Energy Proceedings
Vol 30, 2023
ISSN 2004-2965

Climate resilience promotion in China's crop production with agricultural mechanization from 1995 to 2020

Dan Fang[1], Jiangqiang Chen[2], Saige Wang[1*], Bin Chen[1,2*]
1 School of Environment, Beijing Normal University, Beijing 100875, China
2 School of Economics, Guangdong University of Finance and Economics, Guangdong 510220, China

ABSTRACT

With the increasing frequency of extreme weather events, promoting crop production's resilience to combat climate disaster is urgent for global food security, however, the driving factors of crop production's resilience are not yet clear to figure out the effective measures to improve it. At the same time, the benefits of agricultural mechanization, especially on resilience are not fully adopted, which may offer solutions for climate change adaptation. Here, we propose a crop production's climate resilience driving factors assessment framework based on modified Pressure-State-Response concept and two-way fixed effect model. Taking China as the study area, we figure out the spatio-temporal evolution of crop production's climate resilience and analyze the effect of rapidly developed agricultural mechanization on it. Our primary results show that food production's climate resilience in China has been promoted since 2005, although drought and flooding events are gradually becoming more frequent. Complementarity among Chinese provinces enhances overall national food production's climate resilience, to which Jilin Province and Xinjiang Province contributed the most. Due to timely policy adjustments, the autumn harvest has played an increasingly important role in enhancing resilience. Besides, agricultural mechanization played a significant role in guaranteeing food productivity to tackle climate impact. By analyzing the effect of agricultural mechanization on food production's climate resilience in China, this study can provide insights for strengthening agriculture sector's resilience and thus avoiding disruptions in food supply chains.

Keywords: climate resilience, food production, spatio-temporal evolution, agricultural mechanization

1. INTRODUCTION

Food systems are highly vulnerable to weather conditions. With more extreme weather events and increased unpredictability of weather patterns, climate change has become a serious threat to global food security, successively affecting the achievement of sustainable development goals, and poverty eradication. Therefore, food systems need transitions to be more productive and reliable, with more efficiency in inputs, less variability and greater stability in their outputs, and resilience to risks, shocks and long-term climate variability.

The food system is a complex web of activities involving production, processing, transport, and consumption. Among them, food production, the supply side of food, is the most affected by climate change and also the most essential for food security. Besides, grain crops play the leading source of plant protein in the human diet. Promoting climate resilience in crop production can effectively deal with the worldwide dilemma of hunger and safety. However, potential approaches to strengthen this resilience are not fully figured out and adopted.

Current research about the evaluation of food resilience involving socioeconomic factors such as GDP per capita, to show the ability to resist hazards, will fall into the trouble of multicollinearity, thus preventing us to identify the drivers of resilience. Here, we propose a crop production's climate resilience driving factors assessment framework based on modified Pressure-State-Response concept and two-way fixed effect model. Taking China as the study area, we figure out the spatio-temporal evolution of crop production's climate resilience and analyze the effect of rapidly developed agricultural mechanization on it.

2. MATERIALS AND METHOD

2.1 Crop production's climate resilience driving factors assessment framework

There are three major approaches for the evaluation of resilience: comprehensive evaluation methods based on the component capabilities of resilience, simulation analysis, and econometric analysis. Most crop production is on an annual cycle and weather conditions varied from year to year, which happens to provide us with realistic and historical weather data, disaster data and crop production data to evaluate the climate resilience in crop production (Figure 1). We define crop production's climate resilience as the ability to safeguard regular crop yield even under severe shocks.

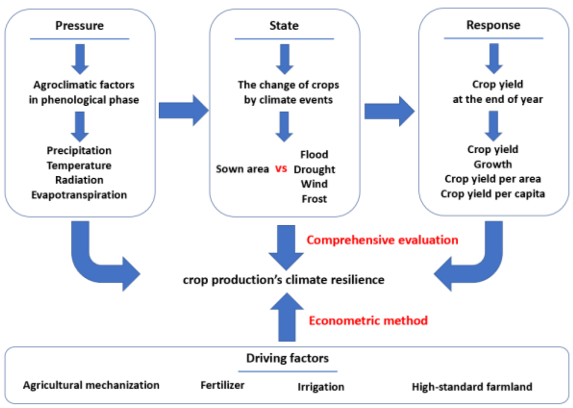

Fig. 1. Framework

The Pressure-State-Response (PSR) framework is a model that covers causes and effects influencing a measurable state (Hammond et al., 1995), which is widely adopted in the construction of indicator systems. The PSR framework include three categories of indicators, which are the Pressure, State and Response indicators respectively (OECD,1993). The Pressure indicators describe the driving factors of changes in the evaluated object, which describe the impacts and stresses from the external factors. The State Indicators mainly refer to the current situation of the evaluated object, which reflects the degree of impacts from the pressure. The Response indicators reflect the performance of the evaluated object in order to mitigate, prevent or recover from the impacts of pressure. Here, we modified the concept of Response to be the ultimate performance of crops, that is the crop yield, rather than human intervention activities. Resilience is assessed by the changes in crop status from seeding to harvest.

Then with time series data, econometric methods offer us solutions to figure out the critical drivers of resilience change and identify the effect of agricultural mechanization on it.

2.2 *Indicators for evaluating crop production's climate resilience*

We built up a comprehensive indicator system based on the PSR concept as shown in Table 1 to evaluate crop production's climate resilience. To reflect the pressures from climate change, several agroclimatic variables were chosen to characterize meteorological disasters. For example, precipitation anomaly percentage based on annual rainfall data was used to measure the extent of drought and flooding. The sum temperature deviation from May to September was applied to reflect the pressure from freezing. The mean temperature form July to August represents the pressure from high temperature. In addition, to describe the state of the post-disaster crop system, we used the damage rate and the hazard rate to measure the extent of crop production losses. The damage rate refers to the ratio of crop area reduction due to disaster to total sown area. Besides, we consider four types of hazards affected crop production, including flood, drought, wind and hail, and frost. Finally, the yield characteristics of crop system at the end of the year could reflect its performance after receiving and tackling disaster shocks during the last year, corresponding to the concept of response in PSR. The annual crop yield, growth rate of crop yield, crop yield per hectare and crop yield per capita were chosen as the Response indicators.

Table 1 Indicators of crop production's climate resilience based on PSR concept

PSR concept	Indicators	Meaning & Calculation
Pressure	Drought and flood	$Ipa = \lvert\frac{R_i - \bar{R}}{\bar{R}}\rvert \times 100\%$, where Ipa is precipitation anomaly percentage, R_i is the rainfall in month i, $\bar{R}$ is average precipitation in the same period of the calendar year
	Heat wave	Average temperature during July to August
	Freezing	$td = \lvert\frac{T_i - \bar{T}}{\bar{T}}\rvert \times 100\%$, where td is temperature deviation from May to September, T_i is the sum of temperature from May to September, $\bar{T}$ is average temperature during the same period of the calendar year
State	Disaster rate	The ratio of yield reduction due to disaster to total sown area
	Hazard rate	Affected area due to disaster to total sown area, including flood, drought, wind and hail, and frost
Response	Crop yield	Crop yield of cereals, potatoes and beans of China
	Growth of crop yield	Annual growth rate of crop yield
	Crop yield per area	Crop yield per hectare
	Crop yield per capita	Crop yield per capita

2.3 Weighting and comprehensive evaluation

Evaluating climate resilience of food production based on multiple indicators is a kind of multiple criteria decision making (MCDM) problems. For MCDM, the weight of the indicators is crucial to measure their importance. The entropy weight (IEW) method based on the information provided by each indicator can objectively determine the weight. Besides, for decision making, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a practical technique for ranking and selecting a number of possible alternatives via measuring Euclidean distances. The TOPSIS is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS). In this study, we determined the weights of indicators using IEW, and identified the ranking of alternative by the TOPSIS.

First, we utilized range standardization to normalize different indicators.

$$x'_{ij} = \frac{x_{ij} - \min_{1\le j\le n} x_{ij}}{\max_{1\le j\le n} x_{ij} - \min_{1\le j\le n} x_{ij}} \qquad (1)$$

$X' = (x'_{ij})_{m\times n}$ is the matrix after range standardization; $\max_{1\le j\le n} x_{ij}$, $\min_{1\le j\le n} x_{ij}$ is the maximum and the minimum value in evaluation index j respectively, the value of X' is $0 \le x'_{ij} \le 1$.

Then, we calculated the information entropy:

$$H_j = -\left(\sum_{i=1}^{m} f_{ij} ln f_{ij}\right)\ i = 1,2,\cdots,m; j = 1,2\cdots,n \qquad (2)$$

Next, according to the value of variation degree, we calculated deviations in the coefficients of indicators j, namely G_j:

$$G_j = 1 - H_j\ \ j = 1,2\cdots,n \qquad (3)$$

The deviation degree of indicator j is greater if the value of H_j is smaller. Generally speaking, if the deviation degree of index j is higher, the information entropy H_j is lower, which indicates that the more the information index j provides, the greater the index j weight is. The weight w_j is defined as:

$$w_j = \frac{G_j}{\sum_{j=1}^{n} G_j} = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j} \qquad (4)$$

After getting the weight w_j, we multiple weight with normalization matrix $X' = (x'_{ij})_{m\times n}$ and can get X^+ and X^- to be the basis to calculate the distances. The PIS X^+ indicates the most preferable alternative while the NIS X^- indicates the least preferable alternative. The formulas are as follows:

$$X^+ = \left(\max_{1\le i\le m} x_{i1}, \max_{1\le i\le m} x_{i2}, \cdots, \max_{1\le i\le m} x_{in}\right) \qquad (5)$$

$$X^- = \left(\min_{1\le i\le m} x_{i1}, \min_{1\le i\le m} x_{i2}, \cdots, \min_{1\le i\le m} x_{in}\right) \qquad (6)$$

The n-indices evaluation distance can measure the separation from the PIS and NIS for each alternative.

$$d^+ = \sqrt{\sum_{j=1}^{n} w_j (x_{ij} - x_j^+)^2}\ \ i = 1,2,\cdots,m; 0 \le d_i^+ \le 1 \qquad (7)$$

$$d^- = \sqrt{\sum_{j=1}^{n} w_j (x_{ij} - x_j^-)^2}\ \ i = 1,2,\cdots,m; 0 \le d_i^- \le 1 \qquad (8)$$

Finally, we calculating the relative closeness c_i to the ideal solution.

$$c_i = \frac{d_i}{d_i^- + d_i^+};\ i = 1,2,\cdots,m; 0 \le c_i \le 1 \qquad (9)$$

If alternative i is the PIS, then c_i=1; however, if alternative i is the NIS, then $c_i = 0$. In other words, if the value of c_i is closer to 1, the alternative i will be closer to the PIS. A set of alternatives can then be ranked according to the descending order of c_i.

3. RESULTS AND DISCUSSION

3.1 National crop production conditions and climate resilience

Figure 2 and Figure 3 presents the growing conditions and weather shocks to crop production in China from 1995-2020. It's clear that flooding and drought has become more frequent and it's common to face heat wave in summer which will affect crops.

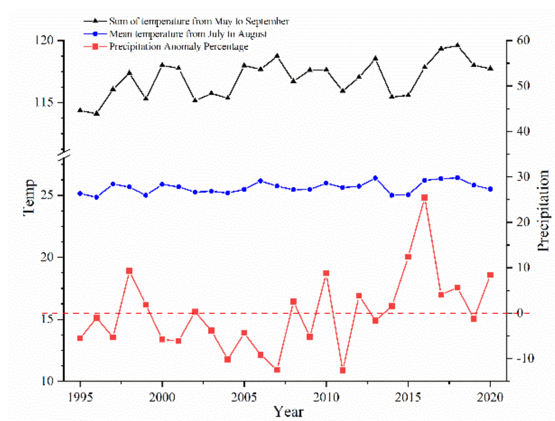

Fig. 2. Weather conditions in China during 1995-2020

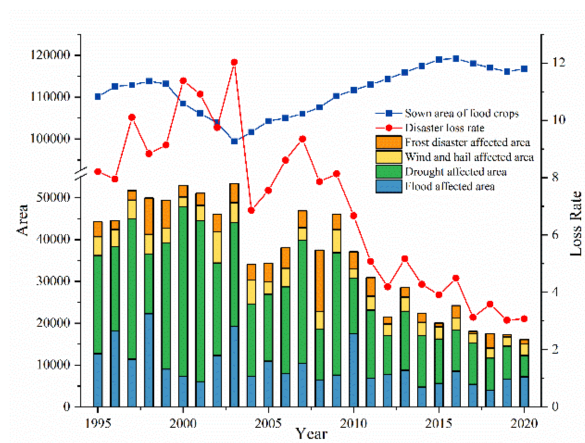

Fig. 3. Agricultural loss by disasters in China during 1995-2020

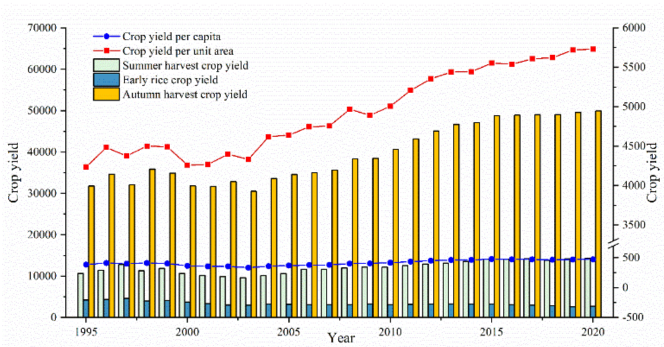

Fig. 4. Crop yield in China during 1995-2020

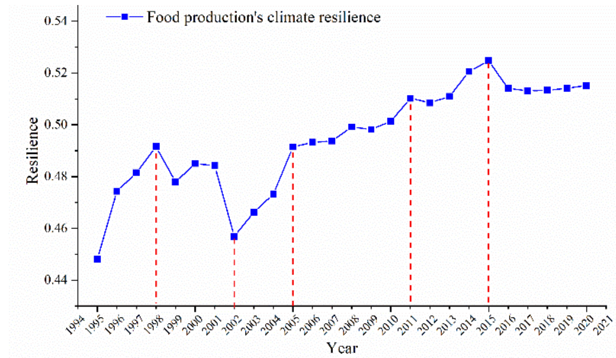

Fig. 5. Crop production's climate resilience in China

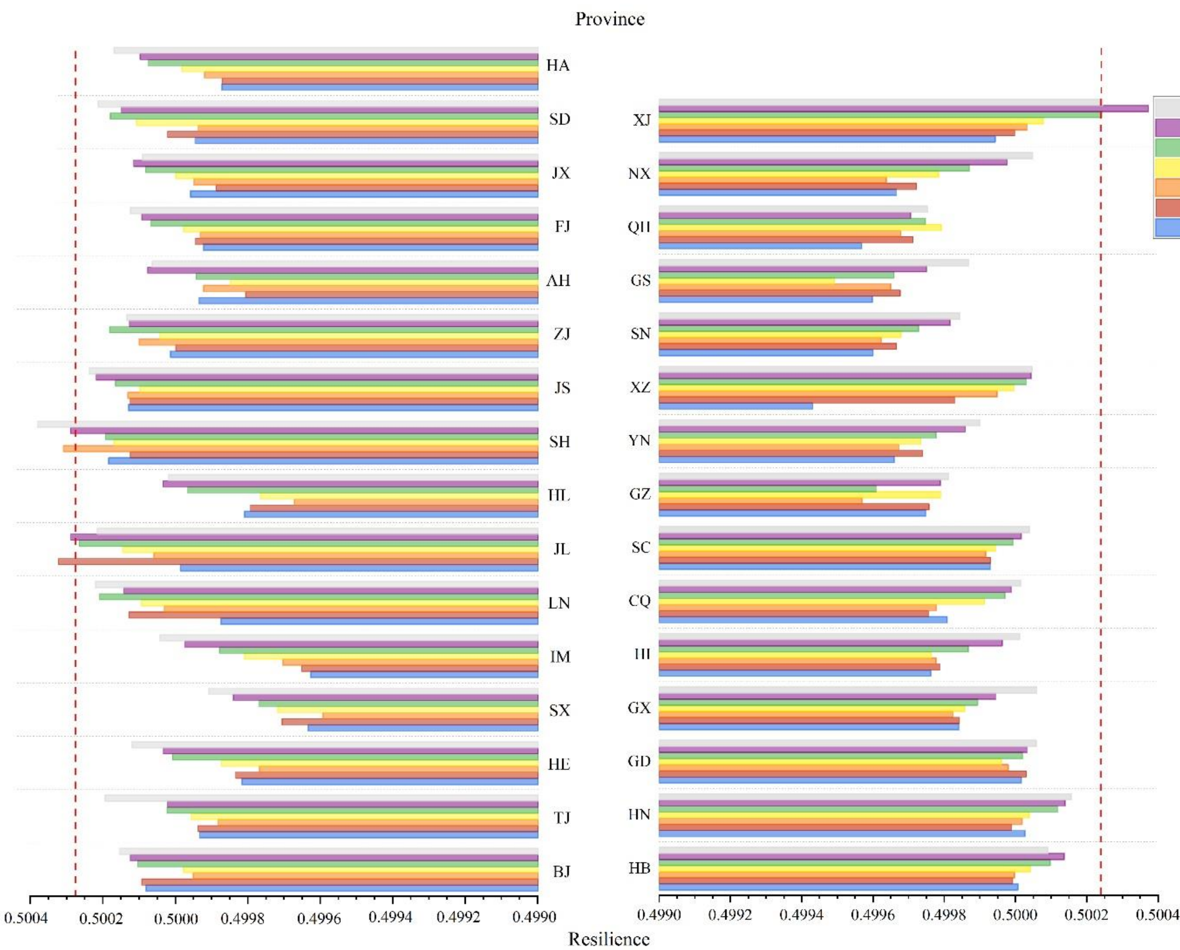

Fig. 6. Crop production's climate resilience in 31 Provinces of China during 1997-2020

Under climate shocks, the loss rate of crops in China has decreased significantly and we have witnessed a phase of double growth in crop yields (Figure 4). As shown in Figure 5, since 2005 China's climate resilience in crop production has steadily improved with more sown area at the beginning of the year and more contribution of autumn harvest crop. Autumn grains support China's food security.

3.2 Provincial crop production's climate resilience

Figure 6 shows the provincial results during 1997-2020. It can be found that Xinjiang, Jilin, Liaoning, Jiangsu and Shandong are source of China's promotion in crop production's climate resilience. Especially Xinjiang, its resilience is increasing with highest efficiency in crop yields.

3.3 Effect of agricultural mechanization on crop production's climate resilience

Figure 7 present the scatter graph of agricultural mechanization and crop production's climate resilience. It can be found that they are positively related, meaning more advance agricultural mechanization showing higher climate resilience in crop production. And empirical analysis will aid us to identify their causal relationship.

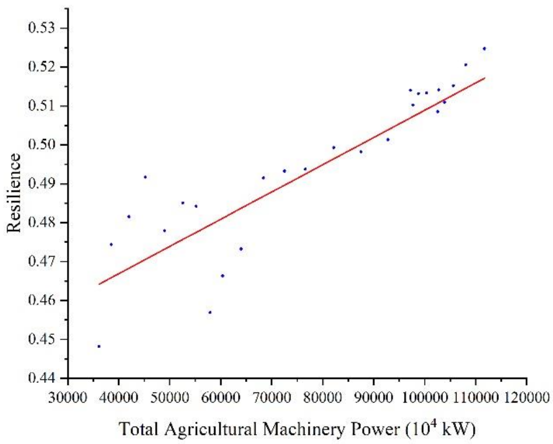

Fig. 7. Scatter graph and linear relationship between agricultural mechanization and crop production’s climate resilience

4. CONCLUSION

China plays an important role in the global food supply. Understanding the state of China's crop production’s climate resilience and the driving factors are critical to global food security. Here, we propose a crop production’s climate resilience driving factors assessment framework based on modified Pressure-State-Response concept and two-way fixed effect model. Taking China as the study area, we figure out the spatio-temporal evolution of crop production’s climate resilience and identify the positive effect of rapidly developed agricultural mechanization on it. However, the indicator selection in this paper is simplified and we should obtain more agricultural management data to find more potential drivers. We will deepen our understanding in this field and provide insights for strengthening agriculture sector’s resilience and thus avoiding disruptions in food supply chains.

ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (Nos. 72091511).

REFERENCE

[1] OECD, 1993. Core Set of Indicators for Environmental Performance Reviews: A Synthesis Report by the Group on the State of the Environment. Environment Monographs, Vol. 83. Organization for Economic Co-operation and Development, Paris.

[2] Hammond, A., Adrianse, A., Rodenburg, E., Bryant, D., Woodward, R.,1995. Environmental Indicators: A systemic approach to Measuring and Reporting on Environmental Policy Performance in the Context of Sustainable Development. World Resources Institute, Washington, DC.

[3] Wolfslehner B, Vacik H. Evaluating sustainable forest management strategies with the Analytic Network Process in a Pressure-State-Response framework. J ENVIRON MANAGE. 2008;88:1-10.

[4] Zhang H, Gu C, Gu L, Zhang Y. The evaluation of tourism destination competitiveness by TOPSIS & information entropy?A case in the Yangtze River Delta of China. TOURISM MANAGE. 2011;32:443-451.

[5] Tendall DM, Joerin J, Kopainsky B, Edwards P, Shreck A, Le QB, et al. Food system resilience: Defining the concept. Global Food Security. 2015;6:17-23.