Estimating the Effects of Climatic Change on Grain Production: Spatial versus Non-spatial Models

Wei Huang[1, 2]
1. Institute of Geographical Sciences and Natural Resources Research
Chinese Academy of Sciences
Beijing 100101, China

Xiangzheng Deng[1, 2 *]
2. Center for Chinese Agricultural Policy
Chinese Academy of Sciences
Beijing 100101, China

Jinyan Zhan[3], Yingzhi Lin[1]
3. State Key Laboratory of Water Environment Simulation, School of Environment,
Beijing Normal University, Beijing 100875,
Beijing 100875, China

Abstract—**This paper aims to estimate the effects of climatic change on grain production in China by doing a cross-sectional analysis based on county-level dataset with variables measuring the total output of grain production, climate, and other economic and geographical data for over 2200 counties of China in the year of 2000. A non-spatial model, using Ordinary Least Squares(OLS) approach, was firstly built to measure the effects of climatic change on grain production, and then a spatial econometric model including the spatially weighted values of the explained and the explanatory variables to obtain more consistent and efficient estimates was developed by using the Maximum Likelihood Estimation approach. We find that spatial lag and spatial error models built on the rationale of spatial econometrics might be serving as an alternative to capture the effects from the dependent variables as well as the independent variables when we explore the impacts of climate change on the grain production in China.**

Keywords-spatial model; spatial lag; spatial error; spatial econometrics; non-spatial model; OLS

I. INTRODUCTION

There have been quite a lot of studies about the impacts of climate change on world grain production [1-3], which varies dramatically across regions, as crop yields and production are very sensitive, especially to precipitation and accumulated temperature. A global assessment of the potential impacts of climate change on world food supply developed by Rosenzweig and Parry [4] suggests that doubling of the atmospheric carbon dioxide (CO_2) concentration will lead to a small decrease in global crop production and the largest reductions are projected for the southern crop areas due to increased temperatures and reduced water availability. Motha and Baier [5] held the idea that a longer growing season and projected increases in CO_2 may enhance crop yields in northern growing areas.

In China, agriculture provides the population with staple food supplies, e.g., significant amounts of rice, wheat and maize. However, the climatic change greatly affects the grain production. Therefore, efforts are needed to be taken to estimate the impacts of climate changes on grain production. There are quite a number of scholars made efforts to assess the impact of climate change on the production of different grain crops (e.g. rice, wheat) in various regions in China [6]. Liu et al. [7] estimated the economic impacts of climate change on China's agriculture based on the Ricardian model by using county-level cross-sectional data on agricultural net revenue, climate, and other economic and geographical data for agriculture dominated counties. Many agronomic models have been used to measure the impacts, such as Regional Climate Model (RCM), Crop Estimation through Resource, Environment Synthesis (CERES)-rice model [6], AEZ model [8]. Although some studies on the impacts of climate change on China's agriculture have been done, these studies were either in a limited area or for the yield of a single crop, such as rice, wheat or maize [9]. Moreover, the current studies did not give much attention to the heterogeneity of the impact of climate change on the grain production to China at a national scale.

Given this situation, this paper introduces a spatial econometrics approach and utilizes it to estimate the impacts of climatic change on grain production. Especially, the application of spatial correlations embedded in the analysis framework in our study would convince more robust and accurate estimation results.

The rest of the paper is organized as follow. The next section introduces the data and model specification in which a brief introduction on the empirical model and estimation strategy was included. The third section depicts the results of spatial econometrics model. The final section makes a brief discussion on the implication and concludes.

* Corresponding author: dengxz.ccap@igsnrr.ac.cn, tel 86 10 64888980; fax 86 10 64856533.

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II. DATA AND MODEL SPECIFICATION

A. Figures and Tables

County statistics on the inputs and outputs of grain production were used in our study. All those dataset with recordings of the year 2000 were derived from China's Rural Household Survey (RHS), which was conducted by the department of rural social and economic survey of National Bureau of Statistics of China (NBSC).

Two terrain variables were utilized in our study. The first variable, *dem*, measures the average elevation of a county's entire land area; the second variable, *slope*, measures the steepness of the county's landforms. The dataset of the two terrain variables were offered by the Data Center of the Chinese Academy of Science.

The climate dataset, including precipitation (*pa*) and accumulated temperature (*at*), were generated by using the raw climatic data ranging from 1995 to 2000 gathered from the National Meteorological Information Center. Records are available for over 400 national meteorological stations. We use these records and our own China-specific climate interpolation models to interpolate the data from site-based observation into climatic surface data at a 1km × 1km grid pixel scale and then aggregate them to county-specific measures.

B. Non-spatial Model

A classical non-spatial model is built and used to estimate the impacts of climate change on the grain production in China. Lessons from previous studies in China [7] and our observations of China's grain production guide us to consider measures of machine power, *mpower*, land fertility, *fertility*, and sowing area, *sowns*. The dependent variable is the total grain production, *grain*, which was measured by the grain production of the year 2000.

Furthermore, the natural logarithm of above variables is used to specify the estimated model.

$$\ln(grain) = f\,[\ln(pa), \ln(at), \ln(mpover), \ln(fertility), \ln(sowns), \ln(dem), \ln(slope)] \quad (1)$$

C. Spatial Autocorrelation Tests

In order to make out the spatial correlation between variables, we perform diagnostics of the spatial autocorrelation for the dependent variable (log of grain production) using Moran's I measurement which is a commonly used test statistics for spatial autocorrelation [10]. When doing this, we generate scatter plots [11] on the horizontal axis and its respective spatial lag (variable weighted by the spatial weight matrix) on the vertical axis (Fig. 1). In essence, the scatter plots illustrate the global Moran's I, and negative (positive) values of Moran's I indicate negative (positive) spatial autocorrelation and a zero value indicates a random spatial pattern. Then *GeoDa* [12, 13] was used to perform these tests as well as to estimate the spatial econometric models in the next section.

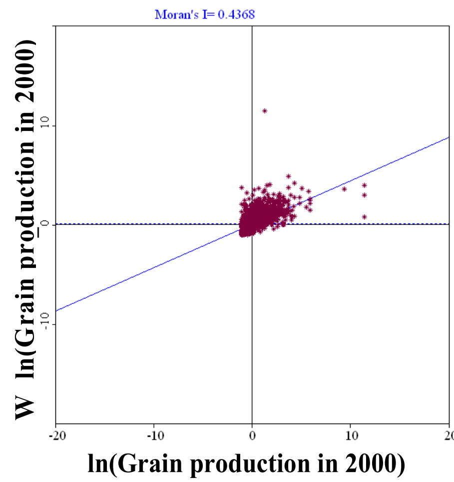

Figure 1. Spatial autocorrelation Moran scatter plot and Permutation empirical distribution for Moran's I

Based on the Moran's I test statistic, we find that the spatial autocorrelation (0.4368) is high for the year 2000 (Fig. 1), which depicts the correlation of regional grain production with the average for its neighbors in 2000.

We then assess the statistical significance of the Moran's I (Fig. 2). In this process, we randomize the data over space and calculate a single value of a Moran's I statistic. We then repeat this procedure by 999 times; and at the same time we obtain an empirical distribution of the Moran's I under the null hypothesis of no spatial autocorrelation. Finally, we compare this distribution with the Moran's I calculated with the original data (that was not randomized over space), p-value in Fig. 2 shows that the Moran's I for 2000 is statistically significant. Therefore, we reject the null hypothesis that there is no spatial association in our data. This result suggests that we should consider the effects from the spatial association in our analysis of the impact of climate change on the grain production over different spatial scales.

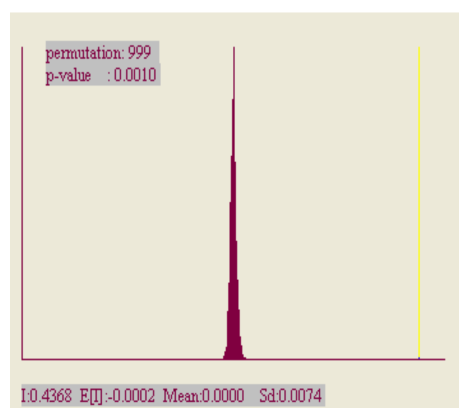

Figure 2. Statistical significance of Moran's I

D. Spatial Econometric Methods

Given that using OLS with the spatial autoagregession of independent and dependent variables over spatial and temporal dimension might lead to either inefficiency or bias and inconsistent estimates [11], we hypothesize that the value of the dependent variable, observed at a particular location was partially determined by some function of its neighbors' values. It is typically formulated as a spatially weighted average of the neighboring values, where the neighbors are specified through the use of a so-called spatial weights matrix [10].

The spatial lag model is as follows:

$$y=\rho_y Wy+\rho_y Wy+X\beta+\varepsilon \tag{2}$$

Empirically, this model is estimated by extending the reduced-form model in (1) and including the spatially lagged variables of the dependent variable, as well as those of the key independent variables:

ln(*grain*) = f[ln(*pa*), ln(*at*), ln(*mpover*), ln(*fertility*), ln(*sowns*), ln(*dem*), ln(*slope*), ln(*w_grain*), ln*(w_pa*), ln*(w_at*), ln(*w_mpover*), ln(*w_fertility*), ln(*w_sowns*), ln(*w_dem*), ln(*w_slope*)] (3)

III. ESTIMATION RESULT

A. Results of the Non-spatial Model

The impact of climate change on grain production is clearly estimated through the model in (1). Holding constant the area of the grain production in 2000, the contribution of machine power in explaining the increase of grain production is clearly illustrated by its positive and highly significant coefficient. The magnitude of the coefficients, 0.07, intuitively means that as *machine power* grows by 100 percent (for example), the grain production increases by 7 percent (TABLE I row 3). Similarly, both *precipitation* and *accumulated temperature* significantly play positive roles in explaining the increase of the grain production. The coefficients, 0.159, illustrates that the grain production will expand 15.9 percent when *precipitation* increases by 100 percent, and 0.018 means that the grain production will increase by 1.8 percent when *accumulated temperature* increases by 100 percents (TABLE I rows 1 and 2).

TABLE I. ESTIMATION RESULTS OF NON-SPATIAL MODEL ON THE IMPACTS OF CLIMATIC CHANGE ON GRAIN PRODUCTION

Dependent variable: ln(*grain*)	
ln(*pa*)	0.159 (9.12)***
ln(*at*)	0.018 (7.45)***
ln(*mpower*)	0.070 (8.00)***
ln(*fertility*)	0.091 (12.30)***
ln(*sowns*)	0.816 (80.91)***
ln(*dem*)	0.016 (2.57)**
ln(*slope*)	-0.045 (5.53)***
Constant	0.243 (3.79)***
Observations	2273
R-squared	0.921

Absolute value of t statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%.

B. Results of the Spatial Econometric Model

We estimate the coefficients through the spatial econometric model and measure the fit to analyze the correlation between the climate change and the grain production (Table II). The spatial autoregressive coefficient is positive (0.001). There are some minor differences in the coefficients of the other regression coefficients between the spatial error model (Table II column 2) and the classical OLS (Table I). However, although the sign and level of significance of the coefficients estimated by the spatial econometric models are nearly the same, their magnitude indicates a decreasing trend in absolute value. Some of the explanatory power of these variables was attributed to the spatial lag of the dependent variable, W_ln(*grain*). Moreover, the effect due to the neighboring location (or the spatial dependence) is now picked up by the coefficients of the spatially lagged variables. Therefore, we can more precisely estimate the coefficients of the model by using spatial econometrics. Based on the above analysis results, we can conclude that the effects of spatial lag and/or error effects should be reconsidered.

TABLE II. RESULTS FROM THE MAXIMAL LIKELIHOOD ESTIMATION FOR THE SPATIAL LAG AND SPATIAL ERROR FUNCTION

Dependent variable: ln(*grain*)		
	Lag	Error
Ln(*pa*)	0.159 (9.11)***	0.173 (8.00)***
Ln(*at*)	0.018 (7.45)***	0.021 (6.95)***
ln(*mpower*)	0.071 (7.94)***	0.026 (2.65)***
ln(*fertility*)	0.092 (12.31)***	0.08 10.56***
ln(*sowns*)	0.815 (79.03)***	0.865 (85.03)***
ln(*dem*)	0.015 (2.20)**	0.008 1.15
ln(*slope*)	-0.023 (2.59)***	-0.044 (4.56)***
W_ln(*grain*)	0.001 -0.43	0.499 (21.23)***
Constant	0.241 (3.76)***	0.233 (3.30)***
Observations	2273	2273

Spatial lag effects of the independent variables were estimated and not reported for the sake of brevity. Absolute value of t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

IV. CONCLUSION AND DISCUSSION

The effects of climate change on the grain production were estimated by used the non-spatial model. The analysis results indicated that the climate change has certain impact on the grain production of China. By doing spatial econometric analysis, we estimate the elasticity of climate change on grain production in China consistently and efficiently. Our analysis results indicated that the effects of climate change on the grain production could be accurately estimated on the spatial dimension. Spatial lag/error model built on the rational of spatial econometrics might be an alternative to capture the effects of the spatial effects from the dependent as well as the independent variables.

Although the correlation between the climate change and the grain production were explored and estimated in this paper, there are still some research limitations to be tackled in future. For example, it is almost impossible for us to include and/then grasps the effects from those political and institutional factors which might impose great effects on the grain production. In addition, the estimated correlation between climate change and the grain production might vary over space in China. Therefore, we should address the heterogeneity of the relationship between the climate change and the grain production among regions, no matter in province level or in regional level, which will uncover a more accurate spatial explicitly effects of climate changes on grain production.

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