C. 2004. Sustainable production of crops and pastures under drought in a Mediterranean environment. *Annals of Applied Biology*, 144(2): 139–174.

Van Ittersum M K, Leffelaar P A, Van Keulen H. 2003. On approaches and applications of Wageningen crop models. *European Journal of Agronomy*, 18(3–4): 201–234.

Wang A H, Lettenmaier D P, Sheffield J. 2011. Soil moisture drought in China, 1950–2006. *Journal of Climate*, 24(13): 3257–3273.

Wang F T, Yu C, Xiong L C, et al. 2019. How can agricultural water use efficiency be promoted in China? A spatial-temporal analysis. *Resources, Conservation and Recycling*, 145: 411–418.

Wang J F, Li X H, Christakos G, et al. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *International Journal of Geographical Information Science*, 24(1): 107–127.

Wang J F, Zhang T L, Fu B J. 2016. A measure of spatial stratified heterogeneity. *Ecological Indicators*, 67: 250–256.

Wang J F, Xu C D. 2017. Geographical detector: principles and prospects. *Acta Geographica Sinica*, 72(1): 116–134. (in Chinese)

Wang K, Wei Y M, Huang Z M. 2016. Potential gains from carbon emissions trading in China: A DEA based estimation on abatement cost savings. *Omega-International Journal of Management Science*, 63: 48–59.

Wang Y J, Xie Z K, Malhi S S, et al. 2011. Effects of gravel-sand mulch, plastic mulch and ridge and furrow rainfall harvesting system combinations on water use efficiency, soil temperature and watermelon yield in a semi-arid Loess Plateau of northwestern China. *Agricultural Water Management*, 10(1): 88–92.

Wu Y R. 1995. Productivity growth, technological progress, and technical efficiency change in China: A three-sector analysis. *Journal of Comparative Economics*, 21(2): 207–229.

Xiao G J, Zhang Q B, Zhang F J, et al. 2016. Warming influences the yield and water use efficiency of winter wheat in the semiarid regions of Northwest China. *Field Crops Research*, 199: 129–135.

Xu S W, Li G Q, Li Z M. 2015. China agricultural outlook for 2015–2024 based on China Agricultural Monitoring and Early-warning System (CAMES). *Journal of Integrative Agriculture*, 14(9): 1889–1902.

Xu Y B, Li J Y, Wan J M. 2017. Agriculture and crop science in China: innovation and sustainability. *Crop Journal*, 5(2): 95–99.

Yao Y B, Wang R Y, Yang J H, et al. 2011. Impact of climate warming on flax growth and water use efficiency in semiarid regions of the loess plateau. *Journal of Applied Ecology*, 22(10): 2635–2642.

Zhang B C. 2008. Discussion on basic characteristics and developmental status of rainfall-harvesting technique in arid areas. *Journal of Irrigation & Drainage*, 27(2): 119–122.

Zhang C J, Liao Y M, Duan J Q, et al. 2016. The progresses of dry-wet climate divisional research in China. *Research in Climate Change Progress*, 12(4): 261–267.

Zhang L, Pang J X, Chen X P, et al. 2019. Carbon emissions, energy consumption and economic growth: Evidence from the agricultural sector of China's main grain-producing areas. *Science of the Total Environment*, 665: 1017–1025.

Zhao H, Wang R Y, Ma B L. 2014. Ridge-furrow with full plastic film mulching improves water use efficiency and tuber yields of potato in a semiarid rainfed ecosystem. *Field Crops Research*, 161: 137–148.

Zhou L M, Jin S L, Liu C A, et al. 2012. Ridge-furrow and plastic-mulching tillage enhances maize-soil interactions: opportunities and challenges in a semiarid agroecosystem. *Field Crops Research*, 126: 181–188.

Note: Figure translations are in progress. See original paper for figures.