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# Potential Impact of Future Climate Change on Crop Yield in Northeastern China

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ABSTRACT

We evaluated the potential impact of future climate change on spring maize and single-crop rice in northeastern China (NEC) by employing climate and crop models. Based on historical data, diurnal temperature change exhibited a distinct negative relationship with maize yield, whereas minimum temperature correlated positively to rice yield. Corresponding to the evaluated climate change derived from coupled climate models included in the Coupled Model Intercomparison Project Phase 5 (CMIP5) under the Representative Concentration Pathway 4.5 scenario (RCP4.5), the projected maize yield changes for three future periods [2010–39 (period 1), 2040–69 (period 2), and 2070–99 (period 3)] relative to the mean yield in the baseline period (1976–2005) were 2.92%, 3.11% and 2.63%, respectively. By contrast, the evaluated rice yields showed slightly larger increases of 7.19%, 12.39%, and 14.83%, respectively. The uncertainties in the crop response are discussed by considering the uncertainties obtained from both the climate and the crop models. The range of impact of the uncertainty became markedly wider when integrating these two sources of uncertainty. The probabilistic assessments of the evaluated change showed maize yield to be relatively stable from period 1 to period 3, while the rice yield showed an increasing trend over time. The results presented in this paper suggest a tendency of the yields of maize and rice in NEC to increase (but with great uncertainty) against the background of global warming, which may offer some valuable guidance to government policymakers.

**Key words**: northeastern China, statistical crop models, climate models, projection, uncertainty

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## 1. Introduction

Global warming is an important issue that is attracting increasing attention from various social sectors. For China, the general tendency of warming is similar to that of the Northern Hemisphere, albeit with significant differences in the specific process of evolution and the magnitudes of warming (Ding and Dai, 1994). Climate change and the potential impact on society are enormous challenges for mankind. Agriculture is one of the sectors most sensitive to climate change. Global warming could lead to an earlier onset of spring events for the mid-high latitudes (Menzel et al., 2006; Inouye, 2008) and cause a northward movement of the northern limits of cropping systems (Yang et al., 2010). Also, increased temperature could alter the dynamics and intensity of crop damage by pests and diseases, such as insects and plant pathogens (Cannon, 1998; Scherm, 2004). Meanwhile, a higher atmospheric concentration of carbon dioxide could improve photosynthesis, enhance biomass accumulation and increase production (Schmidhuber and Tubiello, 2007). The overall effect of climate change on crop yield is positive in some agricultural regions and negative in others (Parry et al., 2004). Lobell et al. (2011) revealed that in the past 30 years the net impact of the climate trend on rice output was insignificant because the gains in some countries were cancelled out by losses in others. Therefore, it is necessary to assess crop yield responses to future climate quantitatively on the regional scale and, where necessary, use developments in science and technology to mitigate the adverse impacts.

Northeastern China (NEC), one of the country's most productive agricultural regions, is comprised of Heilongjiang, Jilin and Liaoning provinces and includes a total area of $1.82 \times 10^5$ km$^2$ of farmland (Chen et al., 2012). Spring maize, single-crop rice, soybean and some other cash crops are popular in this region. Against the background of global warming, the climate in NEC is changing dramatically, and thus large fluctuations in crop yield are common (Cheng and Zhang, 2005; Zhao et al., 2009). Hence, the projection of future yield responses for this region is crucial for policymakers in taking strategic decisions to guarantee food security and stabilize the provisions market.

Several methods exist for evaluating the impact of climate change on crops across regions. The first is to apply process-

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based crop models that emphasize physiological processes of crop growth but do not consider losses caused by pests and diseases (Lobell et al., 2007a). A substantial amount of data is needed to calibrate the parameters for specific locations, which limits the application of such dynamic models (Lobell et al., 2008). The second option, which we employ in the present study, is to develop statistical models based on historical yield data and climate variables. Statistical models assume that the past relationship will hold in the future, regardless of whether or not field management practices change. Such models can synthesize comprehensively the effects of processes involved in the growing season and are widely used. Peng et al. (2004) used a statistical method to show a 10% decline in rice yield in the Philippines with a 1°C increase in the growing-season minimum temperature. Schlenker and Roberts (2006) developed a nonlinear model to simulate the relationship between temperature and yield in the eastern United States. Moreover, statistical models can successfully capture the crop response to climate change at broader spatial scales (Lobell and Burke, 2010). Furthermore, quantitative uncertainties can be more readily evaluated by applying statistical models, as compared to process-based models, for which it is necessary to consider enormous parametric uncertainties (Iizumi et al., 2009) and then widen the uncertainty estimates substantially (Lobell and Burke, 2010).

When assessing the uncertainties of climate change impacts on crops, the uncertainties in both the future climate and in the crop model itself should be considered (Lobell et al., 2006). Recently, the latest generation of coupled climate models included in the Coupled Model Intercomparison Project Phase 5 (CMIP5) has been released and can be used to project the future climate. Previous studies have indicated that the contribution of the $CO_2$ effect to the overall uncertainty of yield change is smaller than that of climate and the crop model (Tebaldi and Lobell, 2008), especially for C4 crops (e.g. maize) (Rosenzweig et al., 2014). As a consequence, in this study we only use one of the Representative Concentration Pathway (RCP) scenarios—RCP4.5, which refers to a radiative forcing stabilized at 4.5 W $m^{-2}$ (~650 ppm) by the year 2100 (Zhang, 2012)—for the future climate projections, thus excluding in our assessment the potential effect of the uncertainties in the emissions scenarios. A couple of points are important to note here: first, the temperature changes at small regional scales are predictable from the outputs of global climate models (Joshi et al., 2011; Deser et al., 2012). Terray and Boé (2013) quantified the future climate change and related uncertainties in France for the 21st century by applying the coupled models within the framework of CMIP5. Second, the projected changes of meteorological variables from global climate models have been widely used to assess the impact of climate change on crop yield at the regional scale; for instance, in Germany (Lobell, 2007) and Tanzania (Rowhani et al., 2011).

The structure of this paper is as follows: First, the data and method used are described. Then, we present the results. The climate models are briefly assessed before their results are inserted into to the statistical equations to project the potential impact of future climate change on crop yield in NEC under the RCP4.5 scenario. Next, the quantitative uncertainties caused by the evaluated climate change and statistical crop models are analyzed. And finally, we provide a summary and conclusion to the study, including some perspective in terms of the value of our findings for policymakers.

## 2. Data and method

The annual province-level data of crop area and production were obtained from China Agricultural yearbooks. Yields were computed by dividing production by crop area and were selected as the response variables. Weather data from ground observation stations including daily average temperature ($T_{avg}$), minimum temperature ($T_{min}$), maximum temperature ($T_{max}$) and precipitation ($P$) were obtained from the China Meteorological Administration (CMA). Diurnal temperature range (DTR) refers to the difference between daily maximum and minimum temperatures. Average $T_{avg}$, $T_{min}$, $T_{max}$ and DTR, as well as total $P$ for summer (June–July–August), were computed for each selected weather station located in NEC. Then, the seasonal fields of variables on $1.0^\circ \times 1.0^\circ$ grids were derived by Cressman interpolations. Regional-level time series of meteorological factors in summer were obtained by computing weighted averages of grid data; that is to say, the variations of the grid area with latitude were considered.

The 30 climate models participating in CMIP5 were used in this study, the details of which are shown in Table 1 (Taylor et al., 2012). For convenience, all of the model outputs were re-gridded to a common resolution of $1.0^\circ \times 1.0^\circ$ using bilinear interpolation. Since the majority of historical runs ended in 2005, the period spanning from 1976 to 2005 in historical simulations, hereafter known as the baseline period, was selected to compare with the corresponding observations to assess the model reproducibility. The future climate under the RCP4.5 scenario was analyzed with three target periods of 2010–39 (period 1), 2040–69 (period 2), and 2070–99 (period 3). The multi-model ensemble (MME) result is the equally weighted mean of the CMIP5 model outputs used.

To minimize the influence of long-term changing factors on the yield, such as the development of science and technology, we used the year-to-year increment approach (Fan et al., 2007), which is an effective detrending method proposed for studies of climate variability, such as the annual number of tropical cyclones making landfall over China (Fan, 2009), the wintertime heavy snow activity in Northeast China (Fan and Tian, 2013), and so on. The year-to-year increment for a variable refers to the absolute difference between the value in the current year and that in the preceding year. We established linear equations on the basis of the year-to-year increment of crop yield and climate and assumed that the statistical relationship would still be applicable in the future. All variables in the year-to-year increment form are expressed as $\Delta$ (e.g. $\Delta$ yield). To further evaluate the performance of the prediction

**Table 1.** Summary of the climate models from CMIP5 used in this paper.

| No. | Model | Country | Resolution (Grids, lon $\times$ lat) |
|---|---|---|---|
| 1 | ACCESS1-0 | Australia | $192\times145$ |
| 2 | BCC-CSM1-1 | China | $128\times64$ |
| 3 | BCC-CSM1-1-M | China | $320\times160$ |
| 4 | BNU-ESM | China | $128\times64$ |
| 5 | CanESM2 | Canada | $128\times64$ |
| 6 | CCSM4 | USA | $288\times192$ |
| 7 | CESM1-BGC | USA | $288\times192$ |
| 8 | CESM1-CAM5 | USA | $288\times192$ |
| 9 | CMCC-CMS | Italy | $192\times96$ |
| 10 | CNRM-CM5 | France | $256\times128$ |
| 11 | CSIRO-MK3-6-0 | Australia | $192\times96$ |
| 12 | FGOALS-g2 | China | $128\times60$ |
| 13 | FIO-ESM | China | $128\times64$ |
| 14 | GFDL-CM3 | USA | $144\times90$ |
| 15 | GFDL-ESM2G | USA | $144\times90$ |
| 16 | GFDL-ESM2M | USA | $144\times90$ |
| 17 | HadGEM2-AO | South Korea | $192\times145$ |
| 18 | HadGEM2-CC | UK | $192\times145$ |
| 19 | HadGEM2-ES | UK | $192\times145$ |
| 20 | INM-CM4 | Russia | $180\times120$ |
| 21 | IPSL-CM5A-LR | France | $96\times96$ |
| 22 | IPSL-CM5A-MR | France | $144\times143$ |
| 23 | IPSL-CM5B-LR | France | $96\times96$ |
| 24 | MIROC5 | Japan | $256\times128$ |
| 25 | MIROC-ESM | Japan | $128\times64$ |
| 26 | MIROC-ESM-CHEM | Japan | $128\times64$ |
| 27 | MPI-ESM-LR | Germany | $192\times96$ |
| 28 | MPI-ESM-MR | Germany | $192\times96$ |
| 29 | MRI-CGCM3 | Japan | $320\times160$ |
| 30 | NorESM1-M | Norway | $144\times96$ |

models, the cross-validation test was applied (Fan and Wang, 2010), conducted as follows: We removed the data in the $i$th year ($1 \leqslant i \leqslant 30$) from the training set (1976–2005), generated a new set of regression coefficients based on the retained years, and then predicted the yield in the $t$th year using the new model. The process was repeated 30 times.

To analyze the uncertainties in the parameter estimations of the crop models, the Markov Chain Monte Carlo (MCMC) method was used. The MCMC technique is a generally effective method for fitting statistical models in recent decades (Browne and Rasbash, 2009). The basis of the MCMC method is to sample from probability distributions based on constructing a Markov Chain that can converge to its equilibrium distribution after several iterations (Andrieu et al., 2003; Robert and Casella, 2004).

## 3. Results

### 3.1. *Crop models*

The climate plays a key role in agriculture. In NEC, the growing seasons of spring maize and single-crop rice extend from May to September (Zhang and Huang, 2012). However, here we only focus on the climate change in summer (June–July–August) when maize experiences its jointing stage, and rice its tillering stage, ahead of the grain filling stage. We explore the individual impact on yield of each local meteorological variable using Pearson correlation analysis. The most prominent meteorological variable that explains the highest proportion of maize (rice) yield variance is the summer DTR (summer $T_{\rm min}$), with correlation coefficients of $-0.5147$ (0.4641) (Fig. 1). The DTR can explain approximately 26% of the variance of the increment of maize yield changes, while the $T_{\rm min}$ can explain 22% of the variance of the increment of rice yield changes. Note that choosing DTR as the predictor for the crop model is meaningful (Chaudhari et al., 2009; Tatsumi and Yamashiki, 2012) since crops respond differently to increased temperature during the day and during night. Here, for a given $T_{\rm avg}$, increased DTR could lead to a reduction in maize production, probably because the associated increase in $T_{\rm max}$ could increase water stress and result in depressed rates of photosynthesis. Also, the increase of DTR could decrease the grain filling rate and subsequently result in crop failure (Lobell and Ortiz-Monasterio, 2007). To eliminate as much as possible the effect of multicolinearity between the various predictors, a simple linear regression model was used. We repeated the analysis using a higher-order equation by adding the quadratic component of the predictors, but there was no significant effect on the result. The final statistical models for maize and rice are:

$$\Delta Y_{\rm m} = -0.0465 \times \Delta D + 0.0067\,, \tag{1}$$

$$\Delta Y_{\rm r} = 0.0339 \times \Delta T_{\rm min} + 0.0051\,, \tag{2}$$

where $\Delta Y_{\rm m}$ and $\Delta Y_{\rm r}$ refer to the increment of maize and rice yield, respectively; $\Delta D$ is the summer DTR.

The correlation coefficient is 0.41 (0.31) between the predicted year-to-year variations derived from the cross-validation test and the historical year-to-year variations for maize (rice), significant at the 95% (90%) level. Hence, DTR and $T_{\rm min}$ could be valid predictors for grain production in NEC.

### 3.2. *Climate models*

Before projecting the future climate change, we first assessed the model reproducibility of CMIP5. The Taylor diagram is an efficient tool for quantitatively evaluating how well climate models match with observations (Taylor, 2001). The radial distances from the origin to the points are the ratios of the standard deviations between models and observations. The azimuthal angle represents the spatial correlation between the two fields. The distance between the point and the reference point indicates the centered root-mean-square error (RMSE); that is, the closer a model is to the reference point, the better its performance (Gleckler et al., 2008; Jiang and Tian, 2013). The summer minimum temperature and diurnal temperature change in NEC during the baseline period were considered. As is shown in Fig. 2, the minimum temperature can be effectively simulated by the models, with most of the spatial correlation coefficients significant at the 99%

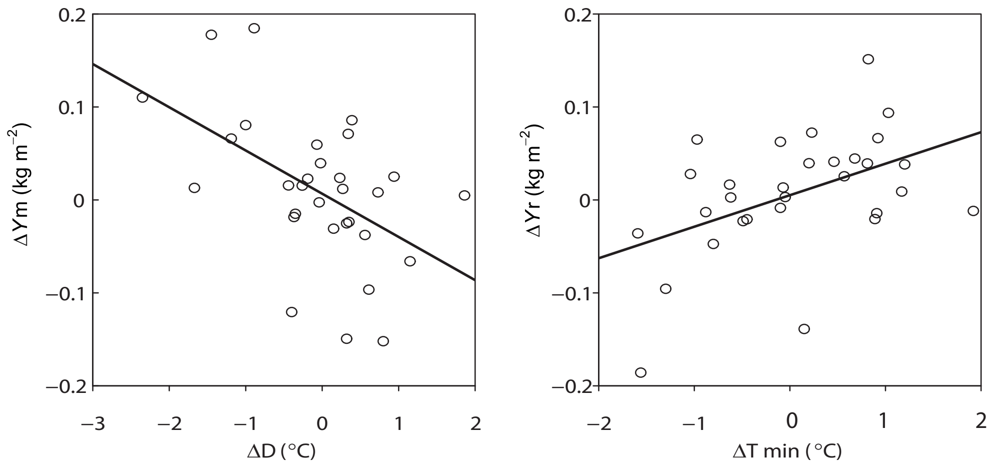


**Fig. 1.** Relationship between the increment of maize yield and summer diurnal temperature change (left panel) and between the increment of rice yield and summer minimum temperature (right panel) in the baseline period (1976–2005). The lines are best-fit regression lines.

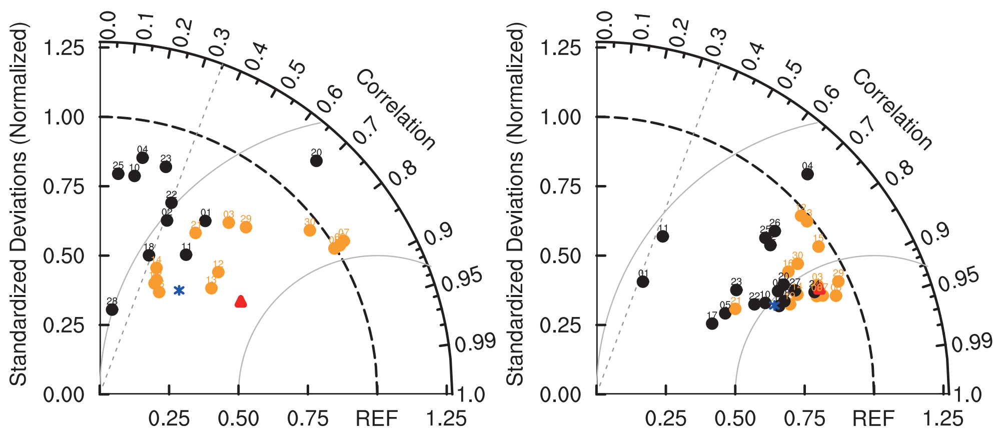


**Fig. 2.** Taylor diagram describing normalized pattern statistics of the summer diurnal temperature change (left panel) and minimum temperature (right panel) over Northeast China. Observation is considered as the reference (REF). The numbers on the *x*-axis and *y*-axis refer to the ratio of standard deviations between models and observations. The numbers in the arc are the corresponding correlation coefficients between models and observations. The numbered dots correspond to the models summarized in Table 1. The orange dots correspond to the 14 selected models in our analysis. The blue asterisk indicates the ensemble mean of all the models in Table 1, and the red triangle is the ensemble mean of the selected 14 models (yellow dots). The dashed line is the boundary where the spatial correlation coefficients are significant at the 99% confidence level.

level. In addition, the normalized centered RMSE for most models was less than 1.0. For the DTR, the performances of the models were relatively poor. Some models could not effectively simulate the spatial distribution of the DTR, and some showed high centered RMSEs. These results may have occurred because the DTR is calculated by the daily maximum and minimum temperatures, which could further increase the uncertainty and lead to a larger error. Therefore, it is necessary to select relatively reliable models from CMIP5 based on specific criteria. The first is that the correlation coefficient between the model output and observation is significant at the 99% level. The second is that the centered RMSE should be less than one standard deviation. In this manner, 14 of 30 models were selected to project future climate change. As Fig. 2 shows, the MME of these 14 models (red triangle) has better capability for simulating temperature in NEC.

Figure 3 illustrates the spatial pattern of the projected summertime temperature change in period 2 relative to the baseline period, represented by the MME of the 14 selected models. For minimum temperature (Fig. 3b), all regions covering NEC show significant increases with a magnitude of warming greater than 1.5°C. However, the variation of diurnal temperature (Fig. 3a) is not obvious between future and current climates. The region essentially exhibits a slight decreasing trend, which is consistent with previous research results (Dai et al., 2001; Lobell et al., 2007b). This is probably because, against the background of global warming, the expected change in $T_{\min}$ is larger than the associated change in

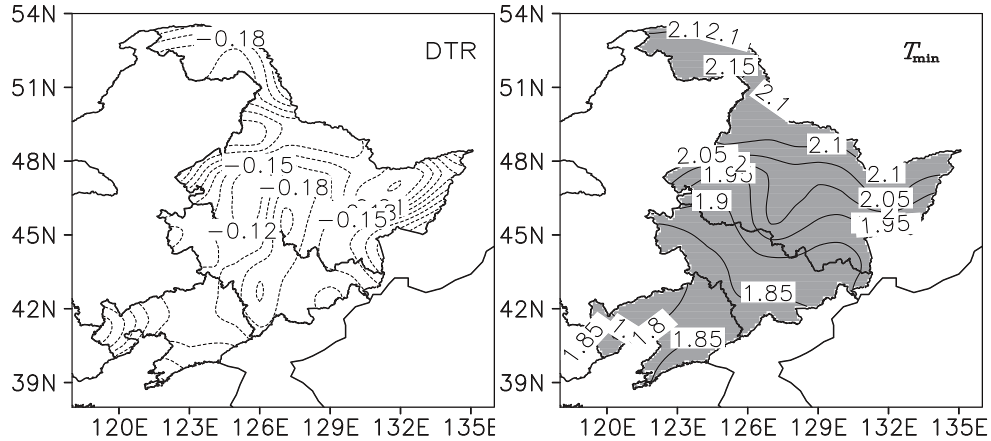


**Fig. 3.** Geographical distribution of projected change (multimodel ensemble mean) for summer diurnal temperature range (DTR (°C); left panel) and minimum temperature [$T_{min}$ (°C); right panel] in period 2 (2040–69) with respect to the baseline period (1976–2005). Shading indicates values statistically significant at the >99% confidence level.

$T_{max}$. The evaluated regional-averaged temperature changes of the MME mean in periods 1–3 with respect to the baseline period are summarized in Table 2. The greatest warming of minimum temperature occurs at the end of the 21st century due to the ever-increasing radiative forcing. The change of DTR is relatively stable because of the almost synchronized growth in minimum and maximum temperature over the next 100 years.

Uncertainties in the projected future climate arise from differences between individual models; for instance, some absent or misrepresented physical processes. Confidence intervals for projected climate change, estimated by resampling the model's results for 10 000 repetitions, are shown in parentheses in Table 2.

### 3.3. *Projected yield impacts*

We assessed the potential yield response to future climate change under the RCP4.5 scenario based on the historical relationships between crops and meteorological variables. To compare intuitively, yield change in various periods of the future is expressed as the percentage of mean production covering the reference period. The MME means of DTR and $T_{min}$ were calculated and inserted into the models expressed by Eqs. (1) and (2) respectively. The projection for maize yield increased by 2.92%, 3.11% and 2.63% in periods 1–3 respectively, which suggests a very small change over the next century. The potential rice changes, meanwhile, are larger, with the percentages relative to the historical yield of 7.19%, 12.39% and 14.83% respectively.

**Table 2.** Summary of the projected multimodel ensemble mean (shown in bold) of summer diurnal temperature change and minimum temperature for different periods in the 21st century relative to the baseline period (1976–2005). The values shown in parentheses indicate the 95% confidence interval of the projected climate change.

| | DTR (°C) | $T_{min}$ (°C) |
|---|---|---|
| 2010–39 | −**0.1572** (−1.0579, 0.2590) | **1.0648** (0.3224, 2.0997) |
| 2040–69 | −**0.1766** (−1.1638, 0.3170) | **1.9504** (0.8739, 3.7061) |
| 2070–99 | −**0.1264** (−1.3083, 0.4079) | **2.3643** (0.4700, 4.4919) |

Uncertainties in the climate change impacts on crops were calculated by considering the uncertainties in the climate and crop models. The climate change uncertainties were evaluated by utilizing the model outputs from CMIP5, as discussed previously in section 3.1. The MCMC method was used to explore the uncertainty of regression coefficients (Jackman, 2000; Iizumi et al., 2013). The main procedure was as follows: The projected area-averaged summer climate change was first randomly sampled from the CMIP5 database. Then, we resampled the regression coefficients randomly from their probability distributions determined by the MCMC method and created the new statistical crop models. The above two steps were iterated 10 000 times.

Figure 4a/b shows a box-and-whisker graph for maize/rice yield changes, based on the projected climate change only (left), on the resampled crop model's coefficients only (middle), and the combined effects of crop and climate (right). The 95% confidence interval of the projected impact derived from the aforementioned 10 000 iterations can also be identified. For brevity, only the result for period 2 is examined. The results for maize and rice are dramatically similar, notwithstanding a difference in the absolute value. First, the uncertainty is much larger in the positive direction, especially for rice. Second, the ranges of the uncertain interval caused by climate change and the crop model are almost equal. Third, the integration of climate change uncertainty and crop model uncertainty could magnify the total uncertainty. We further analyzed the probability distribution of projected maize and rice yield changes during periods 1–3, as presented in Fig. 5. From the histogram for period 2, we can see that the maximum probability of maize yield change compared to that of the historical period is located in the 0% to 10% group (Fig. 5a). However, the probabilities of yield

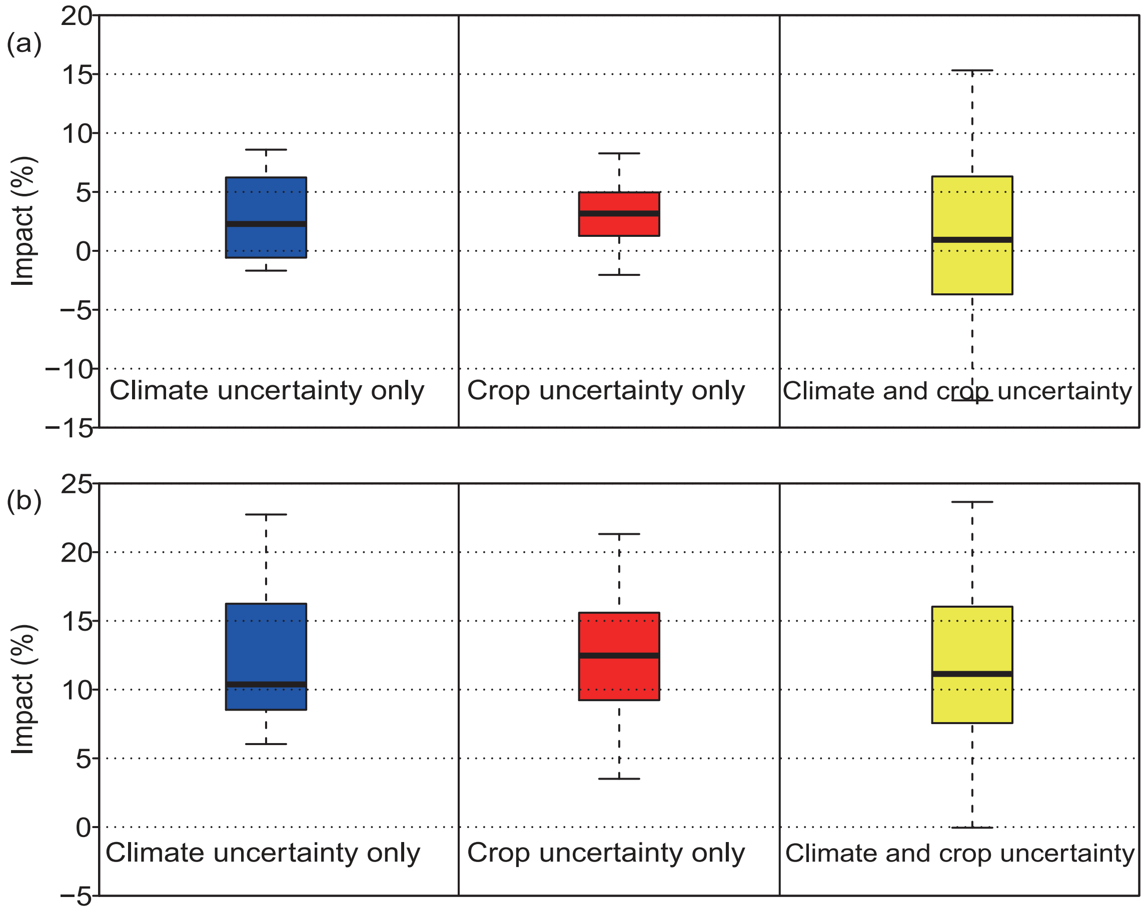


**Fig. 4.** Boxplots of evaluated climate impacts on (a) maize and (b) rice yield after accounting for either climate change only uncertainties (left panel), crop model only uncertainties, or uncertainties from both the climate and the crop model. The boxes extend from the 25th to 75th percentile of projection. The middle horizontal line within each box is the median value. The impacts are expressed as the percentage anomaly of yields in period 2 relative to the baseline (1976–2005) average yields.

change in the −10% to 0% and 0% to 10% groups are approximately the same. For rice yield, the change in the 10% to 20% group has the highest probability (by up to 45%) (Fig. 5b). Comparing the three kernel density estimate curves (Fig. 5a), we can see that the potential change for maize yield is relatively stable from period 1 to period 3. And yet, for rice, the mean of the probability distribution function shifts more to the positive side and the positive tail expands to a wider scope from period 1 to period 3 (Fig. 5b). The changes indicate a likelihood that rice yield will increase over time.

## 4. Conclusion

Climate change has a potential effect on agricultural production. In the present reported study, we projected the summer climate-induced variations in yield in NEC. We first constructed statistical crop models, in which all variables were detrended by adopting the year-to-year increment approach. Simple linear regression was used to eliminate the colinearity caused by the high correlations between predictors. Note that we did not consider the influences of crop cultivar use or other adaptive management changes. Also, $CO_2$ fertilization effects were ignored. The results showed that historical maize yields during the baseline period strongly correlated with summer diurnal temperature change, with a correlation coefficient of −0.5147. Furthermore, the rice model was designed on the basis of summer minimum temperature, which could explain 22% of the variance of the increment of historical changes. For rice as a thermophilic crop, the temperature increase properly in NEC could to a certain extent cut down the incidence of delayed-type and sterile-type cooling damage and ensure the required accumulated temperature for growth. Meanwhile, an increase in nighttime temperature could prompt the products of photosynthesis to translocate to grain more effectively (Zhou et al., 2013).

To project future climate change better under the RCP4.5 scenario, the models included in CMIP5 that showed good ability in simulating present-day climate were selected. The MME means of summer minimum temperature change in three future periods (periods 1–3; see section 2 for definitions) showed a distinct increase compared to the baseline

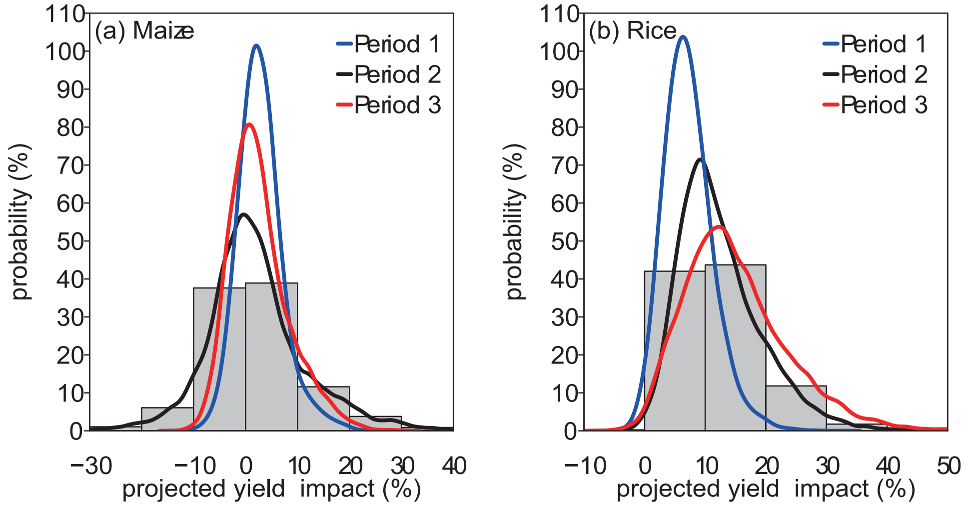


**Fig. 5.** Histograms showing the probability distribution of (a) maize and (b) rice yield changes in period 2 (expressed as the percentage of average yields during the baseline period, 1976–2005). That is, the numbers on the *y*-axis refer to the possibility of the yield change in the particular group, and the numbers on the *x*-axis are the specified groups of percentage change. The different color lines are the curves of kernel density estimation of the three future periods (i.e. period 1, 2010–39, blue; period 2, 2040–69, black; period 3, 2070–99, red).

time, which were all generally greater than 1°C. And yet, the decreasing trend could be seen in the summer diurnal temperature change, with an amplitude of less than 0.5°C. A possible reason why the variations of DTR were smaller than those of $T_{\rm min}$ over NEC is that the rate of warming between $T_{\rm max}$ and $T_{\rm min}$ becomes increasingly similar in the future, and when subtracted from each other the tendency of the differences will not be apparent.

The expected maize yields caused by future climate change increased by 2.92%, 3.11%, and 2.63% for periods 1–3, with 95% confidence intervals of (−3.50%, 24%), (−11.74%, 19.60%) and (−5.14%, 13.76%) respectively, in terms of the percentage of the historical mean yield when considering the uncertainties of both the climate and the crop models. The rice yield in NEC appeared to benefit more from warming, with percentages of 7.19%, 12.39%, and 14.83%, respectively. Moreover, the uncertainty intervals did not span zero [(1.37%, 14.29%) for period 1, (3.54%, 25.29%) for period 2, and (3.11%, 30.77%) for period 3], indicating that the likelihood of the increase is robust. The integrated total uncertainties of the climate change and crop model were magnified significantly, possibly due to the interaction between the two uncertainty sources. For instance, when estimating the effect of climate uncertainty, different types of crop models applied could lead to different results.

It is of great practical significance to project crop responses to climate change skillfully (Yao et al., 2007). Unfortunately, the exiting assessment system is not sufficient on account of the large uncertainties involved. In particular, the effects of $CO_2$ fertilization and the adaptive change of crops, which are not considered in this paper, will also contribute to the total level of uncertainty. However, our aim was to provide a rough indication of the impact of climate change on agricultural production in NEC. Providing definitive quantification of the potential yield change based on existing climate and crop models is beyond the scope of this paper. Nevertheless, the results are valuable for guiding adaptation efforts and providing reference information for policymakers.

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## REFERENCES

Andrieu, C., N. De Freitas, A. Doucet, and M. I. Jordan, 2003: An introduction to MCMC for machine learning. *Machine Learning*, **50**, 5–43.

Browne, W. J., and J. Rasbash, 2009: MCMC Estimation in MLwiN v2.1. Centre for Multilevel Modelling, University of Bristol.

Cannon, R. J. C., 1998: The implications of predicted climate change for insect pests in the UK, with emphasis on non-indigenous species. *Global Change Biology*, **4**, 785–796.

Chaudhari, K. N., M. P. Oza, and S. S. Ray, 2009: Impact of climate change on yields of major food crops in India. *Proceedings of ISPRS Archives XXXVIII-8/W3 Workshop Proceedings: Impact of Climate Change on Agriculture*, 100–105.

Chen, C. Q., C. R. Qian, A. X. Deng, and W. J. Zhang, 2012: Progressive and active adaptations of cropping system to climate change in Northeast China. *European Journal of Agronomy*, **38**, 94–103.

Cheng, Y. Q., and P. Y. Zhang, 2005: Regional patterns changes of Chinese grain production and response of commodity grain base in Northeast China. *Scientia Geographica Sinica*, **25**, 513–520.

Dai, A., T. Wigley, B. Boville, J. Kiehl, and L. Buja, 2001: Climates of the twentieth and twenty-first centuries simulated by the NCAR climate system model. *J. Climate*, **14**, 485–519.

Deser, C., R. Knutti, S. Solomon, and A. S. Phillips, 2012: Communication of the role of natural variability in future North American climate. *Nature Climate Change*, **2**, 775–779.

Ding, Y. H., and X. S. Dai, 1994: Temperature variation in China during the last 100 years. *Meteorological Monthly*, **20**(12), 19–26. (in Chinese)

Fan, K., 2009: Seasonal forecast model for the number of tropical cyclones to make landfall in China. *Atmos. Oceanic Sci. Lett.*, **2**, 251–254.

Fan, K., and H. J. Wang, 2010: Seasonal prediction of summer temperature over Northeast China using a year-to-year incremental approach. *Acta Meteorologica Sinica*, **24**, 269–275.

Fan, K., and B. Tian, 2013: Prediction of wintertime heavy snow activity in Northeast China. *Chinese Science Bulletin*, **58**, 1420–1426.

Fan, K., H. J. Wang, and Y. J. Choi, 2007: A physically-based statistical forecast model for the middle-lower reaches of the Yangtze River valley summer rainfall. *Chinese Science Bulletin*, **52**, 2900–2905.

Gleckler, P. J., K. E. Taylor, and C. Doutriaux, 2008: Performance metrics for climate models. *J. Geophys. Res.*, **113**, D06104, doi: 10.1029/2007JD008972.

Iizumi, T., M. Yokozawa, and M. Nishimori, 2009: Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: Application of a Bayesian approach. *Agricultural and Forest Meteorology*, **149**, 333–348.

Iizumi, T., and Coauthors, 2013: Prediction of seasonal climate-induced variations in global food production. *Nature Climate Change*, **3**, 904–908.

Inouye, D. W., 2008: Effects of climate change on phenology, frost damage, and floral abundance of montane wildflowers. *Ecology*, **89**, 353–362.

Jackman, S., 2000: Estimation and inference via Bayesian simulation: An introduction to Markov chain Monte Carlo. *American Journal of Political Science*, **44**, 375–404.

Jiang, D. B., and Z. P. Tian, 2013: East Asian monsoon change for the 21st century: Results of CMIP3 and CMIP5 models. *Chinese Science Bulletin*, **58**, 1427–1435.

Joshi, M., E. Hawkins, R. Sutton, J. Lowe, and D. Frame, 2011: Projections of when temperature change will exceed 2°C above pre-industrial levels. *Nature Climate Change*, **1**, 407–412.

Lobell, D. B., 2007: Changes in diurnal temperature range and national cereal yields. *Agricultural and Forest Meteorology*, **145**, 229–238.

Lobell, D. B., and J. I. Ortiz-Monasterio, 2007: Impacts of day versus night temperatures on spring wheat yields. *Agronomy Journal*, **99**, 469–477.

Lobell, D. B., and M. B. Burke, 2010: On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology*, **150**, 1443–1452.

Lobell, D. B., C. B. Field, K. N. Cahill, and C. Bonfils, 2006: Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agricultural and Forest Meteorology*, **141**, 208–218.

Lobell, D. B., K. N. Cahill, and C. B. Field, 2007a: Historical effects of temperature and precipitation on California crop yields. *Climatic Change*, **81**, 187–203.

Lobell, D. B., C. Bonfils, and P. B. Duffy, 2007b: Climate change uncertainty for daily minimum and maximum temperatures: A model inter-comparison. *Geophys. Res. Lett.*, **34**, doi: 10.1029/2006GL028726.

Lobell, D. B., M. B. Burke, C. Tebaldi, M. D. Mastrandrea, W. P. Falcon, and R. L. Naylor, 2008: Prioritizing climate change adaptation needs for food security in 2030. *Science*, **319**, 607–610.

Lobell, D. B., W. Schlenker, and J. Costa-Roberts, 2011: Climate trends and global crop production since 1980. *Science*, **333**, 616–620.

Menzel, A., and Coauthors, 2006: European phenological response to climate change matches the warming pattern. *Global Change Biology*, **12**, 1969–1976.

Parry, M. L., C. Rosenzweig, A. Iglesias, M. Livermore, and G. Fischer, 2004: Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global Environmental Change*, **14**, 53–67.

Peng, S., and Coauthors, 2004: Rice yields decline with higher night temperature from global warming. *Proceedings of the National Academy of Sciences of the United States of America*, **101**, 9971–9975.

Robert, C. P., and G. Casella, 2004: *Monte Carlo Statistical Methods.* Springer.

Rosenzweig, C., and Coauthors, 2014: Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, **111**, 3268–3273.

Rowhani, P., D. B. Lobell, M. Linderman, and N. Ramankutty, 2011: Climate variability and crop production in Tanzania. *Agricultural and Forest Meteorology*, **151**, 449–460.

Scherm, H., 2004: Climate change: Can we predict the impacts on plant pathology and pest management? *Canadian Journal of Plant Pathology*, **26**, 267–273.

Schlenker, W., and M. J. Roberts, 2006: Nonlinear effects of weather on corn yields. *Review of Agricultural Economics*, **28**, 391–398.

Schmidhuber, J., and F. N. Tubiello, 2007: Global food security under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, **104**, 19703–19708.

Tatsumi, K., and Y. Yamashiki, 2012: Sensitivity analyses of crop yields and changes in climate variables simulated with iGAEZ. *Hydrological Processes*, **26**, 2482–2500.

Taylor, K. E., 2001: Summarizing multiple aspects of model performance in a single diagram. *J. Geophys. Res.: Atmos.*, **106**, 7183–7192.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498.

Tebaldi, C., and D. Lobell, 2008: Towards probabilistic projections of climate change impacts on global crop yields. *Geophys. Res. Lett.*, **35**, doi: 10.1029/2008GL033423.

Terray, L., and J. Boé, 2013: Quantifying 21st-century France climate change and related uncertainties. *Comptes Rendus Geoscience*, **345**, 136–149.

Yang, X. G., Z. J. Liu, and F. Chen, 2010: The Possible effects of global warming on cropping systems in China I. The possible effects of climate warming on northern limits of cropping systems and crop yields in China. *Scientia Agricultura Sinica*, **43**, 329–336.

Yao, F., Y. Xu, E. Lin, M. Yokozawa, and J. Zhang, 2007: Assessing the impacts of climate change on rice yields in the main rice areas of China. *Climatic Change*, **80**, 395–409.

Zhang, T., and Y. Huang, 2012: Impacts of climate change and inter-annual variability on cereal crops in China from 1980 to 2008. *Journal of the Science of Food and Agriculture*, **92**, 1643–1652.

Zhang, Y., 2012: Projections of 2.0 C warming over the globe and China under RCP4.5. *Atmospheric and Oceanic Science Letters*, **5**, 514–520.

Zhao, J. F., X. G. Yang, and Z. J. Liu, 2009: Influence of climate warming on serious low temperature and cold damage and cultivation pattern of spring maize in Northeast China. *Acta Ecologica Sinica*, **12**, 6544–6551.

Zhou, M., H. Wang, S. Yang, and K. Fan, 2013: Influence of springtime North Atlantic Oscillation on crops yields in Northeast China. *Climate Dyn.*, **41**, 3317–3324.