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ScienceDirect
Journal of Integrative Agriculture
2013, 12(7): 101-108
July 2013
RESEARCH ARTICLE

Climate Change, Risk and Grain Yields in China[1]

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Abstract

Adopting Just and Pope (1978, 1979) style yield functions, this paper proposes a new method to analyze the impacts of regional climate change on grain production in China. We find that changes in climate will affect grain production in North and South China differently. Specifically, it emerges that a 1°C increase in annual average temperature could reduce national grain output by 1.45% (1.74% reduction in North China and 1.19% reduction in South China), while an increase in total annual precipitation of around 100 mm could increase national grain output by 1.31% (3.0% increase in North China and 0.59% reduction in South China).

Key words: grain yield, climate change, yield risk, China

INTRODUCTION

Farmers usually have no knowledge of the precise output when they make their production decisions, which is mainly due to the fact that agriculture in general has a long production cycle and is affected by a large number of endogenous and exogenous uncertainty factors (Just and Pope 1979; Kumbhakar and Tsionas 2008; Meyer and Yu 2013). The prevailing climate conditions for instance are important sources of uncertainty because factors such as temperature or precipitation are characterized by inter-annual variability, part of which can be explained by gradual shifts in mean climate conditions caused by global climate change, whereas another part is constituted by seemingly random fluctuations. Since the precise patterns of the variations are beyond farmers' control and their predictive capabilities, production risk emerges.

To our knowledge, currently no study exists that covers the influences of climate factors on both the general production conditions and on the level of production risk in the context of Chinese grain farming, even though the impacts of food security issues in China on both domestic and world food markets can be substantial (von Braun 2007). Yu and Zhao (2009) and Tian and Yu (2012) provide good reviews of the existing studies on agricultural production in China. However, with the exception of Zhang and Carter (1997), Wang *et al*. (2009), Mendelsohn (2009), and Chen *et al*. (2013) most studies have not explicitly considered climate factors in their analyses of the state and prospects of Chinese agriculture. The issue of output risks receives even less attention.

The world climate is changing (Christensen 2007; Parry *et al*. 2007; Shortle *et al*. 2009) and the consequences of this are expected to be considerable. However, the various studies on the impacts of climate change on agricultural production produce a multitude of different results. Some studies for instance find that

Received 29 January, 2013 Accepted 18 March, 2013
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increases in temperatures could benefit agricultural production in some developed countries, such as the US (Mendelsohn and Dinar 2003; Deschênes and Greenstone 2007; Shortle *et al*. 2009) or Germany (Lippert *et al*. 2009). Others conclude that global warming could harm agricultural production in many developing countries in Africa and South America (Féres *et al*. 2008; Mendelsohn 2009). Regarding China, Mendelsohn (2009) finds that global warming could be harmful to famers in general by reducing their revenues, while Wang *et al*. (2009) conclude that global warming is only harmfaul to farmers without access to irrigation, whereas it is beneficial to farmers with access to irrigation. In addition, Chen *et al*. (2013) find that the contribution of climatic factors is positive and significant to grain production in China in 2005-2009. Wang *et al*. (2010), who provide a comprehensive review regarding the impact of climate change on Chinese agriculture, however warn that the overall net effects on production and rural income heavily depend on the assumed climate change scenario and the modes of production.

Regarding the future development of East Asia's climate, it is expected that both annual average temperatures and total annual precipitation levels as well as climatic variability could increase (Christensen *et al*. 2007). In particular, the increase in China's annual average temperature could be as high as 2.3-3.3°C by 2050, whereas the national precipitation level could increase by 5-7% until then (Wang *et al*. 2010).

As a result of the country's exposure to the East Asian monsoon, its climate and particularly precipitation patterns are already characterized by a high degree of variability (Tao *et al*. 2004), which frequently leads to droughts and floods (Smit and Cai 1996). The expected increase in climatic variability implies that even more extreme climate events are likely to occur in the future.

These changes will likely have profound impacts on Chinese agriculture. Hence, the main objectives of this paper are to develop a method, which uses Just and Pope (1978, 1979) style yield functions to analyze (1) how climate change affects the expected grain output in China and (2) how the level of output risk immanent in grain farming is affected. In contrast with several prior studies, which adopt Just and Pope style functions for climate change impact assessments (e.g., Chen *et al*. 2004), we also control for the influences of regular input factors in the production process. We use a data set for a panel of 26 Chinese provinces comprising variables relevant for grain production and climate information from 1985 through 2009.

MODELS AND ESTIMATION APPROACHES

Background of the models

In the current literature, the production function and the Ricardian approach are the two predominant approaches to estimate the economic impacts of climate change. The Ricardian approach, which analyzes the influences of climate factors and other exogenous variables on the productivity of farmland as measured by land rent (Lippert *et al*. 2009), land value (Féres *et al*. 2008), net revenue per unit of land (Mendelsohn and Dinar 2003; Mendelsohn 2009) or profit per unit of land (Deschênes and Greenstone 2007; Wang *et al*. 2009), has frequently been applied in recent years. However, when using this approach, heterogeneities related to unobserved variables are often embedded in the error terms. Certain inputs (e.g., fertilizers), landscape features, or soil characteristics can be correlated with climate variables and can thus cause endogeneity problems in regressions, which lead to inconsistent estimation results (Deschênes and Greenstone 2007). Moreover, it is a fact that the agricultural land in China is equally distributed to farmers and that there is no open market for farmland, so that neither rents nor values of farmland can be observed. Nevertheless, in a study on China, Wang *et al*. (2009) use the Ricardian approach to analyze farmers' net income. However, since some important variables, such as the land prices or land rents and food prices, are not included, their results might be biased.

The production function approach, which has the advantage that it provides a good structural form, in turn suffers from the drawback that it, as pointed out by Deschênes and Greenstone (2007), cannot incorporate farmers' adaptations to climate change, which may bias the estimates with respect to long-run climate influences. However, this approach has the benefit that it can be used to study the impacts of climate change on output levels and output fluctuations (i.e., risks), which are of great importance as it comes to food se-

curity considerations.

In light of the above facts, we resort to estimating aggregate grain yield with climate factors and normal agricultural inputs as independent variables. This represents a mixed approach as it on the one hand provides a structural model that enables us to analyze output quantities and risk levels, and on the other hand allows us to overcome some of the inflexibility that puts the production function approach at a disadvantage to the Ricardian approach. The reason for this is that combining all grain varieties in an aggregate output variable implies that farmers' possibilities to change their cultivated grain variety in response to a changing climate are accounted for.

Base model

In this study, following the discussions about production functions by Yu and Zhao (2009), Tian and Yu (2012), Yu (2012) and Chen *et al*. (2013), we draw on the Cobb-Douglas functional form to specify the basic model as follows:

$$\ln y_{it}=\alpha_0+\sum_{k=1}^{K}\alpha_k \ln x_{kit}+h\ (C_{it})+\varepsilon_{it} \tag{1}$$

Where y_{it} is the grain yield in region i in year t, x_{kit} is the input quantity of factor k per unit of land area under grain cultivation in the respective region and year, a_k are the parameters to be estimated with respect to the various conventional input factors. $h(C_{it})$ in turn is a function of climate variables, which models the impacts of a vector of climate variables (C_{it}) on grain yield and thus turns the model into a weather and input yield function similar to the function used by Zhang and Carter (1997) and Chen *et al*. (2013). Finally, ε_{it} is a normally distributed error term.

The model however needs to be adjusted in the presence of yield risks, which doubtlessly affect agricultural production, and which can be assumed to take the form of heteroskedasticity in the yield function (Just and Pope 1979). The most important issue is that many stochastic production functions with log-linear disturbances, such as eq. (1) or the conventional Cobb-Douglas function, impose the strong constraint of a positive correlation between the use of any input factor and the yield variance (i.e., the level of yield risk) (Just and Pope 1978, 1979)[1], which is a rigid assumption and obviously unrealistic. This clearly also has implications for the suitability of conventional estimation procedures, such as fixed effects (FE) or feasible generalized least squares (FGLS) estimation. Moreover, both FE and FGLS estimation of eq. (1) would not be informative with respect to the specific marginal effect of any input factor on the level of output risk. Hence, a more flexible functional form and a suitable estimation procedure are needed.

Just and Pope model

Following Just and Pope (1978, 1979), we develop a flexible non-linear fixed-effects panel data model, which is suitable for separately analyzing each input factor's marginal contribution (considering both standard and climate inputs) to the mean yield as well as to yield risk in Chinese grain farming without imposing constraints on the signs of the coefficients. Based on Just and Pope's generalized production function, our model is specified as follows:

$$y_{it}=\exp\left[\alpha_0+\sum_{k=1}^{K}\alpha_k \ln x_{kit}+\gamma t+h_1(C_{it}^1)\right]+e_{it}\sqrt{\beta_0+\sum_{m=1}^{M}\beta_m \ln x_{mit}+h_2(C_{it}^2)} \tag{2}$$

A major property of the model in eq. (2) is that the expected yield (oft also referred to as mean yield) and the variance of the yield (yield risk) are determined independently:

$$E(y_{it})=\exp\left[\alpha_0+\sum_{k=1}^{K}\alpha_k \ln x_{kit}+\gamma t+h_1(C_{it}^1)\right] \tag{3}$$

$$V(y_{it})=\beta_0+\sum_{m=1}^{M}\beta_m \ln x_{mit}+h_2(C_{it}^2) \tag{4}$$

In eqs. (2)-(4), y_{it}, x_{kit} and α_k have the same definitions as in eq. (1), x_{mit} denotes a standard input factor, which can influence the risk level, and β_m is the corresponding coefficient. t is a linear time trend and γ consequently is a coefficient capturing the influence of tech-

[1] Just and Pope (1978, 1979) also provide detailed proof.

[2] Given that technology is only relevant for the production process itself, the time trend has only been included in the mean yield component of eq. (2). Furthermore, introducing a time trend into the variance component of the model might lead to collinearity because of a likely correlation between climate change and time.

nological progress[2]. $h_1(C_{it}^1)$ and $h_2(C_{it}^2)$ are polynomial functions modeling the impacts of different climate variables on the mean and the variance of yield, respectively. Thus, the vector (C_{it}^1) contains climate variables, which are deemed important for the determination of mean yield, whereas the vector (C_{it}^2) comprises climate variables, which are likely to affect yield risk. e_{it} now is a stochastic error term following the standard normal distribution.

Just and Pope (1979) also proposed a three-stage procedure for consistently estimating models based on their flexible functional form, which we will apply with some modifications that account for the panel-data nature of our study to estimate eq. (2): (I) non-linear least squares estimation of the mean yield (eq. (3)) with province dummies included, (II) estimation of eq. (4) as a fixed-effects model using the residuals from the first stage as dependent variable, and (III) re-estimation of the mean yield utilizing a generalized non-linear least squares model with the estimates from stage (II) serving as weights and again with province dummies included.

Introducing province dummies on stages (I) and (III) and resorting to fixed effects estimation on stage (II) is necessary because China's provinces, which will be our panel units, are quite heterogeneous in terms of geographical features, climate regimes, economic development and various other aspects. However, the climatic differences and the differences with respect to cropping systems between the country's subtropical south and its temperate northern part are likely to make a decisive difference with respect to the impact of climate change (Lin 1992; Wang *et al*. 2009). Specifically, the main grain in South China is rice and usually more than one cropping season per year is possible, while the main grain in North China, where usually only one cropping season is possible, is wheat. Rice generally prefers high temperatures, a high-humidity environment and short durations of sunshine, while wheat grows better under long durations of sunshine and a relatively dry weather. Therefore, we will split the sample into northern[3] and southern[4] provinces and will separately apply the above procedure to those subsamples.

Impact analysis

From a policy perspective it is particularly important to quantify the change in output following a marginal change in climate. Drawing on the mean yield function (eq. (3)) we can calculate the change in mean yield following a 1°C increase in annual average temperatures or a 1 mm increase in total annual precipitation as follows:

$$\overline{\Delta y_c} = \frac{\partial E(y)}{\partial c} \tag{5}$$

Where $\overline{\Delta y_c}$ is the change in mean yield induced by a change in climate factor c (annual average temperature or total annual precipitation). y denotes the average mean yield of the considered set of provinces in the last year of the data set. By multiplying the change in yield by the total area under grain cultivation and by the average price of grain products, it is furthermore possible to quantify the corresponding total monetary benefit.

Data

A data set for a panel of 26 Chinese provinces comprising variables relevant for grain production and climate information from 1985 through 2009 is used to carry out the analyses in this study. The main variables regarding grain production, which are used for the regressions, include yearly observations of grain yield[5] (t ha^{-1}), grain acreage (ha), rural laborers per unit area of land under grain cultivation (persons ha^{-1}), irrigated share of the grain acreage (%), power of agricultural machinery per unit area of land under grain cultivation (w ha^{-1}) as well as fertilizer use per unit area of land under grain cultivation (t ha^{-1}), while the data on climate consist of monthly observations with respect to temperature (°C) and precipitation (mm m^{-2}). The data set is constructed from various issues

[3] Northern provinces: Gansu, Hebei, Heilongjiang, Henan, Jilin, Liaoning, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Xinjiang.

[4] Southern provinces: Anhui, Fujian, Guangdong, Guangxi, Guizhou, Hainan, Hubei, Hunan, Jiangsu, Jiangxi, Sichuan, Yunnan, Zhejiang.

[5] Aggregate grain output (measured by weight), as reported by the National Bureau of Statistics of China (NBS), consists of the individual output quantities of the different varieties of rice, wheat, corn, sorghum, millet, tubers and beans. The total weight of harvested tubers (net of the share recorded as vegetables) has been converted by the NBS to grain-equivalent output by assuming that five kilograms of tubers are equivalent to one kilogram of the other grains (National Bureau of Statistics of China 2008).

of the China Statistical Yearbook (National Bureau of Statistics of China 1986-2010).

Except for the land area under cultivation, the available raw input data generally represent aggregate input use regarding all subsectors of a province's agriculture and are thus not specific to grain farming. In order to approximate the province-specific quantities of labor, fertilizer and machine power as well as the size of the irrigated area used for the production of grain, the total input quantities have been multiplied by the share of the grain acreage in total cropland, which entails the simplifying assumption of equal input use per unit area of land for all crops. In the cases of labor and machinery, we furthermore acknowledge that these inputs are also substantially used in parts of agriculture not related to crop cultivation. Consequently, we adjust them a second time by also multiplying them with the share of crop output value in total agricultural output value. Similar adjustment procedures have also been applied by Zhang and Carter (1997) and Lin (1992). Summary statistics of grain yield, the derived input variables and the average climate conditions are presented in Table 1.

Figs. 1 and 2 show the development of aggregate grain output and of grain yield in North and South China.

In this study we use the climate observations of the provincial capital cities as proxies for the average climate of the corresponding provinces. We acknowledge that the temperature data might be affected by the urban heat island effect but we assume that this effect takes the form of a constant mark-up on the average temperatures of the surrounding rural areas over the limited

Table 1 Descriptive statistics[1)]

Variable	Measurement		North China					South China					
			Mean	Std. Dev.	Min	Max	Obs.		Mean	Std. Dev.	Min	Max	Obs.
Yield	10 000 t	Overall	0.3753	0.1148	0.1476	0.7025	N=325	Overall	0.4535	0.0844	0.2411	0.6127	N=322
	1 000 ha^{-1}	Between		0.0972	0.2663	0.5413	n=13	Between		0.0774	0.3270	0.5586	n=13
		Within		0.0666	0.1715	0.5365	T=25	Within		0.0399	0.3322	0.5450	T-bar=24.77
Area	1 000 ha	Overall	4 235.5770	2 757.5240	244.7000	11 391.0300	N=325	Overall	3 876.0730	1 740.3710	402.6400	7 337.7330	N=322
		Between		2 826.1030	343.6083	9 109.6880	n=13	Between		1 781.1360	522.7658	6 815.9720	n=13
		Within		456.8328	2 799.0310	7 429.2100	T=25	Within		410.0143	2 651.5350	4 949.9490	T-bar=24.77
Labor	10 000 persons	Overall	0.1384	0.0569	0.0418	0.2508	N=296	Overall	0.2011	0.0548	0.0985	0.4349	N=309
	1 000 ha^{-1}	Between		0.0564	0.0501	0.2124	n=13	Between		0.0517	0.1131	0.3106	n=13
		Within		0.0133	0.1007	0.1767	T-bar=22.77	Within		0.0240	0.1441	0.3254	T-bar=23.77
Irrigation	Percentage of grain acreage	Overall	0.3655	0.1763	0.0792	0.9500	N=313	Overall	0.3071	0.0875	0.1345	0.5812	N=309
		Between		0.1769	0.1686	0.8986	n=13	Between		0.0846	0.1561	0.4754	n=13
		Within		0.0464	0.2291	0.5104	T-bar=24.08	Within		0.0326	0.2250	0.4803	T-bar=23.77
Machinery	10 000 kW	Overall	0.1961	0.1001	0.0660	0.6013	N=309	Overall	0.1337	0.0647	0.0410	0.4466	N=309
	1 000 ha^{-1}	Between		0.0720	0.1088	0.3522	n=13	Between		0.0460	0.0827	0.2497	n=13
		Within		0.0718	0.0210	0.4525	T-bar=23.77	Within		0.0471	0.0002	0.3306	T-bar=23.77
Fertilizer	10 000 t	Overall	0.0260	0.0143	0.0044	0.0722	N=314	Overall	0.0305	0.0195	0.0093	0.1524	N=310
	1 000 ha^{-1}	Between		0.0127	0.0116	0.0604	n=13	Between		0.0158	0.0140	0.0779	n=13
		Within		0.0072	0.0047	0.0497	T-bar=24.15	Within		0.0130	-0.0038	0.1049	T-bar=23.85
Annual average temperature	°C	Overall	9.9253	3.4831	3.3000	16.0000	N=325	Overall	18.2842	2.8571	13.8333	25.4000	N=321
		Between		3.5432	4.9603	14.8403	n=13	Between		2.9763	15.1310	24.5754	n=13
		Within		0.7124	7.0193	11.6149	T=25	Within		0.5888	16.9866	20.4532	T-bar=24.69
Total annual precipitation	mm m^{-2}	Overall	481.1409	195.8535	74.9000	1 212.9000	N=325	Overall	1 291.8260	385.2733	565.8000	2 678.9000	N=321
		Between		154.2800	186.8880	705.9840	n=13	Between		291.6158	831.7480	1 762.8600	n=13
		Within		127.7475	123.4569	1 350.9690	T=25	Within		266.3850	556.6785	2 207.8660	T-bar=24.69

[1)] Input variables derived as described in Section 3(change another expression according the descripition in the paper).

time period analyzed here. Consequently, the intercept in the regressions should capture most of this effect as long as the climate variables are linear. The results of Li *et al*. (2004) support our assumption as they find that, while the urban heat island effect certainly exists, the difference between the decadal warming trends of urban and non-urban measurement stations is minor.

From the available monthly climate data we construct a total of four different climate variables. The most elementary ones are the annual average temperature and the total annual amount of precipitation. Additionally, because climate change does not only change mean climate conditions but also affects the largely unpredictable climatic variability, which might be particularly relevant with respect to yield risks, we

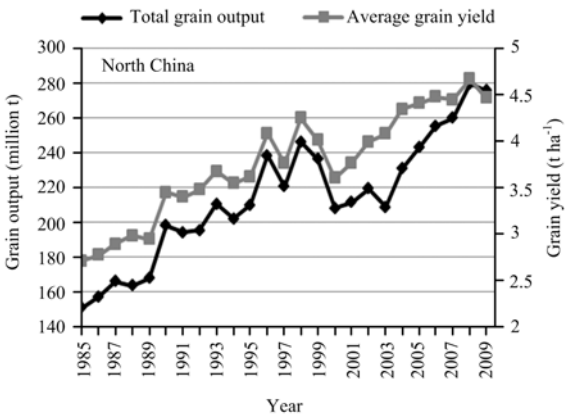

Fig. 1 Grain Production in North China. Data: National Bureau of Statistics of China (1986-2010)

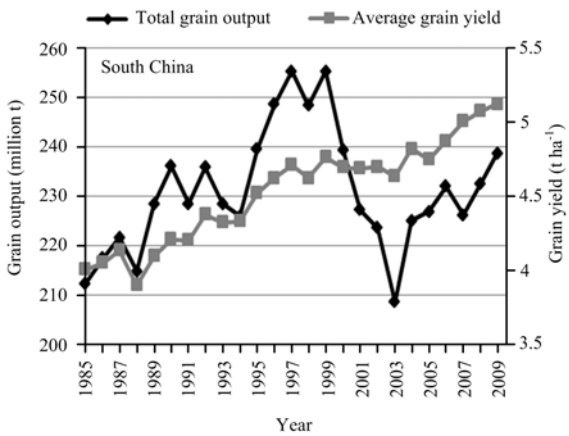

Fig. 2 Grain Production in South China. Data: National Bureau of Statistics of China (1986-2010)

construct measures of aggregate deviation from long-term trends. They can be algebraically denoted as follows:

$$AGDEV_{cit}=\sum_{s=1}^{12}|c_{its}-\overline{c_{its}}| \tag{6}$$

Where $AGDEV_{cit}$ represents the aggregate deviation of climate factor c (temperature or precipitation) in province i during year t from the linear trends of the individual months. c_{its} are actual climate observations for month s in the respective year and province and $\overline{c_{its}}$ are estimates obtained by calculating a linear trend for month s in province i over the time period under consideration in this study (1985-2009).

Figs. 3-6 show the development of North and South China's annual average temperature and total annual precipitation between 1985 and 2009. In particular, regressions of annual average temperatures against time find positive and highly significant trends for the past 25 yr, which supports the hypothesis that China is already experiencing climatic changes.

ESTIMATION RESULTS AND DISCUSSION

Model comparison

For the estimation of the yield functions, it is important to correctly specify the climate functions $h_1(C_{it}^1)$ and $h_2(C_{it}^2)$. In particular, some studies arrived at the conclusion that the impacts of climatic changes (particularly of changes in temperatures) are of a non-linear nature (e.g., Quiggin and Horowitz 1999; Horowitz 2009; Schlenker and Roberts 2009). Hence, we estimated the Just and Pope models both with and without inclusion of quadratic temperature and precipitation terms into the mean yield component of our model. The results revealed that when quadratic terms are included, none of the quadratic terms and nearly none of the first-order terms are statitistically significant. In contrast, without inclusion of quadratic terms all first-order terms are statistically significant, as is reported in Table 1. Hence, the specification without quadratic terms is obviously superior to the specification with quadratic terms. This might be caused by the fact that we use highly aggregated data in our samples, which

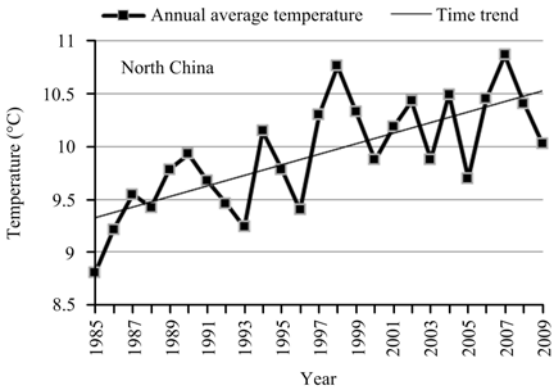

Fig. 3 Annual average temperature, North China (1985-2009). Data: National Bureau of Statistics of China (1986-20010). Trend significant at 1%-level, coefficient: 0.05, t-value: 18.32.

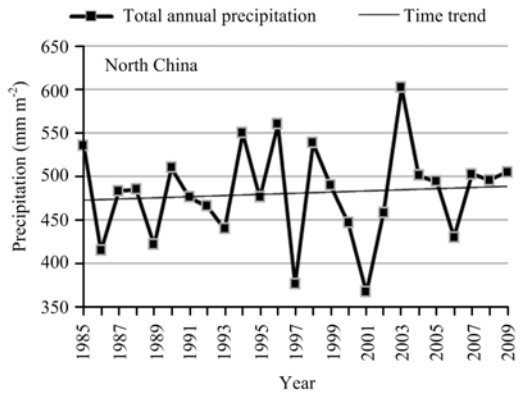

Fig. 5 Total annual precipitation, North China (1985-2009). Data: National Bureau of Statistics of China (1986-2010). Trend not significant, coefficient: 0.6581, t-value: 1.58.

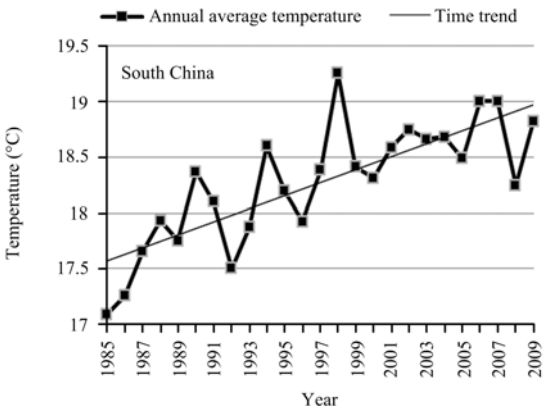

Fig. 4 Annual average temperature, South China (1985-2009). Data: National Bureau of Statistics of China (1986-2010). Trend significant at 1%-level, coefficient: 0.0578, t-value: 22.10.

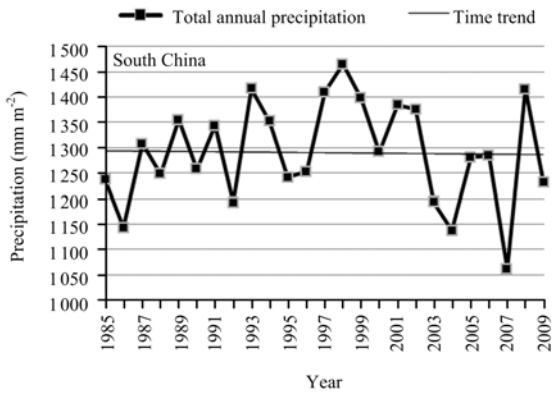

Fig. 6 Total annual precipitation, South China (1985-2009). Data: National Bureau of Statistics of China (1986-2010). Trend not significant, coefficient: -0.4552, t-value: -0.59.

might have smoothed away the nonliearity and might also result in relatively small variances of annual temperatures and precipitation levels. Given the above arguments, we only report the results of the models, which feature only the first-order terms of the climate variables.

The regression results of our multi-stage analysis are presented in Table 2. Models A and B use FGLS estimation whereas Models C and D report the results of the Just and Pope estimation procedure. In both cases the results are presented separately for North and South China[6]. In general, the signs of the coefficients of the significant climate variables are not contradictory between the FGLS and the Just-Pope models, even though their results are not directly comparable due to the aforementioned constraint on the marginal contributions to the output variance of the model in eq. (1) (Just and Pope 1978, 1979), which affects the FGLS results. Hence, it does not come as a surprise to find that Model B is unable to identify any climate impacts on grain production in South China, whereas Model D1 clearly shows that climate factors play a significant role

[6] *F*-tests reject the null-hypothesis of there being no significant difference between the provinces for both the northern and southern samples. Therefore, irrespective of the sample, the introduction of province dummies is warranted. Furthermore, LR-tests also reject the null-hypothesis of there being no significant differences between North China and South China, which supports our approach of separating the national sample into a North China and a South China sub-sample. The validity of the LR test and the *F*-test in a non-linear regression context is confirmed by Wooldridge (2002).

Table 2 Regression analysis of Chinese grain yields[1)]

Sample	North China		South China		North China				South China			
model	**A:** FGLS		**B:** FGLS		**C1:** GNLS		**C2:** FE		**D1:** GNLS		**D2:** FE	
					J-P mean function		J-P risk function		J-P mean function		J-P risk function	
	Coeff.	z-value	Coeff.	z-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Area	0.1049	5.86***	0.1211	7.09***	0.0239	0.58	0.1707	0.19	-0.0044	-0.21	-0.6106	-0.87
Labor	-0.0744	-1.84*	0.0252	0.76	0.1198	1.50	-0.6796	-1.06	-0.0338	-1.00	-1.7123	-2.14**
Irrigation	0.2360	7.57***	0.2958	8.27***	0.2623	2.63***	-1.1933	-3.30***	0.1360	3.71**	1.8427	2.13**
Machinery	0.0792	1.61	0.0537	1.69*	-0.0659	-1.38	-0.3117	-0.77	-0.0263	-1.16	-0.8097	-2.83***
Fertilizer	0.3412	11.23***	0.0406	2.15**	0.3798	10.22***	0.5435	2.03**	0.0412	4.55***	0.1327	0.49
Annual average temperature	-0.0125	-2.07**	0.0043	1.26	-0.0174	-1.70*	0.0749	0.39	-0.0119	-2.11**	-0.2655	-1.96**
Total annual precipitation	1.76E-04	4.35***	-7.67E-06	-0.81	0.0003	4.53***	-0.0005	-0.59	-0.00005	-4.57***	-0.0005	-1.69*
AGDEV temperature	0.0019	2.32**	-0.0008	-1.00	-0.0013	-1.02	0.0061	0.66	0.0001	0.15	0.0112	0.46
AGDEV precipitation	-1.70E-04	-3.23***	2.81E-06	0.18	-0.0005	-3.22***	0.0017	1.56	0.00002	1.47	0.0002	0.44
Time trend	-8.52E-05	-0.03	0.0075	4.90***	0.0086	2.64***			0.0064	7.36		
Constant	-0.2705	-1.32	-1.2532	-6.68***	0.5594	1.79*	-7.7416	-0.87	-0.1606	-0.65	1.8427	0.67
No. of obs.	296		308		296		296		308		308	
R-squared	-		-		0.995		0.0429		0.998		0.0026	

[1)] A time trend is included in the mean yield functions in order to capture the technological change in agricultural production, but it is excluded from the risk functions due to possible collinearity with climate variables. Fixed-effects dummies are included in all regressions, but are not reported.
* significant at 10% level; **, significant at 5%-level; ***, significant at 1% level.

in that region[7].

Specifically, the above constraint on the FGLS model could also be responsible for the negative marginal effect of labor in North China (Model A), which seems to be contrary to traditional economic theory. It cannot be ruled out that the coefficients in Model A and B confound the contributions to mean yield and to yield risk and might thereby lead to wrong policy conclusions, as the point estimate of the marginal labor effect in the mean production function (Model C1) is positive, but that in the risk function (Model C2) is negative. It again shows the deficiency of normal production functions. In addition, the fact of over-input of labor forces in China is realistic.

Because the Just and Pope models are not affected by this constraint and additionally allow us to identify the marginal contributions of individual input factors to the level of yield risk (yield variance), we generally consider them superior to Models A and B.

Mean yield function

Regarding the marginal contributions of the standard physical input factors to mean yield, we find a similar pattern for North China (Model C1) and South China (Model D1). The amount of fertilizer per unit area of land as well as the irrigated share of the grain acreage reaches positive and highly significant output elasticities for both samples. This implies that increasing the use of chemical fertilizer and an expansion of irrigation can significantly increase mean grain yields in China.

Other regular input variables, such as the grain acreage, which in a yield regression captures scale effects, the number of laborers and the use of machinery per unit area of land have no significant impacts on mean yield at the margin. All these results are plausible and consistent with the current literature (e.g., Lin 1992; Yu and Zhao 2009; Ji *et al*. 2012), in which particularly machinery and labor input levels are believed to have reached a saturation point in Chinese agricultural

[7] *R*-squared values in Models C2 and D2, which are not so high, imply that the explanatory power of the risk function is not so high. It makes sense, because of the nature of production risks, most of which cannot be captured by farmers or economists. In addition, due to the nonlinear nature, high *R*-squared values in Models C1 and D1 do not necessarily imply high explanatory power of the mean-production function.

Table 3 Marginal impacts of climate change on grain production in China

Regions	Climate changes	Yield change	Total output change		CNY value	US$ Value
		Quantity (kg ha^{-1})	Quantity (million tons)	%	(billion CNY)	(billion US$)
North China	1°C increase in temperature	-77.60	-4.61	-1.74	-8.12	-1.19
	100 mm increase in precipitation	133.80	7.95	3.00	14.01	2.05
South China	1°C increase in temperature	-60.82	-2.83	-1.19	-4.98	-0.73
	100 mm increase in precipitation	-26.16	-1.22	-0.59	-2.14	-0.31
Whole China	1°C increase in temperature		-7.44	-1.45	-13.10	-1.92
	100 mm increase in precipitation		6.73	1.31	11.86	1.74

production.

However, since this study is focused on climate impacts, the regular input factors will only be discussed in as far as their results are related to the climate factors under consideration.

In particular, it emerges that with an output elasticity of 0.262, North China could benefit considerably from expanding the share of its grain acreage under irrigation, which stands in contrast to the relatively small elasticity of 0.136 in South China. We attribute this to the fact that North China is more frequently affected by droughts and generally is a much more arid region than South China, precipitation is relatively abundant. However, any long-term benefits from increasing the irrigated share of the grain acreage are certainly conditional upon sufficient water availability, which cannot be taken for granted since the North suffers from a marked scarcity of surface water and already has to obtain a substantial part of the current irrigation water from ground water sources, which in turn has led to a drastic lowering of the ground water table in some regions, for example in the North China Plain and other northern regions (Smit and Cai 1996; Wang *et al*. 2010).

Comparing the marginal impacts of the climate factors on mean yield, it turns out that the impacts on North China are slightly different from those on South China. With respect to the northern provinces we find that a higher annual average temperature would have a negative and significant effect on mean yield (coefficient: -0.017) and that a higher total annual precipitation would increase mean yield (coefficient: 0.0003). For South China, the marginal effect of the annual average temperature is also negative and statistically significant (coefficient: -0.012), whereas increases in total annual precipitation would decrease mean yield (coefficient: -0.0001).

The results regarding the negative impact of higher annual average temperatures might not be immediately intuitive, but are consistent with the current literature (Xiong *et al*. 2007; Mendelsohn 2009; You *et al*. 2009). Wang *et al*. (2010) offer an explanation by pointing out that higher temperatures, ceteris paribus, also increase the water requirements in agricultural production due rising evaporation and transpiration losses, which in our case is aggravated by the fact that water resources are generally scarce in China, particularly in North China (Brown 1995). Correspondingly, Wang *et al*. (2010) also find that farmers without access to irrigation are particularly vulnerable to increases in temperature. However, as compared to North China, South China has more water resources, so that the negative impact of increasing temperatures is smaller in the South.

In light of its serious water scarcity, it is also reasonable to find that North China could benefit from increases in precipitation, which would alleviate this problem and would hence improve grain yields. However, more precipitation in South China might harm grain production as it could cause floods.

It furthermore turns out that the variability of precipitation, as measured by our aggregate deviation variable, significantly influences grain yields in North China, which is likely due to the fact that particularly negative deviations of precipitation from the trend, perhaps in form of droughts, could have severe effects on grain production. Obviously, the possibly beneficial effects of positive deviations cannot compensate for this. Due to the good local irrigation system (Wang *et al*. 2010), South China might better be able to compensate for negative deviations and might even benefit from positive deviations as long as they do not turn into destructive floods. Hence, the overall effect of an increasing aggregate deviation of precipitation from current trends on grain yields in South China is positive. However, it is not statistically significant.

Regarding temperature variability, we cannot find any significant impacts on the mean grain yield in either

North or South China.

Marginal climate change impacts

Drawing on the results just described and using information on grain production in the last year of our data set, we can calculate the economic net benefits or net losses of Chinese grain farming following marginal increases in annual average temperature and total annual precipitation. The results are reported in Table 2.

In 2009, North China was characterized by an average grain yield of 4.46 t ha^{-1}. Hence, drawing on the respective climate coefficients from Model C1, a 1°C increase in annual average temperature would reduce North China's grain yield by around 0.078 t ha^{-1}, whereas a 100 mm increase in total annual precipitation would increase it by 0.134 t ha^{-1}. The changes correspond to a 1.74% decline and a 3% improvement, respectively. Given that the grain acreage in North China amounted to approximately 59.41 million ha in 2009, the changes in yield imply changes in total output of -4.61 million t for the change in temperature and of +7.95 million t for the change in precipitation. Assuming an average grain price around 1.762 CNY kg^{-1} for 2009 (National Development and Reform Commission of China 2010), the corresponding economic gains (losses) would be around -8.1 billion CNY (-1.19 billion US$[8]) and +14 billion CNY (2.05 billion US$), respectively.

Based on South China's average grain yield of 5.12 t ha^{-1} in 2009, the effect of a 1°C increase in annual average temperature would be a decrease in grain yield of around 0.06 t ha^{-1}, which would represent a 1.2% decline. Given the fact that South China featured a grain acreage of approximately 46.46 million ha, the corresponding change in output and value of output would be around -2.83 million t and around -5.0 billion CNY (-730 million US$), respectively. By similar calculations, we find that an increase in total annual precipitation by 100 mm in South China would reduce grain output by 1.22 million t, or 0.59 % of the grain output in that region, which has a value of 2.14 billion CNY (310 million US$).

Adding up the gains and losses of North and South China, we find that a 1°C increase in annual average temperature would reduce grain production in China as a whole by around 7.45 million t, which amounts to 1.45% of China's total grain production, and would have a value of 13.1 billion CNY (1.9 billion US$). A 100 mm increase in precipitation however would increase grain output by 6.73 million t, which corresponds to 1.31% of current national grain production and would have a value of 11.86 billion CNY (1.74 billion US$).

Yield risk function

Our analyses of yield risk in Chinese grain farming by means of Just and Pope's procedure (Models C2 and D2 for the northern and southern provinces, respectively) reveal that several of the standard physical input factors have a highly significant influence. Generally we acknowledge that yield risks are typically rather specific to the operational environment of farmers, to their specific crops and personal experiences in handling risks. Nevertheless, using a highly aggregate analysis (provinces as panel units and aggregate grain yield as dependent variable) we find that that a higher irrigation share in North China would lead to a reduction in yield risk and that an increasing use of fertilizer might increase yield risk. Both would be reasonable due to the relative water scarcity in North China that renders using large amounts of fertilizer a risky procedure and that could at least partially be compensated for if a larger share of the grain acreage could be irrigated.

For South China, we find that increases in the input levels of labor and machinery can significantly reduce the yield variance, which does make sense as more labor or machinery could allow producers to compensate for other downside risks in the long process of agricultural production. It is however puzzling that the share of irrigated land is positively correlated with the yield variance, which is the opposite of what we find for North China. A possible explanation might be that an overcapacity of irrigation in South China could incentivize producers to inconsiderately convert non-

[8] Average official exchange rate in 2009: US$ 1≙ CNY 6.83. Source: People's Bank of China, http://www.pbc.gov.cn/publish/html/2009s08.htm

irrigated land into irrigated land, so that the newly planted crops, such as rice, are unsuitable on that land, which would render them very susceptible to environmental influences.

In accordance with our earlier assumption that climatic changes affect yield risk, it emerges that increases in temperature and precipitation could both significantly reduce the yield variance in South China. The reason might be that an increase in temperature generally implies a decreasing probability of extreme cold events, which would be harmful for crops particularly in South China. Moreover, due to its better irrigation systems, South China should be able to employ increasing precipitation quantities in a productive way, which could help to reduce the probability of drought losses. Probably because the conditions in North China are considerably different, the corresponding impact on North China is not statistically significant.

Moreover, we find the coefficient estimates for temperature and precipitation variability to be positive both in North and South China, which is consistent with our assumption that increasing climatic variability would increase the yield risks. However, they don't reach conventional levels of significance.

CONCLUSION

This paper has contributed to the current literature in several ways. We have used recent data to analyze the influences of annual climate factors and of climatic variability on grain yields in China. In particular, we have modified the method of Just and Pope (1978, 1979) to be able to separately determine the marginal contributions of both regular input factors and climate factors to mean yield and to yield risk in a panel data context.

Our results have several implications for Chinese agricultural and climate-related policies. In an environment already characterized by a changing climate, a stabilization or expansion of grain yields can in both North and South China be achieved by increasing the quantity of fertilizer per unit area of land under grain cultivation, even though China already possesses the most fertilizer-intensive agriculture in world. However, it should also be kept in mind that further increments in the application of fertilizer could have adverse impacts on the environment, which could have a severe negative impact on agriculture in the long-run. Moreover, since China is characterized by a relative water scarcity, it would benefit from increasing the percentage of its grain acreage under irrigation, particularly in the northern regions. Hence, building irrigation infrastructure and securing a steady and sustainable water supply for this irrigation are both important challenges.

One of the main results with respect to the influences of the different climate factors is that North and South China will be differently affected by climatic changes. Specifically, both North and South China would experience decreasing mean yields as a consequence of rising annual average temperatures, but the northern part would be more severely affected, which is consistent with the current literature (Xiong *et al*. 2007; Mendelsohn 2009; You *et al*. 2009). Here, the different water availability in the two regions again seems to play a crucial role, which is also supported by the finding that the relatively water scarce northern provinces would likely benefit from increasing annual precipitation quantities, whereas the southern provinces, where water is relatively abundant, could be adversely affected. Moreover, we find that an increasing variability of precipitation, as measured by our aggregate deviation variables, would likely reduce mean yield in North China but would have no significant impact on South China.

Regarding the influence of climate factors on yield risk, our main findings are that increases in temperature and precipitation can significantly reduce yield risks in South China, but have no significant impacts on yield risk on North China. In addition, we find that the variabilities of temperature and precipitation are positively correlated with the yield variances. However, the relationships are not statistically significant.

Overall, we arrive at the conclusion that global warming would on the one hand reduce grain output in China as a whole, but on the other hand might have the benefit of reducing yield risks in South China.

Moreover, our results also allowed us to calculate the economic losses of a marginal increase in annual average temperature. It emerges that grain output, ceteris paribus, would decrease by 4.6 million t in North China and by 2.8 million t in South China in a scenario

of a 1°C increase in annual average temperature. Hence, the national loss would be 7.44 million t, which corresponds to 1.45% of current grain production and would have a value of 13.1 billion CNY.

Moreover, we find that grain output, ceteris paribus, would increase by 7.95 million t in North China but would decrease by 1.22 million t in South China in a scenario of a 100 mm increase in total annual precipitation. In total, the national output would increase by 6.73 million t, which would amount to 1.31% of current grain production with a value of 1.74 billion CNY.

This study is consistent with the current literature, which finds that China would suffer losses in grain production from global warming. Given the immense size of the Chinese population, the Chinese government should take active measures to alleviate the negative impacts of global warming to ensure food security.

Acknowledgements

We are grateful to Prof. Funing Zhong at Nanjing Agricultural University, and Prof. Bernhard Bruemmer at the University of Goettingen for their constructive comments.

References

Brown L R. 1995. *Who Will Feed China? Wake-Up Call for a Small Planet*. W.W. Norton and Company, New York.

Chen C C, McCarl B A, Schimmelpfennig D E. 2004. Yield variability as influenced by climate: a statistical investigation. *Climatic Change*, **66**, 239-261.

Chen Y, Wu Z, Zhu T, Yang L, Ma G, Chien, H, (need full authors, ten authors), *et al*. 2013. Agricultural policy, climate factors and grain output: evidence from household survey data in rural China. *Journal of Integrative Agriculture*, **12**, 169-183.

Christensen J H, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli R K, Kwon W T, Laprise R, *et al*. 2007. Regional climate projections. In: Solomon S D, Qin M, Manning Z, Chen M, Marquis K B, Averyt M T, Miller H L, eds., *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge and New York.

Deschenes O, Greenstone M. 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *The American Economic Review*, **97**, 354-385.

Féres J G, Reis E J, Speranza J. 2008. Assessing the impact of climate change on the brazilian agricultural sector. [2012-11-6]. http://www.anpec.org.br/encontro2008/artigos/200807181438190-.pdf

Horowitz J. 2009. The income-temperature relationship in a cross-section of countries and its implications for predicting the effects of global warming. *Environmental and Resource Economics*, **44**, 475-493.

Ji Y, Yu X, Zhong F. 2012. Machinery investment decision and off-farm employment in rural China. *China Economic Review*, **23**, 71-80.

Just R E, Pope R D. 1978. Stochastic specification of production functions and economic implications. *Journal of Econometrics*, **7**, 67-86.

Just R E, Pope R D. 1979. Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, **61**, 276-284.

Kumbhakar S C, Tsionas E G. 2008. Estimation of production risk and risk preference function: a nonparametric approach. *Annals of Operations Research*, **176**, 369-378.

Li Q, Zhang H, LiuX, Huang J. 2004. Urban heat island effect on annual mean temperature during the last 50 years in China. *Theoretical and Applied Climatology*, **79**, 165-174.

Lin J Y. 1992. Rural reforms and agricultural growth in China. *The American Economic Review*, **82**, 34-51.

Lippert C, Krimly T, Aurbacher J. 2009. A Ricardian analysis of the impact of climate change on agriculture in Germany. *Climatic Change*, **97**, 593-610.

Mendelsohn R. 2009. The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, **1**, 5-19.

Mendelsohn R, Dinar A. 2003. Climate, water, and agriculture. *Land Economics*, **79**, 328-341.

Meyer S, Yu X. 2013. The Impacts of Production Uncertainties on World Food Prices. Accepted by *China Agricultural Economic Review*. doi?

National Bureau of Statistics of China (1986-2010). *China Statistical Yearbook* (Various Editions). China Statistics Press, Beijing. (in Chinese)

Parry M L, Canziani O F, Palutikof J P, van der Linden P J, Hanson C E. 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge.

National Development and Reform Commission. 2010. *Price Yearbook of China 2010*. Editorial Office of Price Yearbook of China, Beijing. (in Chinese)

Quiggin J, Horowitz J K. 1999. The impact of global warming on agriculture: a ricardian analysis: comment. *American Economic Review*, **89**, 1044-1045.

Schlenker W, Roberts M J. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, **106**, 15594-15598.

Shortle J, Abler D, Blumsack S, Crane R, Kaufman Z, McDill M, Najjar R, Ready R, Wagener T, Wardrop D. 2009. *Pennsylvania climate impact assessment*. Report to the Department of Environmental Protection, Environment and Natural Resources Institute, The Pennsylvania State University, USA.

Smit B, Cai Y. 1996. Climate change and agriculture in China. *Global Environmental Change*, **6**, 205-214.

Tao F, Yokozawa M, Zhang Z, Hayashi Y, Grassl H, Fu C. 2004. Variability in climatology and agricultural production in China in association with the East Asian summer monsoon and El Niño Southern Oscillation. *Climate Research*, **28**, 23-30.

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

von Braun J. 2007. The world food situation, new driving forces and required actions. IFPRI-Food Policy Report. International Food Policy Research Institute, Washington, D.C., USA.

Wang J, Huang J, Rozelle S. 2010. Climate change and China's agricultural sector: an overview of impacts, adaptation and mitigation. ICTSD-IPC Platform on Climate Change, Agriculture and Trade, Issue Brief No. 5, International Centre for Trade and Sustainable Development, Geneva, Switzerland and International Food & Agricultural Trade Policy Council, Washington, D.C., USA.

Wang J, Mendelsohn R, Dinar A, Huang J, Rozelle S, Zhang L. 2009. The impact of climate change on China's agriculture. *Agricultural Economics*, **40**, 323-337.

Wooldridge J M. 2002. *Econometric Analysis of Cross Section and Panel Data*. The MIT Press, Cambridge and London.

Xiong W, Lin E, Ju H, Xu Y. 2007. Climate change and critical thresholds in China's food security. *Climatic Change*, **81**, 205-221.

You L Z, Rosegrant M W, Wood S, Sun D S. 2009. Impact of growing season temperature on wheat productivity in China. *Agricultural and Forest Meteorology*, **149**, 1009-1014.

Yu X. 2012. Productivity, efficiency and structural problems in Chinese dairy farms. *China Agricultural Economic Review*, **4**, 168-175.

Yu X, Zhao G. 2009. Chinese agricultural development in 30 years: a literature review. *Frontiers of Economics in China*, **4**, 633-648.

Zhang B, Carter C A. 1997. Reforms, the weather, and productivity growth in China's grain sector. *American Journal of Agricultural Economics*, **79**, 1266-1277.

(Managing editor WENG Ling-yun)