How ENSO affects maize yields in China: understanding the impact mechanisms using a process-based crop model

Jiabing Shuai,^{a,b} Zhao Zhang,^a Fulu Tao^{c*} and Peijun Shi^{a*}

^a State Key Laboratory of Earth Surface Processes and Resource Ecology/Academy of Disaster Reduction and Emergency Management, Beijing Normal University, China

^b Agricultural Reinsurance Department, China Property and Casualty Reinsurance Company Ltd, Beijing, China

^c Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

ABSTRACT: The El Niño Southern Oscillation (ENSO) is one of the main factors influencing global climate variability and consequently has a major effect on crop yield variability. However, most studies have been based on statistical approaches, which make it difficult to discover the underlying impact mechanisms. Here, using process-based crop model Model to Capture the Crop-Weather relationship over a Large Area (MCWLA)-Maize, we found a consistent spatial pattern of maize yield variability in association with ENSO between MCWLA-Maize model outputs and observations. During El Niño years, most areas of China, especially in the north, experience a yield increase, whereas some areas in the south have a decrease in yields. During La Niña years, there is an obvious decline in yields, mainly in the north and northeast, and a general increase in the south. In-depth analyses suggest that precipitation P rather than temperature T and solar radiation S during the maize growing season is the main cause of ENSO-induced maize yield variability in northern and northeastern China. Although a 2 °C change of T can affect maize yields more than a 20% change of P , greater changes of P contribute more to maize yield variability during ENSO years. In general, maize yields in drier regions are much more sensitive to P variability than those in wetter areas. All changes in meteorological variables, including T , P , S , and vapour pressure deficit (V_{pd}) during ENSO years, affect yield variability mainly through their effects on water stress. Our results suggest that more effective agricultural information can be provided to government decision makers and farmers by developing a food security warning system based on the MCWLA-Maize model and ENSO forecast information.

KEY WORDS ENSO; maize yields; water stress; China; climate variability; crop model

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1. Introduction

Maize is one of the main essential cereals in China, comprising 33.5 million hectare of sown area and 193 million metric tons of production in 2011 (National Bureau of Statistics of China, 2013). China accounts for 21.7% of global maize production and was the second largest producing country behind the United States in 2011 (Food and Agriculture Organization, FAO: <http://faostat.fao.org/site/567/default.aspx#ancor>). However, maize yields are subject to large interannual variability caused by climate variation (Tao *et al.*, 2004). This variability directly affects crop growth, development, and yields, and also indirectly influences pest dynamics and fertilizer efficiency (Thompson, 1986; Lima *et al.*, 1999; Almaraz *et al.*, 2008; Chen *et al.*, 2011).

The El Niño Southern Oscillation (ENSO), which refers to fluctuations of both sea surface temperature (SST) in

the tropical Pacific and sea level pressure in the southern Pacific (Southern Oscillation Index, SOI), is well-known as one of the strongest drivers of global interannual climate variability (Diaz and Markgraf, 2000). The entire atmospheric circulation responds dramatically to the more slowly varying SST in the tropical Pacific. The warm pools of seawater, low-level westerlies, attendant tropical convection, and low-pressure centre shift from the western Pacific to the central or eastern Pacific at the height of El Niño events (Chu, 2004; Sun and Frank, 2010). Consequently, climate in many regions all over the world, especially in the Pacific Rim, is influenced to varying degrees (Kenyon and Hegerl, 2008; Alexander *et al.*, 2009). The climate of China, one of the countries in the Pacific Rim, is also strongly affected by ENSO (Chang *et al.*, 2000a, 2000b; Wang *et al.*, 2000; Wang and Zhang, 2002; Wu *et al.*, 2003; Feng and Li, 2011). Generally, there will be greater than average precipitation in most regions of China during summers in the decaying stage of El Niño years and less than average in years following La Niña years (Huang and Wu, 1989). In some extreme events, ENSO-related changes to climate have caused major meteorological disasters (Dilley and Heyman, 1995). For instance, during 1997/1998,

* Correspondence to: F. Tao, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China. E-mail: tao@igsnrr.ac.cn; or P. Shi, State Key Laboratory of Earth Surface Processes and Resource Ecology/Academy of Disaster Reduction and Emergency Management, Beijing Normal University, Beijing 100875, China. E-mail: spj@bnu.edu.cn

the strongest El Niño event in the 20th century, China suffered massive flooding of 25 million hectares of farmland, which caused over 20 billion USD in estimated damages (Sun and Zhou, 2008). In the 2010/2011 La Niña year, China experienced two consecutive seasonal droughts (winter and spring) that, according to the Ministry of Land and Resources of China, affected 20% of farmland and 35% of all wheat crops in eight provinces, including Henan, Shandong, and Hebei (See XINHUA news: <http://www.webcitation.org/5wVDplgm4>). All these facts emphasize the need for studies that can provide sound climate and crop production forecast information for crop management. With the development of climate models, ENSO prediction skill is maturing and ENSO information can be accurately predicted at least 1 year in advance (Cane, 2005; Ludescher *et al.*, 2013). Providing such information early enough to adjust critical agricultural decisions offers significant potential to enhance the efficiency of agricultural management and food and livelihood security.

Therefore, the relationship between ENSO climate variability and agricultural production has been a major concern (Hansen *et al.*, 1998; Hansen *et al.*, 1999; Podestá *et al.*, 1999; Tao *et al.*, 2004; Hansen *et al.*, 2006). As early as the 1980s, correlation between SST and crop production in the United States (Handler, 1984) and Austria (Nicholls, 1985) was identified, evidencing the potential for translating ENSO information into agricultural terms. When the predictability of ENSO was demonstrated in the late 1980s and early 1990s, much more attention was given to issues of ENSO and agriculture (Cane *et al.*, 1994; Phillips *et al.*, 1998; Phillips *et al.*, 1999). There have been many studies on this topic worldwide (e.g. Garcia *et al.*, 2010; Royce *et al.*, 2011; Paz *et al.*, 2012). In China, for example, Tao *et al.* (2004) investigated the statistical relationship of three staple crops in the country with ENSO phases and the Asian monsoon, using data from seven major provinces. They showed large annual crop yield variability to be associated with ENSO and the Asian monsoon. Based on Tao *et al.* (2004), Shuai *et al.* (2013) studied the spatial pattern of ENSO impacts on staple crop yields during ENSO decaying stages, suggesting that the mechanism of ENSO impact on crop yield varies with location and crop variety.

However, most studies have been based on statistical approaches (e.g. Hansen *et al.*, 1998, 1999; Tao *et al.*, 2004), which make it difficult to identify underlying mechanisms of ENSO-induced climate variability effects on crop yield. Although historical maize yields can be easily obtained, they are limited to certain locations or regions. Also, information on maize water use during growing season is not available and can only be estimated using historical weather data and empirical approaches. The lack of simultaneous availability of historical maize yield and water use data limits their use in studies related to climate variability such as ENSO. However, crop yield and water use as a function of crop management and environmental factors, such as weather and soil, can be simulated by different crop models. These models can be useful tools for

understanding mechanisms of spatial and temporal yield variability related to ENSO.

In several studies, crop models (e.g. Crop Environment Resource Synthesis model (CERES)) have been used to address the impact of ENSO on crop yield only at certain sites (e.g. Phillips *et al.*, 1998; Hansen *et al.*, 2006) because of the point-based nature of the models. Nonetheless, ENSO-induced climate variability and its impacts on crop yield generally occur at large scale. Crop models that account for key impact mechanisms of climate variability and are accurate over a large area should be used. In this study, we use a large-scale crop model, the Model to Capture the Crop–Weather relationship over a Large Area (MCWLA)-Maize. This model is applied to assess mechanisms of maize yield variability in association with ENSO in China and to suggest possible adaptation measurements to cope with climate variability in ENSO years. MCWLA-Maize has been used to investigate the impacts of climate variability on crop productivity in major maize production areas in China (Tao *et al.*, 2009a, 2009b) and other regions (Bassu *et al.*, 2014), as well as to quantify the contributions of various options for adapting to climate change (Tao and Zhang, 2010). Studies have shown that MCWLA-Maize has good performance in simulating the response of crop growth and yield to climate variability.

2. Materials and data

2.1. Study area

Maize is planted extensively and in a variety of climates in our study area, which is mainland China. This area extends from 18° to 53°N and 74° to 134°E. Maize cultivation areas were divided into six sub-regions: North China spring maize (R1), Huang-Huai-Hai Plain summer maize (R2), Southwest China maize (R3), South China maize (R4), Northwest China maize (R5), and Tibet maize (R6) (Tong, 1992). R1 in northeastern China and R2 in northern China are the two major maize production areas in the country (Figure 1). Spring maize dominates in R1 with approximate growing season from April through October, and summer maize in R2 with approximate growing season from May through October. R5 and R6 are not included in this study because maize cultivation fractions in the two regions are small. Most areas in R1 (main1) and R2 (main2) were selected as the two major areas (Figure 2) for in-depth analyses.

2.2. MCWLA-Maize crop model

Details of MCWLA-Maize model development, parameter optimization, and uncertainty analyses are found in Tao *et al.* (2009a, 2009b). Briefly, MCWLA-Maize simulates crop growth and development with a daily time-step. The model is designed to investigate the impacts of weather and climate variability on crop growth, development, and productivity at large scale. Growing degree days are drivers for the processes of canopy development, flowering, and maturity. Daily growth of crop leaf area is simulated by heat-dependent potential growth

Figure 1. The cultivation fraction (originally from Qiu *et al.*, 2003) and agroecological zones (Tong, 1992) for maize in China. There are totally six agroecological zones: North China spring maize area (R1), Huang-Huai-Hai plain summer maize area (R2), Southwest China maize area (R3), South China maize area (R4), Northwest China maize area (R5), and Tibet maize area (R6).

Figure 2. The two main areas (the main1 and main2 areas). As Figure 1, the cultivation fractions are originally from Qiu *et al.* (2003).

rate and stresses from water. MCWLA adopts a robust, process-based representation of coupled CO_2 and H_2O exchanges. Impacts on yield from factors other than weather (e.g. pests, disease, and management) are modelled in a simplified way. Biomass is calculated cumulatively from the simulated daily photosyntheses values and converted to crop yield by a harvest index. In Tao *et al.* (2009a), crop yield hindcasts by MCWLA effectively captured interannual variability of crop yield in all four investigated provinces from 1985 to 2002. The impact of extreme temperature on a crop is measured

by inhibited and function-limiting photosynthesis at low and high temperatures. Water stress on yield is simulated through soil-moisture stress on daily leaf area index (LAI) development and transpiration, and subsequently on root development, photosynthesis, and canopy conductance (Tao *et al.*, 2009a).

2.3. Data

MCWLA-Maize requires at least four meteorological variables: daily mean temperature T , daily mean vapour pressure V_{pr} , daily mean solar radiation S , and daily total

precipitation P . Monthly data for T , V_{pr} , S , P and wet days (W_{et}) were obtained from the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn/>). Monthly means of temperature, vapour pressure, and solar radiation were interpolated to daily values using spline interpolation (Press *et al.*, 1992). Monthly precipitation was interpolated to daily values using a weather generator, with monthly total precipitation and wet days as inputs, after Gerten *et al.* (2004). Studies have shown that simulations using interpolated and observed daily data are nearly identical (Tao *et al.*, 2009a, 2009b). T , V_{pr} , P , and W_{et} were obtained from 755 weather stations all over China for the period 1963–2008. Because only 122 of these stations had S records, S was calculated from sunshine duration (Yang *et al.*, 2001; Yang *et al.*, 2006), which was available at all 755 stations. The MCWLA-Maize model was run on a $0.5^\circ \times 0.5^\circ$ grid with maize cultivation fraction (ratio between maize cultivation area and total area at a grid) ≥ 0.0 across the study area (Figure 1). There were a total of 1879 grids in China. As inputs to MCWLA-Maize, the 755-station meteorological data were all interpolated to the $0.5^\circ \times 0.5^\circ$ grid using a nearest-neighbour method. The sowing date for agrometeorological stations (constructed in 1991) during 1991–2008 was also obtained from the China Meteorological Data Sharing Service System, and average dates during this period were interpolated to the grid. Besides the weather data, soil texture and hydrologic property data were obtained from the FAO soil dataset (Zobler, 1986; FAO, 1991) and used as inputs to MCWLA-Maize.

Maize yield data of each province used for model evaluation in China were taken from China Planting Information, from the China Agricultural Statistical Yearbook and China Statistical Yearbook (<http://zzys.agri.gov.cn/nongqing.aspx>). Eighteen provinces have continuous maize yield records from 1961 to 2010. To remove technological influence on the yields, a 5-year running mean was used to obtain yield residuals (the difference between actual yield and running mean), which were used as observed yields in later analyses, following Zhang *et al.* (2008). For the simulated yields, the spatially weighted averages for each province were calculated. Weights were defined by the spatial distribution of maize area on a 0.5° grid (Qiu *et al.*, 2003), assuming that the yearly growing area ratio at each grid did not change throughout the period, as in Tao *et al.* (2008). Both observed and simulated yields were normalized to the mean technology level of 1990–2000.

For the definition of El Niño (La Niña) events, there are some alternative definitions in the literatures such as Cane *et al.* (1994), Phillips *et al.* (1998), Hsiang *et al.* (2011), and Tack and Ubilava (2013). The sea surface temperature anomaly (SSTA) in the eastern equatorial Pacific is always used as a criterion to distinguish warm/cold ENSO phases from a neutral phase (Royce *et al.*, 2011), such as Niño 1 + 2, Niño 3, Niño 3.4, and so on. Following Shuai *et al.* (2013), El Niño (La Niña) events were defined such that if SSTAs in the region 150° – 90° W and 4° N– 4° S were at least $+0.5^\circ\text{C}$ ($\leq -0.5^\circ\text{C}$ for La Niña)

Table 1. Selected model parameters and prior intervals (See Tao *et al.*, 2009a).

Parameters	Prior interval
Phenological parameters	
T_b ($^\circ\text{C}$)	5–15
T_0 ($^\circ\text{C}$)	20–31
T_m ($^\circ\text{C}$)	31–36
TDD ₀ (degree-days)	50–200
TDD ₁ (degree-days)	200–800
TDD ₂ (degree-days)	500–1000
TDD ₃ (degree-days)	700–1200
TDD ₄ (degree-days)	1200–1800
Light, water use, and yield formation parameters	
Y_{gp}	0.2–1.0
$\frac{\partial H_i}{\partial t}$	0.002–0.02
$R_{r:l}$	0.2–5.0
S_{cr}	0.2–0.8
S_{le}	0.2–0.8
α	0.033–0.073
T_{max} ($\text{mm m}^{-2} \text{ day}^{-1}$)	3.0–15.0
g_m	2.0–10.0
λ_l	0.2–0.6
R_{m25} ($\text{g C m}^{-2} \text{ day}^{-1}$)	0.2–0.9
m_t (g C m^{-2})	10.0–100.0
α_g	0.1–0.5
W_0 (g C m^{-2})	0.01–0.2

for at least six consecutive months and if this 6-month period began prior to or including October and included October–December, the year (October–September) was classified as El Niño (La Niña) (see the definition from the Center for Ocean-Atmospheric Prediction Studies: <http://coaps.fsu.edu/jma.shtml>). According to this classification, the study period from October 1962 through September 2008 included 12 El Niño (1963/1964, 1965/1966, 1969/1970, 1972/1973, 1976/1977, 1982/1983, 1986/1987, 1987/1988, 1991/1992, 1997/1998, 2002/2003, and 2006/2007) and 11 La Niña events (1964/1965, 1967/1968, 1970/1971, 1971/1972, 1973/1974, 1974/1975, 1975/1976, 1988/1989, 1998/1999, 1999/2000, and 2007/2008).

2.4. Calibration and validation of MCWLA-Maize model in each region

There are 21 parameters in MCWLA-Maize that are relatively important to crop phenology, water use, and yield (Tao *et al.*, 2009a). As in Tao *et al.* (2009a), approximate ranges of these parameters are specified in Table 1 according to prior knowledge of the parameters. Certain sets of coefficients may be representative of a group of varieties with similar characteristics in a particular geographic area. We assumed that one maturity group variety was sown and the same management practice was implemented across all of one maize cultivated sub-region. A province that was almost entirely included in a sub-region and had large maize cultivated areas was selected as a representative province for calibration. Latin hypercube sampling (Stein, 1987) was used to generate 5000 sets of the 21 parameters as initial parameter sets in each sub-region. The

gridded weather, soil, and provincial yield data from 1963 to 1985 were used for calibration. Validation for the representative province in each sub-region was done using data from 1986 to 2008. Performance of the MCWLA-Maize model was evaluated by the Pearson correlation coefficient r and root mean square error (RMSE) between the simulated and observed yield at provincial scale. Correlations were considered significant at $P < 0.10$. In each sub-region, the 10 best sets of parameters were selected, and then an ensemble-mean yield prediction (EnY) in each grid was obtained by averaging the output of model simulations using those 10 sets (TeY).

2.5. Analyses of mechanisms of ENSO-induced climate variability effects on maize yields

To understand mechanisms underlying the ENSO–yield relationship, we analysed spatial changes of variables related to crop growth and yields during the three ENSO phases. These variables include vapour pressure deficit V_{PD} , soil water stress factor S_{tress} , canopy conductance g_c , total precipitation P , daily mean solar radiation S , maximum temperature T_{max} , and minimum temperature T_{min} during the maize growth period. Uncertainties of these variables were estimated using the 10 best parameters for each sub-region. Because the uncertainties were very small (not shown here), only ensemble mean values of those variables are presented.

First, we examined the influences of ENSO on maize yields (both model outputs and observed yields) and variables related to maize growth (T_{max} , T_{min} , P , S , V_{PD} , g_c , and S_{tress}) during the growing season. Analysis of variance (ANOVA) was used to test the influence of ENSO phases on maize yield and other variables, and the significance ($P < 0.10$ or $P < 0.05$) of ENSO effects on those variables and maize yields was identified by an F -test.

To understand the impact mechanisms of ENSO-induced climate variability on maize yields, most parts of R1 (main1 area) and R2 (main2 area), both with large maize cultivation fractions, were selected as the two main areas for in-depth analyses (Figure 2).

In addition, three simulation experiments for neutral years in the main areas were conducted to investigate which meteorological variable contributes most to the reduction of maize yields during La Niña years. The three simulations experiments are (1) reduced T by 2°C on all days (with all other variables maintained at earlier levels); (2) reduced P by 20% on all days (affecting only days with precipitation), and (3) increased S by $4\text{ MJm}^{-2}\text{day}^{-1}$ ($\sim 20\%$ of average solar radiation in neutral years) on all days.

3. Results

3.1. Validation of MCWLA-Maize in major maize production provinces of China

Heilongjiang, Henan, Sichuan, and Guangxi were chosen as representative provinces for model parameter calibration and validation in R1, R2, R3, and R4, respectively,

because these provinces all have large maize cultivation areas. In these provinces, for both TeY and the EnY, r between modelled and observed yield series from 1963 to 2008 was significant, and RMSE values were less than 1400 kg ha^{-1} (Table 2). MCWLA-Maize simulated well the interannual variability of maize yields in all four provinces. The r between modelled and observed yield series for EnY was 0.449 ($P < 0.01$) in Heilongjiang Province, 0.376 ($P < 0.05$) in Henan Province, 0.535 ($P < 0.01$) in Sichuan Province, and 0.438 ($P < 0.01$) in Guangxi Province. RMSE was 571 kg ha^{-1} in Heilongjiang, 675 kg ha^{-1} in Henan, 256 kg ha^{-1} in Sichuan, and 388 kg ha^{-1} in Guangxi (Table 2).

In all the other 14 provinces, the performance of MCWLA-Maize was also relatively good. In 6 of the 14, correlations between modelled and observed yields from 1963 to 2008 were highly significant ($P < 0.01$). In 4 of the 14, correlations were significant ($P < 0.05$). RMSEs in 12 of the 14 provinces were less than 1000 kg ha^{-1} (Table 2).

Figure 3 shows the spatial distribution of r and RMSE between modelled and observed yields for EnY in each province. Generally, MCWLA-Maize performed well in nearly all provinces. r in North and Northeast China was higher than in South China, and RMSE in Southwest China was slightly lower than in other areas.

3.2. Spatial patterns of maize yield variability in association with ENSO based on model-simulated and observed yields

Spatial patterns of maize yield variability in association with ENSO using the crop model outputs and observed data are presented in Figure 4. Because EnY simulates well the variability in observed yields, only the pattern of ensemble mean yield variability is shown here. Although the spatial scale is different, the spatial pattern of maize yield variability in association with ENSO derived from the crop model is consistent with that based on observed yields. Results based on the crop model-simulated (Figure 4(a)) and observed yields (Figure 4(c)) both show that during El Niño years, most areas of China (especially the north) had a maize yield increase, whereas some regions in the south had a yield decrease. The results also show an obvious yield decrease mainly in northern and northeastern China and a general increase in the south during La Niña years (Figure 4(b) and (d)). The yield reduces at many northern grids during La Niña years at 90% and 95% confidence levels (Figure S1(b), Supporting Information).

Because the spatial scale of the crop model output yields is a $0.5^\circ \times 0.5^\circ$ grid, much smaller than the province scale of the observed yields, using the crop model outputs can capture the spatial variability of maize yield change at small scales, whereas the observed yields cannot. For example, the statistical results using observed yields only show that yields in Henan Province increased during El Niño years. In contrast, the MCWLA-Maize model results show that total yields increased in that province primarily because of the contribution of southern and northern

Table 2. The correlation and RMSE between simulated and observed yields at province scale during 1963–2008 for 10 top sets of parameters (The 11th row and the 22nd row are the correlation and RMSE of ensemble mean yields).

	Beijing	Hebei	Shanxi	Liaoning	Jilin	Heilongjiang	Jiangsu	Zhejiang	Anhui	Shandong	Henan	Hubei	Hunan	Guangxi	Sichuan	Guizhou	Yunnan	Shanxi
Correlation	0.167	0.363 ^{**}	0.271 [*]	0.417 ^{***}	0.367 ^{***}	0.398 ^{***}	0.078	0.322 ^{**}	0.300 ^{**}	0.451 ^{***}	0.374 ^{**}	0.337 ^{**}	0.155	0.399 ^{***}	0.482 ^{***}	-0.134	0.017	0.208
	0.143	0.355 ^{**}	0.385 ^{***}	0.525 ^{***}	0.414 ^{***}	0.449 ^{***}	0.093	0.208	0.306 ^{**}	0.441 ^{***}	0.381 ^{***}	0.269 [*]	0.282 [*]	0.378 ^{**}	0.406 ^{***}	0.155	0.150	0.419 ^{***}
	0.037	0.340 ^{**}	0.320 ^{**}	0.566 ^{***}	0.411 ^{***}	0.446 ^{***}	0.127	0.280 [*]	0.274 [*]	0.536 ^{***}	0.333 ^{***}	0.028	0.297 ^{**}	0.404 ^{***}	0.419 ^{***}	0.216	0.199	0.390 ^{***}
	0.047	0.451 ^{***}	0.306 ^{**}	0.550 ^{***}	0.374 ^{**}	0.435 ^{***}	0.155	0.291 [*]	0.284 [*]	0.495 ^{***}	0.332 ^{**}	0.227	0.283 [*]	0.417 ^{***}	0.412 ^{***}	0.152	0.156	0.307 ^{**}
	0.089	0.387 ^{**}	0.437 ^{***}	0.558 ^{***}	0.402 ^{***}	0.451 ^{***}	0.162	0.265 [*]	0.205	0.444 ^{***}	0.375 ^{***}	0.236	0.191	0.371 ^{**}	0.397 ^{***}	0.030	0.254 [*]	0.446 ^{***}
	-0.067	0.404 ^{***}	0.408 ^{***}	0.464 ^{***}	0.360 ^{**}	0.444 ^{***}	0.181	0.030	0.210	0.341 ^{**}	0.365 ^{**}	0.238	0.281 [*]	0.362 ^{**}	0.419 ^{***}	0.016	0.215	0.264 [*]
	0.155	0.462 ^{***}	0.430 ^{***}	0.516 ^{***}	0.375 ^{**}	0.451 ^{***}	0.175	0.237	0.297 ^{**}	0.503 ^{***}	0.319 ^{**}	0.220	0.309 ^{**}	0.377 ^{**}	0.432 ^{***}	0.334 ^{**}	0.268 [*]	0.512 ^{***}
	0.198	0.322 ^{**}	0.359 ^{**}	0.501 ^{***}	0.410 ^{***}	0.416 ^{***}	0.140	0.256 [*]	0.233	0.436 ^{***}	0.378 ^{**}	0.340 ^{**}	0.166	0.361 ^{**}	0.466 ^{***}	-0.090	0.159	0.287 ^{**}
	0.073	0.375 ^{**}	0.502 ^{***}	0.573 ^{***}	0.416 ^{***}	0.445 ^{***}	0.141	0.228	0.308 ^{**}	0.370 ^{**}	0.367 ^{**}	0.051	0.233	0.435 ^{***}	0.415 ^{***}	0.162	0.263 [*]	0.441 ^{***}
	0.143	0.377 ^{**}	0.336 ^{**}	0.540 ^{***}	0.415 ^{***}	0.429 ^{***}	0.193	0.269 [*]	0.337 ^{**}	0.472 ^{***}	0.336 ^{**}	0.222	0.246	0.359 ^{**}	0.437 ^{***}	0.236	0.186	0.394 ^{***}
	0.111	0.415 ^{***}	0.389 ^{***}	0.548 ^{***}	0.410 ^{***}	0.449 ^{***}	0.160	0.303 ^{**}	0.302 ^{**}	0.488 ^{***}	0.376 ^{**}	0.316 ^{**}	0.297 ^{**}	0.438 ^{***}	0.535 ^{***}	0.116	0.223	0.409 ^{***}
RMSE	701.236	748.610	638.582	935.957	875.319	655.186	2147.741	2581.664	626.014	976.437	560.445	1323.695	921.895	543.314	792.889	3006.478	2149.095	429.455
	718.063	1035.631	563.899	785.565	763.278	680.979	1467.674	1137.887	1074.669	666.428	892.113	1271.621	1212.134	706.574	641.007	668.291	1590.362	1244.987
	994.202	892.253	568.522	645.101	1011.753	592.702	1721.860	699.489	879.003	924.696	766.916	728.310	478.169	523.594	217.356	1600.033	2798.620	1365.619
	1193.443	1433.120	639.450	615.138	1265.583	611.584	1346.840	845.175	1316.115	603.226	1227.825	771.066	629.489	617.685	485.893	1121.198	692.077	640.528
	768.636	1111.916	599.781	743.587	838.447	637.897	1261.372	744.765	1166.321	719.646	844.292	667.969	614.916	356.177	224.011	1461.206	1391.405	1621.089
	675.651	840.747	519.489	685.022	808.364	722.926	1306.850	708.901	902.775	906.889	577.801	582.411	558.412	742.885	290.420	1403.447	1206.911	1405.442
	1076.078	537.642	781.156	587.431	1161.906	471.367	1877.335	599.073	667.340	1487.531	682.286	954.559	809.152	365.035	217.587	1100.688	2750.676	816.993
	595.725	754.643	583.655	681.306	1043.450	641.249	1827.242	1818.464	712.203	899.519	582.913	971.369	779.717	1341.632	752.043	2524.751	1882.712	526.824
	1067.666	1233.396	773.904	628.121	1010.182	636.310	1324.389	913.830	1123.471	619.847	773.051	1001.214	773.450	735.262	760.099	332.584	1438.871	1408.722
	1003.408	1057.667	756.924	1388.182	827.346	1015.804	1651.732	1293.389	873.348	878.510	788.198	889.732	757.517	793.718	274.915	1884.014	2952.672	1631.143
	694.023	916.331	555.095	689.866	887.534	571.307	1578.567	929.234	833.032	805.708	675.376	882.255	679.772	387.630	255.890	395.756	968.999	1074.472

*90% confidence level; **95% confidence level; ***99% confidence level.

Figure 3. The correlation (a) and the RMSE (b; unit: kg ha^{-1}) between simulated and observed maize yields at province scale during 1963–2008.

portions of the province, but yields declined in the western and eastern portions (Figure 4(a) and (c)). Also, the observed yields cannot be used for some provinces, such as Gansu, because there are no continuous yield records. The crop model, however, may be used to simulate yields using meteorological and environmental data.

3.3. Variability of climate and soil water conditions in association with ENSO

According to the results of MCWLA-Maize simulations, the warm phase of ENSO has a positive effect on the amount of P . As a result, all China, but especially its central and southeastern areas, average P in El Niño years is greater than that in neutral years (Figure 5(a)). On the contrary, northern China experienced a notably negative effect of La Niña events on P , but with some regions in the southwest, east, and northeast showing positive P changes (Figure 5(b)). The decreasing values at many grids in northern China were about 20% (15–25%) of average precipitation during one maize-growing season in neutral years (Figure 5(b)), reaching the 99% confidence level (Figure S2(b)). For S , the spatial distribution of changes affected by ENSO was opposite that for P (Figure 5(c) and (d)). This is because the greater the precipitation, generally the greater the cloudiness and therefore less radiation received at the earth surface. However, the changes of S were generally less than $0.5 \text{ MJm}^{-2}\text{day}^{-1}$. In comparison

with P and S , the impact of ENSO on temperature in China was small. Changes of temperature (both $T_{\max}$ and $T_{\min}$) related to ENSO in most regions were no more than $\pm 0.5^\circ\text{C}$, although there were weak spatial changes (Figure 5(e)–(h)). $T_{\max}$ decreased during El Niño years and increased in La Niña years on the North China Plain, but there was a decrease of $T_{\max}$ in central China in both warm and cold ENSO phases (Figure 5(e) and (f)). $T_{\min}$ increases were associated with El Niño events in southern China, whereas La Niña events produced reductions of $T_{\min}$ (Figure 5(g) and (h)).

V_{PD} is a very important variable that affects transpiration, water use, and consequently maize yields (Tao *et al.*, 2009a). V_{PD} is the difference between saturated V_{pr} and V_{pr} , and saturated V_{pr} is calculated from daily mean temperature T (FAO, 1992). Hot and dry days tend to have higher V_{PD} between the saturated leaf interior and ambient air; in contrast, cool and wet days are often related to lower V_{PD} . The increase of precipitation (Figure 5(a)) and reduction of solar radiation (Figure 5(c)) in most Chinese regions together led to lower V_{PD} during El Niño years (Figure 5(i)). In La Niña years, corresponding to climate changes (Figure 5(b) and (d)), most areas in the north and northeast and some grids in the south showed higher V_{PD} , reaching the 95 and 99% confidence levels, respectively (Figure 5(j) and Figure S2(j)). For g_c , spatial differences between warm and cold ENSO phases were most obvious in northern and northeastern China, with higher values during El Niño years than in neutral years, but lower values during La Niña years (Figure 5(k) and (l)). S_{tress} , defined as the ratio between transpiration and the potential transpiration (Tao *et al.*, 2009a), represents water stress in soil. The lower the S_{tress} , the higher the soil water stress. Figure 5(m) and (n) shows that there was a general increase of S_{tress} across China during El Niño years, whereas most areas had a reduction of S_{tress} during La Niña years. Their spatial changes suggest that high V_{PD} corresponds to low g_c and S_{tress} , and low V_{PD} on the contrary corresponds to high g_c and S_{tress} .

3.4. Mechanisms of ENSO-induced climate variability impacts on maize yields in two major production areas

3.4.1. Variability of climate and yield in association with ENSO

Average temperature, precipitation, and solar radiation during the maize-growing season in the main1 area were lower than those in main2 (Figure 6(a) and (b)). Because of differences of maize variety and climate between main1 and main2, average V_{PD} , g_c , S_{tress} , and yield were also different (Figure 6(a) and (b)). Average g_c , S_{tress} , and yield in main2 were all higher than those in main1, and only V_{PD} was slightly lower during neutral years.

Regarding the ENSO impacts, they were generally similar between main1 and main2 areas. $T_{\max}$ and $T_{\min}$ in both areas during El Niño and La Niña years, except $T_{\max}$ during La Niña years in main1, all showed a slight decrease compared with those during neutral years. In El Niño

Figure 4. Difference of yield residuals for maize between El Niño years and neutral years (a, c), and between La Niña years and Neutral years (b, d). The yields used for calculating yield residuals in (a) and (b) are the ensemble mean modelled yields simulated by MCWLA; the yields in (c) and (d) are the statistical yields from China Planting Information (<http://zzyz.agri.gov.cn/nongqing.aspx>). Unit: 100%.

years, P increased from 371 to 390 mm and 382 to 399 mm, i.e. 5.0 and 4.5% of average precipitation in the main1 and main2 areas during neutral years, respectively. Correspondingly, less V_{PD} and greater g_c and S_{tress} (and consequently higher yields) were observed. In La Niña years, P and the subsequent V_{PD} , g_c , S_{tress} , and yield all indicated an opposite change to those in El Niño years. However, P changes during ENSO years in the main1 area were greater than those in main2, especially for P in La Niña years. Also, S_{tress} and yield in main1 decreased much more than those in main2 during La Niña years. The changes of P and S_{tress} were consistent with yield changes in association with ENSO; however, the changes of V_{PD} and S were opposite to those of yield (Figure 6). Typically, the impacts of La Niña years on yields across the main1 and main2 area were stronger than that of El Niño years. The reduction of yields caused by La Niña years was $412.63 \text{ kg ha}^{-1}$ in main1 and $310.18 \text{ kg ha}^{-1}$ in main2 area, respectively.

3.4.2. Mechanisms underlying ENSO-induced variability of maize yields

To evaluate mechanisms underlying ENSO-induced variability of maize yields using MCWLA-Maize, several key

variables for maize growth and yield in the main areas are presented. The changes of P and S_{tress} were consistent with those of yield in association with ENSO. However, the changes of V_{PD} and S were opposite to those of yield (Figure 6), suggesting water stress as a key mechanism for ENSO-induced variability of maize yields. Figure 7 indicates that simulated P , T_{max} , T_{min} , and S all had certain relationships with V_{PD} in the maize growing season, suggesting that those four variables influence yields mainly by modulating V_{PD} and subsequent water stress. The slope of the $T-V_{PD}$ relationship is much steeper than those of $P-V_{PD}$ and $S-V_{PD}$. A reduction of T_{max} from 27°C to 25°C caused $\sim 0.3 \text{ kPa}$ decrease of V_{PD} in the main1 area, whereas a P increase of 200–300 mm or an S reduction from $18\text{--}16 \text{ MJ m}^{-2} \text{ day}^{-1}$ produced no more than 0.1 kPa decrease of V_{PD} . Either directly or through influencing g_c , V_{PD} would affect S_{tress} , thereby controlling maize yields (Figure 7(e)–(h)). In the MCWLA-Maize simulation, the relationship between V_{PD} and g_c is not a simple linear one in which extreme high and low V_{PD} can both lower g_c . Consequently, the relationship between V_{PD} and S_{tress} is also complicated. The relationship between S_{tress} and maize yield is generally a positive one, especially when

Figure 5. The difference of total precipitation (P) (a, b; unit: 100%), daily solar radiation (S) (c, d; unit: $\text{J m}^{-2} \text{ day}^{-1}$), daily maximum temperature ($T_{\max}$) (e, f; unit: $^{\circ}\text{C}$), daily minimum temperature ($T_{\min}$) (g, h; unit: $^{\circ}\text{C}$), vapour pressure (V_{PD}) (i, j; unit: kPa), canopy conductance (g_c) (k, l; unit: $\text{mm m}^{-2} \text{ day}^{-1}$), and soil water stress factor (S_{tress}) (m, n) during maize growing season between El Niño years and neutral years (left column) and between La Niña years and neutral years (right column). All these results are calculated from ensemble runs.

Figure 5. Continued.

S_{tress} is low. However, such a positive relationship becomes weak or even slightly negative when S_{tress} exceeds 0.8 (Figure 7(h)). Therefore, the mechanism of meteorological variable impacts on maize yield is complex. However, V_{PD} is a key factor linking climate and final maize yields. Extreme high or low V_{PD} may both limit yield.

According to the above analysis, the reduction of maize yield in La Niña years is the result of changes to V_{PD} and water stress, which are affected by temperature, precipitation, and solar radiation. However, which meteorological variable contributes most to the yield reduction remains unclear. To answer this question, three modelling experiments using MCWLA-Maize were performed. Surprisingly, yields were most sensitive to changes of T rather than P and S (Figure 8). With a 2°C T decrease, yields declined dramatically by $\sim 30\%$, especially in the

main1 area. V_{PD} dropped significantly in both main areas, with values less than 0.5. Consequently, g_c and S_{tress} in the maize-growing season both declined, with average reductions ~ 0.2 and $\sim 0.12 \text{ mm m}^{-2} \text{ day}^{-1}$, respectively, in the main1 area, and ~ 0.05 and $\sim 0.08 \text{ mm m}^{-2} \text{ day}^{-1}$ in main2. With P reduced by 20%, the response of V_{PD} was weak, and the decreases of g_c and S_{tress} had less impact than the 2°C decrease of T . Except for g_c in main2, S_{tress} in both areas, and g_c in main1, all had more significant responses to T than P . Thus, because of the strong responses of V_{PD} , g_c , and S_{tress} to T , P had relatively little control on maize yield.

The impact of ENSO on P was much more significant than that on T in northern and northeastern China. In the two main areas (Figure 2), the changes of T (both T_{max} and T_{min}) were no more than 0.25°C during ENSO

Figure 6. Bar plot of daily maximum temperature ($T_{\max}$), daily minimum temperature ($T_{\min}$), solar radiation (S), vapour pressure (V_{PD}), canopy conductance (g_c), soil water stress factor (S_{tress}), and total precipitation (P) during maize growing season, and yield in the main1 area (a) and main2 area (b) among different ENSO phases. The black lines on each bar show the standard deviation of the simulation.

years, whereas average P decreased ~ 41 mm (about 11%) in the main1 area and ~ 15 mm ($\sim 4\%$) in main2 during La Niña years. As a result, although maize yields were very sensitive to T changes, the strong P changes during ENSO years had greater impacts on yields in northern and northeastern China. As for the impacts of increased S , the variables V_{PD} , g_c , and S_{tress} all showed few changes relative to the original data, resulting in few yield changes in the simulation results of MCWLA-Maize. Thus, more attention should be paid to the variability of P during ENSO years.

It was also found that the effects of decreasing P on maize were much stronger in the main1 area than in main2. A 20% P reduction led to decreases of $\sim 8.5\%$ in g_c and $\sim 6.0\%$ in S_{tress} in main1, but only $\sim 4.0\%$ and $\sim 3.4\%$ corresponding reductions in main2. As a result, yields in

main1 were reduced by $\sim 11.8\%$, nearly twice that ($\sim 5.0\%$) in main2. This further indicates that P changes had greater effects in drier areas than those in wetter areas, such as main1 *versus* main2.

4. Discussion

4.1. Consistent patterns of variability in climate and soil water conditions in association with ENSO

Spatial patterns of variability in climate and soil water conditions in association with ENSO based on model simulations are consistent with previous studies on the effect of ENSO on precipitation in China (e.g. Huang and Wu, 1989; Zhu *et al.*, 2007). With SSTA rise in the eastern tropical Pacific, the subtropical high over East Asia is

Figure 7. Scatter plots between variables shown in Figure 6. In each figure, the blue crosses represent the main1 area while the red dots represent the main2 area. [(a) V_{PD} (unit: kPa) versus T_{max} (unit: $^{\circ}\text{C}$); (b) V_{PD} (unit: kPa) versus T_{min} (unit: $^{\circ}\text{C}$); (c) V_{PD} (unit: kPa) versus P (unit: mm); (d) V_{PD} (unit: kPa) versus S ($\text{J m}^{-2}\text{day}^{-1}$); (e) g_c (unit: $\text{mm m}^2\text{day}^{-1}$) versus V_{PD} (unit: kPa); (f) S_{tress} versus V_{PD} (unit: kPa); (g) S_{tress} versus g_c (unit: $\text{mm m}^2\text{day}^{-1}$); (h) yield (kg ha^{-1}) versus S_{tress}].

Figure 8. Plot of daily mean V_{PD} , g_c , S_{tress} , and yield during maize growing season in neutral years with different scenarios (1: original, 2: reduce 2°C per day; 3: reduce 20% precipitation per day; 4: increase $4\text{E}6$ J radiation per day). The up row is for the main1 area, and the bottom row is for the main2 area. The lines on each point show the standard deviation of the simulation.

much stronger, and there is a corresponding anticyclonic anomaly in the low-level wind field under the subtropical high. Air with more moisture over low-latitude seas is thereby transported to China by southeasterly winds to the southwest of the anticyclonic anomaly; the situation is reversed for La Niña events (Wu *et al.*, 2003; Feng and Li, 2011). The resultant impact of ENSO on temperature in China is small, but consistent with Liu and Ding (1995). The spatial patterns of all meteorological variable changes are also generally consistent with the statistical results of Shuai *et al.* (2013). There are slight inconsistencies, however, which may result from differences of spatial

scale and growing season dates between the present study and Shuai *et al.* (2013). In the latter study, the spatial scale was that of the province and the growing season was defined by approximate months. In our model simulation, the grid was the spatial scale and average sowing dates for each agrometeorological station were used to derive the growing season at each grid.

The spatial changes in V_{PD} , g_c , and S_{tress} suggest that high V_{PD} corresponds with low g_c and S_{tress} , and low V_{PD} in contrast corresponds with high g_c and S_{tress} . Such phenomena are consistent with crop growth mechanisms in which plants typically respond to high V_{PD} by reducing stomatal

conductance (g_c), which effectively retains soil moisture for periods with less evaporative demand (Sinclair *et al.*, 1984) and meanwhile reduces S_{tress} (Ray *et al.*, 2002; Hetherington and Woodward, 2003; Liu *et al.*, 2004; Ribaut *et al.*, 2009).

4.2. ENSO effect on yield variability via its primary influence on water stress

We found that changes of P and S_{tress} are consistent with yield variations in association with ENSO. However, changes to V_{PD} and S are opposite to those of yield, suggesting water stress as the key mechanism of ENSO-induced variability of maize yields. In-depth analyses show that the ENSO-induced meteorological impacts on yields, not only those of P but also of T and S , all proceed by influencing soil water conditions (i.e. V_{PD} , g_c , and S_{tress}). Modelling experiments suggest that the responses of V_{PD} , g_c , and S_{tress} to a 2 °C decrease of T are much stronger than a 20% decrease of P , indicating that change of T should have great impacts on V_{PD} , g_c , S_{tress} , and consequently yield. The findings are consistent with the model simulations of Lobell *et al.* (2013), which revealed that large P changes are required to rival the effect of T on water stress and maize yield. Effects of S on V_{PD} , water stress, and yield are complex. An increase of S can increase photosynthesis and transpiration, which can benefit crop yield, especially in well-fertilized and irrigated fields (Fischer, 1985). However, an S increase can also augment evapotranspiration and consequently aggravate water stress and reduce yield (Tao *et al.*, 2003). We found that S increases at high S levels boost V_{PD} in dry areas, but had little effect on V_{PD} in wet areas with low S levels in the main1 and main2 areas (Figure 7(d)). Given these contrasting roles and diverse environments, slight increases of S in La Niña years slightly increased V_{PD} , water stress, and yield in main1 and main2.

Soil water balance is an important intermediary variable that converts climatic variability to yield variability. Because soil water conditions are important in controlling land surface–atmosphere interaction through processes such as evapotranspiration, latent heat and sensible heat fluxes, and atmospheric boundary layer dynamics, they are a part of ENSO-related hydroclimatic anomalies (Wu and Kinter, 2009; Poveda *et al.*, 2011). Further, crop yields are closely related to amounts of available soil water that can be taken up by plant roots during crop growth and development seasons (Nielsen *et al.*, 2009; Grassini *et al.*, 2011). Thus, soil water conditions serve as a bridge between ENSO-induced climate change and maize yield.

This linking role of soil water gives insight into adaptations to ENSO-related climate changes. In practice, we cannot reduce yield losses from disastrous climate effects such as those during La Niña years in the main areas, but it is feasible to use certain measurements to alter soil water conditions and increase potential yields. In our case, the reduction of maize yields in La Niña years is mainly caused

by lack of soil water caused by changes of T , S , and especially P . Thus, properly increasing irrigation water in the main areas may be useful.

Northern and northeastern China are relatively water-short parts of the country, and limited precipitation always restricts crop yield there (Mo *et al.*, 2005; Lin *et al.*, 2013). Many studies have suggested that there is potential to increase yields in this region if sufficient irrigation water is supplied (Zhang *et al.*, 1999; Mo *et al.*, 2005; Sun *et al.*, 2006). Although efficient use of irrigation water and advancements of production efficiency in China have improved over recent decades (Li and Barker, 2004; Shahbaz *et al.*, 2006), water shortages in the dry regions remain severe, with typical agricultural water use efficiency about 0.46 kg m⁻³ (Deng *et al.*, 2006). Thus, to cope with the disadvantageous climate in La Niña years, it is advisable to improve irrigation systems in the main areas, especially the dry portions, to ensure adequate irrigation water for agriculture.

4.3. Uncertainties of the study

The parameters in our study were calibrated in one province in each sub-region, and the ensemble predictions can account for physical and biological uncertainty (Challinor *et al.*, 2005). Similar to other works (e.g. Tao *et al.*, 2009a, 2009b; Tao and Zhang, 2010), the biophysical uncertainties in the MCWLA-Maize impact assessments are considered using 10 sets of optimal crop model parameters. The reductions of maize yield during La Niña years ranged from 3736 to 4437 kg ha⁻¹ and 4504 to 5208 kg ha⁻¹ in the main1 and main2 areas, respectively. Although uncertainty in phenological parameters of crop cultivars is considered to some extent, the parameters were calibrated based on average conditions during 1963–2008. Maize cultivars were assumed invariant over those 46 years. Furthermore, uncertainties from meteorological variables, such as those of responses of precipitation to ENSO, were not examined herein. The data analysis, including yield detrending, interpolation of the meteorological data, and others, might have also introduced uncertainties in the present results. Although the crop model has good simulation performance in most areas, a relatively low r in certain areas (such as in southwestern China) may hinder accuracy in assessing the impacts of climate variability on maize yield. Finally, although the spatially heterogeneous effects of ENSO we presented here are fairly reasonable, further tests of the spatial differences are still necessary.

5. Conclusion

Using the process-based model MCWLA-Maize, we simulated the growth and development of maize to understand how ENSO impacts its yield in China at 0.5° × 0.5° grid scale. The simulations were consistent with our previous statistical study (Shuai *et al.*, 2013) and furnished additional insights regarding the ENSO–yield relationship in the country.

From the national spatial simulations, temperature had little connection with the ENSO–yield relationship, but P and S had significant contributions to that relationship. Specifically, increases (decreases) of P and reductions (increases) of S in the decaying phase of El Niño (La Niña) years generated decreases (increases) of V_{PD} , increases (decreases) of g_c and S_{tress} , and ultimately increases (decreases) of yields in northern and northeastern China. In-depth analyses of two main areas (i.e. northern and northeastern China) suggest that relationships between temperature and yield are very complex and that a 2°C change of temperature exerts more control on yields than a 20% change of P or $4\text{ MJm}^{-2}\text{day}^{-1}$ change of S . However, the effect of ENSO on P on most grids in northern and northeastern China was about 20%, whereas variations of T and S were relatively small. This demonstrates that P is the main influence on the ENSO–yield relationship. A comparison between two sub-main areas indicated that maize yields in dry regions are much more sensitive to meteorological variable changes than those in wet regions. Thus, it is advisable to pay more attention to P changes during ENSO years in relatively dry areas.

Finally, based on the above analysis, we recommend development of a food security warning system that predicts potential yield variations based on ENSO forecast information. To understand accurately the impacts of ENSO on crop yield, meteorological uncertainties should be considered as an integral part of that system. Therefore, more integrated assessments that consider ENSO and agricultural systems as a whole should be conducted to provide effective agricultural information to government decision makers and farmers.

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Supporting Information

The following supporting information is available as part of the online article:

Figure S1. The significance of ANOVA test of yield residuals for maize between El Niño years and Neutral years (a), and between La Niña years and neutral years (b). Only the grids with $p < 0.1$ are filled with colour.

Figure S2. The significance of ANOVA test of total precipitation (P) (a, b), daily solar radiation (S) (c, d), daily maximum temperature ($T_{\max}$) (e, f), daily minimum temperature ($T_{\min}$) (g, h), vapour pressure (V_{PD}) (i, j), canopy conductance (g_c) (k, l), and soil water stress factor (S_{tress})

(m, n) during maize growing season between El Niño years and neutral years (left column) and between La Niña years and neutral years (right column). Only the grids with $p < 0.1$ are filled with colour.

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