studies have made efforts to isolate impact of climate change on crop yield in China by statistical approach (e.g., Carter and Zhang, 1998; Peng et al., 2004; You et al., 2009; Zhou and Turvey, 2014). These inter-regional studies on the basis of data at either site or regional scale (Shi et al., 2013) do not treat climatic variables as pure random terms since regional differences in these variables are known by local farmers to a reasonable extent (Demir and Mahmud, 2002).

One typical assumption in these studies is constant elasticity of crop yield with respect to a climate variable, meaning that one percentage change in a climate variable leads to the same percentage change in crop yield for all the reasonable values of the climate variable (e.g., You et al., 2009). The constant elasticity is then used to estimate climate change impact on crop yield. In a large region such as China, the elasticity is, on the contrary, likely to vary with changes in climate variables such as temperature (Aaheim et al., 2012; Li et al., 2011; Schlenker and Roberts, 2009). For example, the average temperature of wheat growth season from 1980 to 2008 is as low as 6 °C in Shanxi and as high as 18 °C in Guangdong while the national average is around 12 °C. It might be too cold for wheat growth in Shanxi and too warm in Guangdong. We could not expect that the same change rate in temperature has the same effect in both regions (i.e., constant elasticity). In crop science, non-linear response curves (Normal Heat Hours methods) have been proposed to study effects on thermal resources for crops (e.g., Mariani et al., 2012; Wang and Engel, 1998; Yan and Hunt, 1999). Hence, it is necessary to relax the assumption of constant elasticity in the case of China as indicated by a study showing nonlinear temperature impact on crop yield in the United States (Schlenker and Roberts, 2009).

Recently Zhou and Turvey (2014) examine the interaction between a climate variable and a socio-economic variable in addition to the constant elasticity of the climate variable. They do not, however, check whether or not the elasticity of a climate variable alone is constant. In addition, their dependent variable is total value product per area, where price effect is included. Xin et al. (2013) examine the variable elasticity of a climate variable as well as interaction between a climate variable and a regional dummy on the basis of rural household survey data for three years (2003, 2005, and 2008). The climate variables in their study are seasonal averages and their elasticities vary considerably across regions in China. While the hypothesis of variable elasticity is supported by household survey data (Xin et al., 2013), we will, in the present paper, study whether or not the hypothesis is supported by the aggregated provincial data, compare our results with other studies, and analyze its implications for crop harvest and food security.

The remainder of the paper is organized as follows. The next section describes data and methodology. Section 3 reports the estimated results and offers a discussion on the implications of the results on crop yield and food security and the last section concludes the paper.

2. Data and methodology

Crop yields are a function of agricultural inputs such as climate, land, capital and labor. To empirically investigate the impact of climate changes on crop yields, we constructed a panel data set that included yields of three crops (wheat, rice and maize) and related inputs from 1980 to 2008. Data include provincial yield and cultivated area of rice (including early, late, and single rice), wheat (including spring and winter wheat) and maize, and irrigated area, agricultural machine power, fertilizer use, and employment in the agriculture sector. The relevant crop growth calendar was derived from the Chinese Agricultural Phenology Atlas and can be found from the online Supporting Information (Appendix S2) in Zhang and Huang (2012). Climate data were obtained from the China Meteorological Administration. Table 1 provides the definition and related remarks of the data used in this study.

Table 1
Variable definitions and descriptive statistics.

Variable	Definition (source)	Mean	SD
Agricultural Yield	Crop-specific agricultural yield (tons/ha)		
Wheat	Source: China Statistical Yearbooks	2.89	1.15
Rice		6.01	1.31
Maize		4.18	1.37
Temperature	Crop-specific average temperature during growth season (Celsius)		
Wheat	Source: China Meteorological Administration	11.60	3.16
Rice		22.05	3.02
Maize		23.10	3.48
Precipitation	Crop-specific total rainfall during growth season (mm)		
Wheat	Source: China Meteorological Administration	353.96	221.08
Rice		567.83	208.51
Maize		586.56	308.72
Land	Crop-specific total area sown (1000 ha)		
Wheat	Source: China Statistical Yearbooks	1011.03	1201.35
Rice		1171.55	1240.47
Maize		868.08	839.33
Agri Machine Pwr	Total power of agricultural machinery (10,000 kw) Source: (NBSC, 2010)	1409.40	1628.49
Irrigated Area	total irrigated area (1000 ha) Source: (NBSC, 2010)	1808.11	1276.67
Fertilizer	Total chemical fertilizer usage (10,000 tons) Source: (NBSC, 2010)	149.29	137.84
Employment	Total agricultural employment (10,000 persons) Source: (NBSC, 2010)	1190.50	896.76

*Data summary: 29 periods (1980–2008); 27 units (provinces); due to missing data, omit Hainan, Qinghai and Tibet for all periods, Tianjin, Fujian, and Zhejiang for 1980–84 and Gansu for 1980–82.

To examine the relationship of changes in climate on crop yields, we estimate the following panel model of crop yields for wheat, rice and maize:

$$Y_{it} = \beta_1 Climate_{it} + \beta_2 Land_{it} + \beta_3 Capital_{it} + \beta_4 Labor_{it} + \omega_i + \phi_t + \varepsilon_{it}, (1)$$

where Y_{it} is the agricultural yield of province i in time t; $Climate_{it}$ is a vector of climate outcomes in province i in time t and includes mean crop-specific temperature and crop-specific rainfall during crop growth season; $Land_{it}$ is the crop-specific total area sown for province i in time t (1000 ha); $Capital_{it}$ is a vector of capital measures for province i in time t and includes the total power of agricultural machinery (10,000 kw), total irrigated area (1000 ha), and total chemical fertilizer usage (10,000 tons); $Labor_{it}$ is the total agricultural labor (10,000 persons) in province i in time t; ω_i is the province-specific effects that capture unobservable time-invariant province characteristics; ϕ_t is the time-specific effects that capture potential non-linear time trends; and ε_{it} is the contemporaneous additive error term. Table 1 provides the descriptive statistics for all the variables, along with definitions and sources.

A few aspects of Eq. (1) warrant further discussion. First, we estimate crop-specific models for wheat, rice and maize. In explaining the crop yields separately, these models include crop-specific temperatures, precipitation, and land sown along with the remaining general measures of capital and labor. Second, all models employ a double-log specification and therefore estimated coefficients are elasticities that measure the proportional responsiveness of one variable to changes in another. Third, since inputs tend to have interior optima (e.g., yields will fall with too much or too little rain), we estimate a second set of models that considers nonlinearities by including squared terms for inputs. With this specification, nonlinear elasticities must be calculated for a specific input value, which is defined as the linear coefficient plus the coefficient of the squared term multiplied by two and the logarithm of the specific input value. Fourth, all models take advantage of the

Table 2
Estimates for double-log panel models of crop yields.

	Wheat		Rice		Maize	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	1.4929**	−0.4164	0.1971	−15.480**	5.0312***	13.9664*
	(0.502)	(1.644)	(1.356)	(6.950)	(1.367)	(7.362)
Temperature	0.0118	−1.2289**	0.2914	16.3509***	−1.4964***	−12.322***
	(0.111)	(0.623)	(0.354)	(4.391)	(0.367)	(4.677)
Temperature^2		0.2649**		−2.6389***		1.7722**
		(0.130)		(0.723)		(0.764)
Precipitation	−0.0589**	2.2389***	0.0310	0.9584***	0.0742**	1.1626***
	(0.030)	(0.279)	(0.037)	(0.380)	(0.036)	(0.369)
Precipitation^2		−0.2031***		−0.0742**		−0.0873***
		(0.024)		(0.031)		(0.030)
Land	−0.0469***	−0.0962***	0.1323***	0.3121***	0.2165***	0.1535***
	(0.0559)	(0.027)	(0.018)	(0.026)	(0.020)	(0.049)
Land^2		0.0088**		−0.0223***		0.0027
		(0.003)		(0.004)		(0.006)
Agri machine Pwr	0.1508***	0.2330**	−0.1088***	0.5025***	0.0704**	0.3814***
	(0.034)	(0.120)	(0.034)	(0.129)	(0.034)	(0.135)
Agri machine Pwr^2		−0.0054		−0.0434***		−0.0235***
		(0.008)		(0.008)		(0.009)
Irrigated area	0.2033***	−0.9643**	0.0249	−3.8338***	−0.1668***	−0.3752
	(0.039)	(0.397)	(0.0479)	(0.426)	(0.040)	(0.408)
Irrigated area^2		0.0838***		0.2750***		0.0144
		(0.028)		(0.030)		(0.029)
Fertilizer	0.0556***	0.1268*	0.0551***	0.0601	0.0149	0.16128**
	(0.018)	(0.068)	(0.018)	(0.069)	(0.018)	(0.072)
Fertilizer^2		−0.0077		−0.0027		−0.0166**
		(0.008)		(0.007)		(0.008)
Employment	−0.3965***	−0.3911	−0.0875	−0.3145	−0.0387	1.1552***
	(0.056)	(0.262)	(0.057)	(0.264)	(0.057)	(0.289)
Employment^2		0.0038		0.0231		−0.0906***
		(0.019)		(0.019)		(0.021)
F (model)	107.62***	109.85***	25.61***	29.13***	70.87***	69.75***
Adj R^2	0.895	0.906	0.667	0.719	0.851	0.875
N	779	779	750	750	745	745
F (province effects)	63.34***	50.49***	28.25***	27.61***	46.73***	39.81***
F (time effects)	4.23***	6.63***	3.49***	4.41***	8.68***	8.26***

Notes: Dependent variable is crop yield (tons per ha). Coefficients are estimated elasticities. Estimates condition on province- and time-specific effects with Hausman tests suggesting that a fixed-effects specification is appropriate in each case.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

panel nature of the data by controlling for unobserved province heterogeneity and time-specific fluctuations. We conduct Hausman (1978) tests to consider whether the province- and time-specific effects should be considered fixed or random. For all regressions, the test rejects the random effects formulation in favor of the fixed effects model.

3. Results and discussion

Table 2 reports the results from the six models—two double-log model specifications for each of the three crops[1]. Models 1 and 2 provide complementary results, with the estimates of model 2 capturing potential significant non-linear relationships. In all models, tests show the models are significant in explaining agricultural yields. Adjusted R-squares indicate that the explanatory variables explain much of the variation in agricultural yields—about 90% for wheat, 70% for rice and 86% for maize. Individual estimates of the coefficients of Model 1 can be interpreted as elasticities, but additional calculation is required for Model 2. We therefore summarize the estimated elasticities across all models in Table 3. Model 1 provides linear elasticities while Model 2 reports nonlinear elasticities, which are calculated at the mean value of the corresponding input.

Table 3 reveals a few intuitive comparisons between the linear and nonlinear estimated elasticities. First, as expected, allowing for nonlinearity greatly affects estimated elasticities for both the climate and non-climate inputs. In particular, the additive input land area sown has different signs across the linear and nonlinear models for wheat and rice. Second, the estimated elasticities for climate variables are all statistically significant in the non-linear Model 2 while only half of the elasticities in the linear Model 1 are significant at the 5% level. Third, when evaluated at the means of variables, the climate inputs consistently have smaller elasticities in Model 2 except temperature for wheat where the estimated elasticity is not statistically significant at the 5% level in Model 1. Fourth, temperature has larger elasticities than precipitation in both models for both rice and maize when evaluated at the variable means.

Table 3
Elasticities.

	Wheat		Rice		Maize	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Temperature	*0.0118*	0.0696	*0.2914*	0.0250	−1.4964	−1.1932
Precipitation	−0.0589	−0.1452	*0.0310*	0.0173	0.0742	0.0497
Area sown	−0.0469	0.0256	0.1323	−0.0030	0.2165	0.1900
Agri machine Pwr	0.1508	0.1547	−0.1088	−0.1269	0.0704	0.0406
Irrigated area	0.2033	0.2927	*0.0249*	0.2912	−0.1668	*−0.1592*
Fertilizer	0.0556	*0.0497*	0.0551	*0.0331*	*0.0149*	−0.0049
Employment	−0.3965	*−0.3373*	*−0.0875*	*0.0127*	*−0.0387*	−0.1281

Note: Italics indicate underlying estimates are NOT statistically significant at the 5% level.

[1] We have considered other non-linear specifications (e.g., cubed), but they did not fit the data as well.

We first review results concerning the climate inputs, focusing on the nonlinear models—again noting that elasticities are calculated at the mean input value (not its logarithm). The temperature estimates indicate that maize yields are markedly responsive to changes in temperature, suggesting that a one percent increase in temperature mean will cause a 1.2 percent decrease in maize yields. Temperature changes have small effects on wheat and rice yields, with estimates indicating that a one percent increase in temperatures will result in an increase in wheat yields by 0.07% and in rice yields by 0.025%. For precipitation, results show that changes in precipitation levels have a significant impact on the yields of all three crops. Estimates suggest that a one percent decrease in precipitation levels will decrease the yields for rice and maize by 0.017 and 0.05%, respectively. A bit surprisingly, a one percent decrease in precipitation levels will increase wheat yields by 0.15%.

Turning to the non-climate inputs, estimates find that agricultural machine power has the expected positive impact on wheat and maize yields with estimated elasticities as 0.15 for wheat yield and 0.04 for maize yield. Results however find an unexpected negative relationship between agricultural machine power and rice yields. This may indicate that agricultural machine power is not a suitable instrument for capital input in rice production since the effect should be positive when agricultural machine power takes a smaller value as indicated by the linear parameter in Model 2 (Table 2). The same as agricultural machine power, the land area sown is found to have the expected positive influence on wheat and maize yields. Specifically, estimates suggest that a one percent increase in area sown will increase wheat and maize yields by about 0.02%. Results however again find an unexpected negative relationship between land area sown and rice yields. However, the elasticity is very close to zero, indicating positive relationship when the land area sown takes slightly smaller values. Results find that chemical fertilizer has the expected positive impact on the yields of wheat and rice and negligible negative impact on maize yield. Estimated elasticities for chemical fertilizer are relatively small—around 0.05 for both wheat and rice yields. Results offer findings on negative impact of agricultural employment on all crop yields except Model 2 for rice. This may attribute to the over-sufficient labor supply in rural China, as found by previous studies (e.g., Stavis, 1991; You et al., 2009). Also, estimates suggest an expected positive relationship between irrigated area and yields of wheat and rice even though an unexpected negative relationship between irrigated area and maize yields. The unexpected negative relationship may point to that total irrigated area for all crops is not a reliable indicator of irrigated area in maize production.

3.1. Comparing with other studies

Table 4 lists the elasticities with respect to climate variables from both our models and other studies. The signs of temperature in Model 1 for wheat are on the opposite of the results of You et al. (2009). This may be attributed to several reasons. We use longer time series (1980–2008) than You et al. (1978–2000). In addition, we analyze historical climate data provided by the China Meteorological Administration while You et al. use climate data from a dataset (CRU TS2.0) at Climate Research Unit at University of East Anglia. The independent variables included in the econometric models are also different. Particularly we include provincial dummies while You et al. (2009) consider regional dummies in the regression. If we replace the provincial dummies with the same regional dummies as You et al. (2009), we obtain the same signs for both temperature and precipitation as You et al. (2009). This may imply that regional dummies are not plausible since provinces in China generally cover a large area with different climate conditions. Even though, for the common non-climate variables such as fertilizer and machinery, our Model 1 has the same signs as them and particularly for fertilizer, we have almost the same estimate.

A recent study is Xin et al. (2013), who examine the climate impact on crop yield on the basis of rural household survey data of three years (2003, 2005, and 2008). They have four seasonal independent variables for temperature (or precipitation): spring, summer, fall, and winter. They calculate weighted elasticities with respect to temperature and precipitation for the whole country. However, the calculations are probably problematic. For example, the overall country's elasticity of maize yield with respect to precipitation is +1, presented as a weighted average of four negative seasonal elasticities (Page 448, Table III, Xin et al., 2013). Based on personal communications, a weighted elasticity in Xin et al. (2013) is not obtained directly as a weighted average of the elasticities of the four seasons. They first obtain the weighted sum of marginal output of the four seasons and then calculated the elasticity at annual basis. In other words, they first calculate changes in output by seasons by assuming one percent changes in precipitation for each of the four seasons and then sum by weights the seasonal changes in output to yearly change in output. The yearly change in output is interpreted as percentage change in output if yearly precipitation changes by 1%. The interpretation is problematic since the one percent change in seasonal precipitation does not sum up to one percent change in yearly precipitation. Hence, Table 4 lists the ranges of seasonal elasticities by regions from Xin et al. (2013). Their results cover broad ranges of elasticities, indicating various seasonal climate change impacts on crop yields for an individual household. Besides the seasonal and regional variations, the climate impact on a household could to a large extent be canceled out by impacts on other households, resulting in small impact at the provincial level.

Zhou and Turvey (2014) also estimate the elasticities of climate variables where the dependent variable is crop value output instead of crop yield. Hence, the price effect is included in their estimates. Their basic model assumes constant elasticities of climate variables and their adaptation model consider the interaction between climate variables and other socio-economic inputs in addition to the constant elasticities. In some cases, elasticities with respect to climate variables in their adaptation model have different signs from their basic model. The signs of the elasticities in our Model 1 are consistent with their basic model for all the three crops.

Table 4
Elasticities of climate variables evaluated at means of variables.

Crop	Variable	Model 1	Model 2	You et al. (2009)	Xin et al. (2013)[a]	Zhou and Turvey (2014)[b] Basic model	Zhou and Turvey (2014)[b] Adaptation model
Wheat	Temperature	0.0118	0.0696	−0.502	−13.05–13.83	0.182	0.142
	Precipitation	0.0589	−0.1452	0.031	−2.84–1.97	0.002	0.022
Rice	Temperature	0.2914	0.0250		−20.30–27.07	−0.827–0.159	−1.060–0.801
	Precipitation	0.0310	0.0173		−2.86–7.10	−0.107–0.036	−0.032 to −0.023
Maize	Temperature	−1.4964	−1.1932		−153.79–51.94	−0.0001	0.018
	Precipitation	0.0742	0.0497		−20.39–19.00	0.035	0.004

[a] Their elasticities are estimated by season and region for each of the three crops.
[b] The dependent variable in their models is value output per area, not yield. They do not estimate elasticities for rice as a whole. Instead, they estimate elasticities for each of early indica rice, indica rice, later indica rice and japonica price.

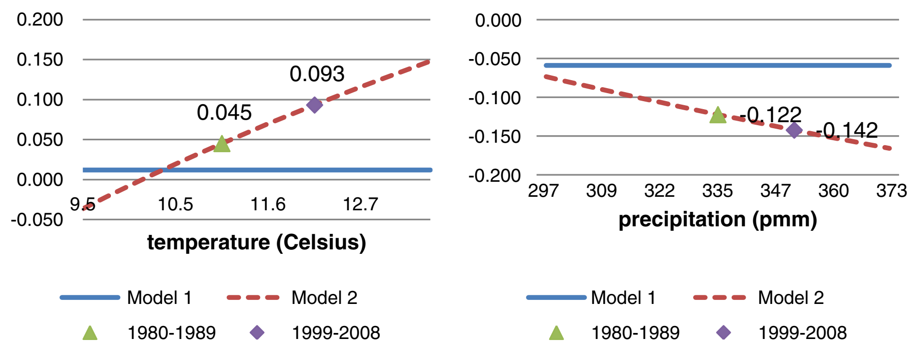

Fig. 1. Elasticities of wheat yield with respect to temperature (left) and precipitation (right).

3.2. Inconstant elasticities with respect to climate variables

In Model 2, we estimate the inconstant elasticities with respect to climate variables, which are not discussed sufficiently in the literature. Our Model 2 shows that the estimated elasticities of yield with respect to climate variables are highly sensitive to the values of climate variables, which is consistent with the non-linear response of agriculture to climate change in the USA (Schlenker and Roberts, 2009). For example, when the temperature is 10 °C, only 1.6 °C lower than the average one, the elasticity of wheat yield with respect to temperature becomes negative, the same sign as You et al. (2009). This indicates that the constant elasticity assumption is not plausible given the high non-linear relations between crop yield and independent variables, including both climate and non-climate variables.

Model 2 indicates that the impact on wheat yield turns from negative to positive with increasing temperature. The turning point is around 10.2 °C (Fig. 1). When a temperature is lower than the turning point, an increase in temperature may be bad for wheat yield even though the negative impact is diminishing and become positive when the temperature is higher than the turning point. It happens that the elasticity with respect to temperature is close to zero at the average temperature over the last three decades and can change dramatically with a small change in temperature. While slightly negative impact of precipitation is obtained with constant elasticity assumption (Model 1), positive impact is possible when precipitation is rather low by Model 2 (Fig. 1). Since the yearly average precipitation during wheat growth months is above 350 mm, more precipitation on average is not good for wheat yield as indicated by both models because the negative impact may increase with more precipitation.

For rice, the elasticity with respect to temperature is decreasing along with higher temperature (Fig. 2). The negative impact on yield happens at high temperature level. An increase in temperature is good before reaching an upper temperature bound even though the positive impact is diminishing. The turning point is between 22 and 23 °C, which is around the average temperature over the last thirty years. Hence, an increase in temperature is likely to reduce rice yield according to Model 2. On the contrary, an increase in precipitation can probably benefit rice production as long as the precipitation is lower than 640 mm per year (Model 2). An increase of precipitation can also increase cloud coverage and consequently decrease global solar radiation. This can justify the decrease in crop production associated with an increase in precipitation when precipitation stays at a high level.

For maize, higher temperature is always bad even though the negative impact is diminishing (Fig. 3). However, more precipitation is always good before reaching a level close to 800 mm per year, while the average one is lower than 600 mm per year during 1980–2008.

Figs. 1–3 also show elasticities in two ten-year periods: 1980–1989 and 1999–2008. The elasticities with respect to temperature change markedly for all the three crops. For wheat, the temperature of the last ten years is about 1 °C more than the first ten years, resulting in over doubled elasticity in the last ten years. For rice, the elasticity changes from positive in the beginning period to negative in the last period.

On the other hand, elasticities with respect to precipitation only change a little since the means of precipitation are almost the same in the two periods. However, the elasticities vary considerably across provinces. Fig. 4 illustrates how different the elasticities change from one province to another.

3.3. Impact on crop yield

Since the elasticities are changing with climate variables, the elasticity estimated at a given level of a climate variable can only indicate the directions and possible impact on yield when the change in the variable is marginally small. To calculate impact on yield when the change in a climate variable is large, e.g., 5%, we have to derive a formula for the calculation of impact on yield. According to our Model 2, we can derive that

$$lnY_{it} = \alpha + \beta_1{}^T lnT_{it} + \beta_2{}^T (lnT_{it})^2 + \beta_1{}^r lnR_{it} + \beta_2{}^r (lnR_{it})^2 \quad (1)$$

where Y is the crop yield, T is the temperature, R is the precipitation, and α and βs are the estimated parameters in Model 2. The equation can be used to calculate crop yield at any reasonable levels of climate variables.

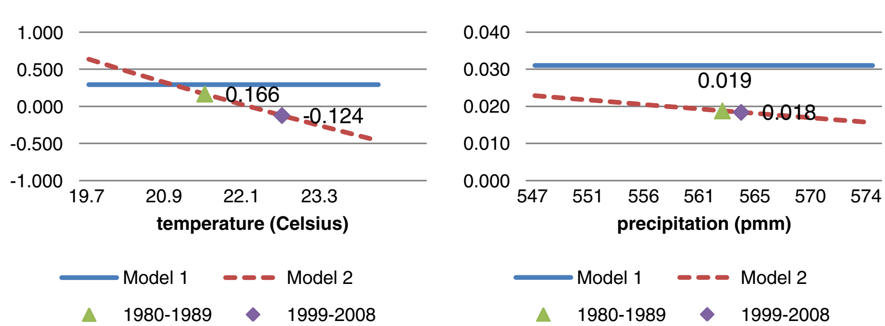

Fig. 2. Elasticities of rice yield with respect to temperature (left) and precipitation (right).

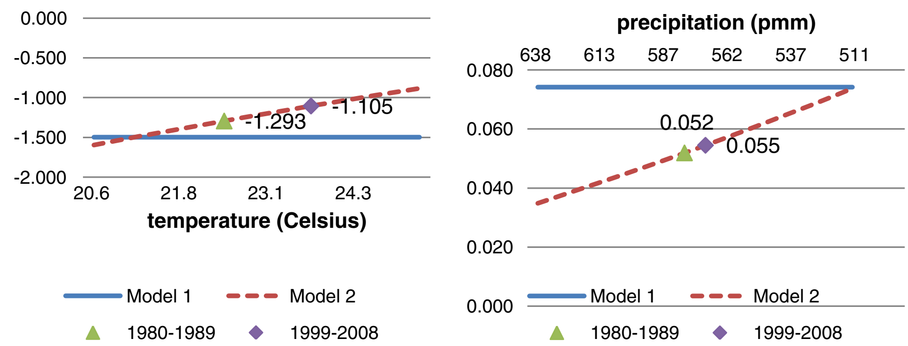

Fig. 3. Elasticities of maize yield with respect to temperature (left) and precipitation (right).

The difference of crop yields corresponding to any two values of a climate variable is the impact of the change in the variable.

By aggregating gridded data at 10 arc min resolution from an existing downscaling climate data set (Hijmans et al., 2005), we obtain monthly climate variables by province for three scenarios: current and two representative concentration pathways (RCPs) scenarios (RCP8.5 and 4.5), where the two RCP scenarios are based on results from a global climate model—NorESM1-M (Bentsen et al., 2012). We use the average temperature and precipitation over 1950–2000 in the current scenario and over 2040–2060 in the two RCP scenarios. Then we average the monthly temperature and sum up the monthly precipitation over the crop growth seasons to obtain crop-specific temperature and precipitation for the three scenarios. By adopting Eq. (1), we estimate the climate change impacts on crop yields. The results show that the impacts vary considerably across provinces. However, at the national level, the impacts are weak for wheat, modest for rice, and strong for maize (Table 5). In the second half of the century, the negative impacts may increase as shown by a recent meta-analysis (Challinor et al., 2014). It seems that climate change may threaten the maize supply considerably in the future. However, the impacts are estimated under the assumption of constant cropland areas and exclusion of impacts of other socio-economic factors.

Hence, we turn to historical data to identify the relative importance of climate change impacts on crop yields. Table 6 shows the climate variable means and yield changes at the national level in the historical periods. The results based on Model 2 show that the temperature changes have much stronger impacts on crop yields than precipitation since temperature changes at greater percentages from 1980–1989 to 1999–2008. At the national average level, the impacts of climate change between the two ten-year periods are positive for both wheat and rice but negative for maize. When compared to total yield changes, the climate change impacts based on Model 2 account for only small shares for wheat (0.97%) and rice (0.44%) but markedly large share for maize (−12.10%). For comparison, we also calculate the climate change impacts based on the linear Model 1. The results based on Model 1 tend to markedly underestimate the climate change impact on wheat yield while overestimate the impacts on both rice and maize. The comparison highlights the importance to consider the nonlinear relations between climate variables and crop yields. Since both models indicate that climate variables have strong impacts on maize, we will have a closer look at the maize case below.

Fig. 5 shows calculated maize yield changes due to climate change including both temperature and precipitation. At the national level, the maize yield is on average reduced by 6.2% due to climate change in the last ten-year period compared to the first ten-year period. However, if the elasticities 1980–1989 in Model 2 are adopted alone, the reduction in yield would be 7.1% of yearly yield 1980–1989. On the other hand, the yield would reduce by 6.1% of yearly yield 1980–1989 if the elasticities 1999–2009 in Model 2 are assumed. As contrast, if the constant elasticities in Model 1 are adopted, the yield reduction would be as high as 8.3% of yearly yield 1980–1989 (Table 6).

However, even though the climate change impacts may be negative and considerably strong, the impacts of other socio-economic factors are positive and stronger so that the yields of all the three crops have increased considerably. For example, the maize yield 1999–2008 at the national level in fact increases by 1.667 t per hectare, corresponding to 40% of the yield 1980–1989.

The other feature observed from Fig. 5 is that the negative impacts due to climate change vary considerably across provinces. In most provinces and at the national level, the negative impact is mainly attributed to increases in temperature. The precipitation has negative impact on

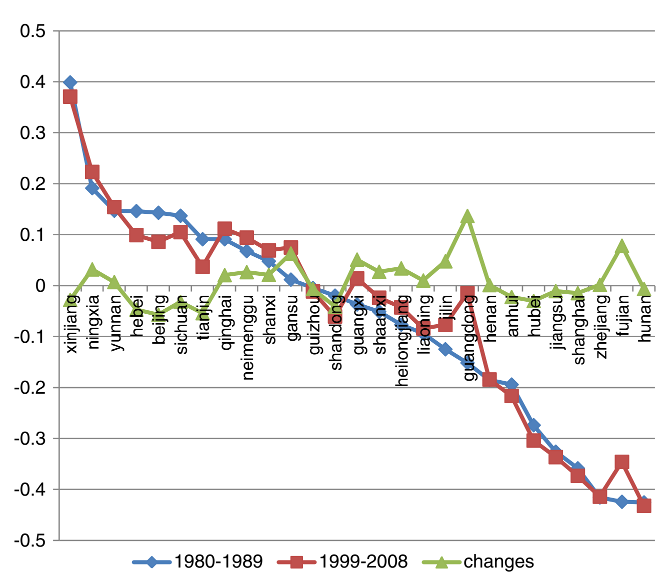

Fig. 4. the changes in elasticities of wheat yield with respect to precipitation 1999–2008 compared to 1980–1989. X-axis is provinces in the ascending order of precipitation from the left to the right.

Table 5
Climate variable means and impacts on crop yields in the two representative concentration pathways (RCP) scenarios.

Crop	Variable	Mean			Climate change impact (% of current yield)	
		Current[a]	RCP8.5[b]	RCP4.5[b]	RCP8.5[b]	RCP4.5[b]
Wheat	Temperature	10.7	13.4	12.7	1.233	0.621
	Precipitation	416.6	444.1	438.2	−1.198	−0.513
Rice	Temperature	20.9	23.4	22.9	−4.786	−3.238
	Precipitation	613.7	662.2	645.2	−0.105	−0.078
Maize	Temperature	21.7	24.3	23.8	−14.917	−12.732
	Precipitation	561.2	607.2	584.4	0.808	0.305

[a] The period from 1960 to 2000.
[b] The period from 2040 to 2060.