

Yu, Chaoqing et al.

**Article — Published Version**

## Assessing the impacts of extreme agricultural droughts in China under climate and socioeconomic changes

Earth's Future

**Provided in Cooperation with:**

Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale)

*Suggested Citation:* Yu, Chaoqing et al. (2018) : Assessing the impacts of extreme agricultural droughts in China under climate and socioeconomic changes, Earth's Future, ISSN 2328-4277, Wiley, Hoboken, NJ, Vol. 6 5, pp. 689-703, <https://doi.org/10.1002/2017EF000768> , <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017EF000768>

This Version is available at:

<https://hdl.handle.net/10419/179965>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



## Earth's Future

### RESEARCH ARTICLE

10.1002/2017EF000768

#### Key Points:

- The development of irrigation in China has alleviated negative drought impacts on food productivity, the presence of irrigation systems explaining  $31 \pm 2\%$  of avoided yield loss
- Frequency and intensity of extreme droughts are projected to increase significantly under future climate change, leading to double the drought-induced yield losses in the largest warming scenarios
- The sharpest drops in grain production during the past 60 years have been driven primarily by socioeconomic disturbances rather than by large droughts

#### Supporting Information:

- Supporting Information S1

#### Correspondence to:

C. Yu and P. Ciais,  
chaoqingyu@gmail.com,  
chaoqingyu@tsinghua.edu.cn;  
philippe.ciais@lsce.ipsl.fr

#### Citation:

Yu, C., Huang, X., Chen, H., Huang, G., Ni, S., Wright, J. S., et al. (2018). Assessing the impacts of extreme agricultural droughts in China under climate and socioeconomic changes. *Earth's Future*, 6, 689–703. <https://doi.org/10.1002/2017EF000768>

Received 21 NOV 2017

Accepted 11 APR 2018

Accepted article online 25 APR 2018

Published online 8 MAY 2018

©2018. The Authors.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

## Assessing the Impacts of Extreme Agricultural Droughts in China Under Climate and Socioeconomic Changes

Chaoqing Yu<sup>1</sup> , Xiao Huang<sup>1</sup>, Han Chen<sup>1</sup>, Guorui Huang<sup>1</sup>, Shaoqiang Ni<sup>1</sup>, Jonathon S. Wright<sup>1</sup> , Jim Hall<sup>2</sup> , Philippe Ciais<sup>3</sup>, Jie Zhang<sup>1</sup>, Yuchen Xiao<sup>1</sup>, Zhanli Sun<sup>4</sup>, Xuhui Wang<sup>3</sup>, and Le Yu<sup>1</sup> 

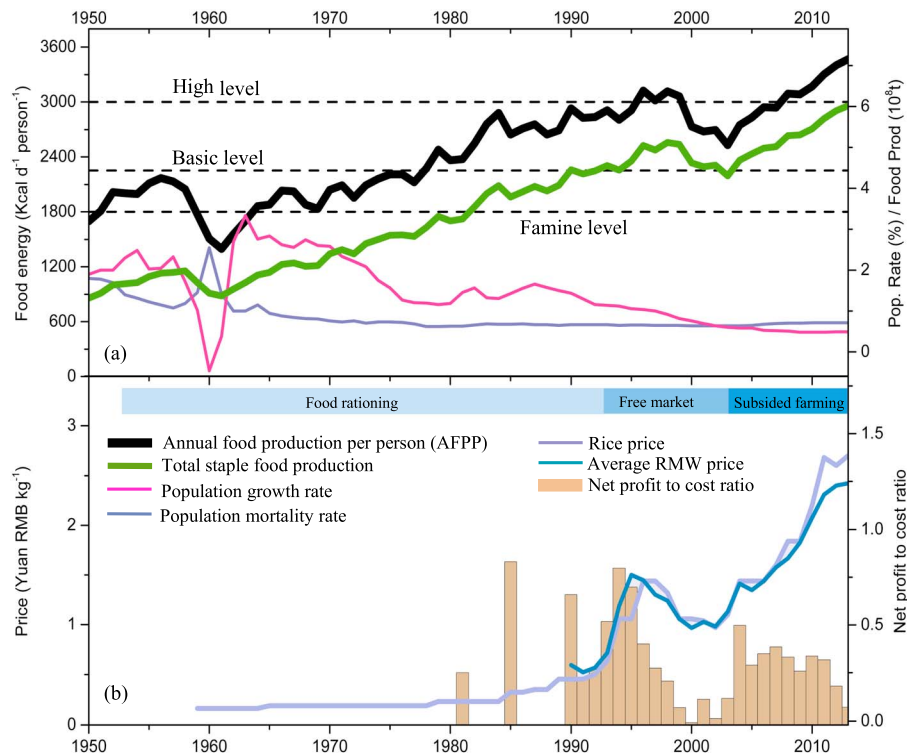
<sup>1</sup>Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing, China, <sup>2</sup>Environmental Change Institute, Oxford University, Oxford, UK, <sup>3</sup>Laboratoire des Sciences du Climat et de l'Environnement, CEA-CNRS-UVSQ, Gif sur Yvette, France, <sup>4</sup>Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale), Germany

**Abstract** Agricultural food production in China is deeply vulnerable to extreme droughts. Although there are many studies to evaluate this issue from different aspects, comprehensive assessments with full consideration of climate change, crop rotations, irrigation effects, and socioeconomic factors in broad scales have not been well addressed. Considering both the probability of drought occurrence and the consequential yield losses, here we propose an integrated approach for assessing past and future agricultural drought risks that relies on multimodel ensemble simulations calibrated for rice, maize, and wheat (RMW) in China. Our results show that irrigation has reduced drought-related yield losses by  $31 \pm 2\%$ ; the largest reductions in food production were primarily attributable to socioeconomic factors rather than droughts during 1955–2014. Unsustainable water management, especially groundwater management, could potentially cause disastrous consequences in both food production and water supply in extreme events. Our simulations project a rise of 2.5~3.3% in average rice, maize, and wheat productivity before 2050 but decrease thereafter if climate warming continues. The frequency of extreme agricultural droughts in China is projected to increase under all examined Representative Concentration Pathway (RCP). A current 100-year drought is projected to occur once every 30 years under RCP 2.6, once every 13 years under RCP 4.5, and once every 5 years under RCP 8.5. This increased occurrence of severe droughts would double the rate of drought-induced yield losses in the largest warming scenario. Policies for future food security should prioritize sustainable intensification and conservation of groundwater, as well as geographically balanced water resource and food production.

### 1. Introduction

Drought and extreme heat are the largest climate-related threats to global agricultural production (Lesk et al., 2015). These threats are particularly acute in China, where agricultural food production is deeply vulnerable to extreme droughts. At least 15 catastrophic drought events lasting longer than 3 years and affecting multiple provinces have occurred during the past 1000 years, along with numerous shorter-lived droughts lasting a few months at a time (Zhang, 2005). The most severe droughts have caused widespread famine and loss of life (Edgerton-Tarpley, 2008; Zhang, 2005; Zhang & Liang, 2010). Despite the recent increase in the severity of meteorological droughts (Piao et al., 2010), annual food production in China has successfully transitioned from near famine-level through basic-level to consistent high-level supply during the past 60 years (Figure 1). These changes occurred as the national economy progressed from food rationing (1955–1993) through a decade-long free market stage (1994–2003) to subsidized farming (2004 up to present).

In the past six decades, the foremost adaptation policy in China for reducing drought-induced yield loss has been the development of irrigation infrastructure. Irrigated area has increased by more than 400% from 1950 (~15 Mha) to 2013 (~63.5 Mha) (NBS of China, 2010). Spatial imbalances between irrigation and economic development have resulted in a northward shift in the center of Chinese food production, particularly after the implementation of the Economic Reform and Opening-up Policy in 1978 (Figure S1a in the supporting information), which replaced the collective farming system with a household responsibility system. Planting area for grain foods in the south (Figure S1b) has declined by 22.4% between 1978 and 2014, owing primarily to the intensive labor inputs relative to economic opportunities associated with urbanization. The rapid expansion of irrigation area in northern China (Figure S1c) has also played a key role in the northward shift of crop production by improving productivity and reducing risk in drought-prone areas. Expansion of



**Figure 1.** Sixty-year changes in food production and food prices in China. (a) Historical evolution of food production in China since 1950 under an assumption of national self-sufficiency. Data include annual food production per person (AFPP, kcal per person per day, left axis), total staple food production ( $10^8$  tons, right axis), and population growth and mortality rates (% and %, right axis). (b) Available historical market prices for rice and the average prices for rice, maize, and wheat (RMW) in Chinese yuan (left axis), as well as profit to cost ratios for cereal crop farming (calculated as net profit divided by cost, right axis). The threshold of annual food production per person for famine-level supply is defined as 1,800 kcal per person per day because the mortality rate has historically increased sharply at values below this level. Basic-level supply is defined as 2,250 kcal per person per day. China did not achieve this level of supply until the institution of the Open Door Policy in 1978. High-level supply, defined as 3,000 kcal per person per day, was not achieved until recent years. The shaded regions along the upper edge of Figure 1b mark the food rationing (1955–1993) and free market (1993–2003) stages. Subsidized farming has been in effect from 2004 through the present, with RMW prices protected and subsidies provided to farming households. Market prices and government subsidies are both included in the net profit ratio shown in Figure 1b. Costs include material, machinery, and labor.

irrigation infrastructure in water-scarce northern China has increasingly been accomplished via the consumption of nonrenewable groundwater resources (Yu et al., 2011). Irrigation expansion slowed in the south after the 1960s because the area of flat and irrigable lands is limited in this part of China. Government policies for exploiting groundwater in northern China commenced in the late 1960s (Qian, 2009). The number of irrigation wells has subsequently increased from 0.19 million in 1965 to 5.01 million in 2010 (Ministry of water Resources, China, 2011), with more than 90% of these wells located in the north. Groundwater has become the primary source of water for irrigation in many northern provinces (Figure S2). Available records indicate that total groundwater storage in the plains in northern China declined by 91 billion cubic meters between 1996 and 2011 (Figure S1c) (Ministry of water Resources, China, 2014). Groundwater depletion threatens future water availability and food security in the face of a changing climate and must be considered in quantifying agricultural drought impacts.

Quantitative evaluation of meteorological drought impacts on past and future food supplies provides important context of policy making for agricultural sustainability. It requires a comprehensive understanding of the relations among the spatiotemporal variations of climate, the complex cropping systems, the irrigation effects, and the availability of water resources. There are multiple approaches being reported to address such relations. For example, survey methodology is helpful to collect first-hand information of how drought has affected crop yields and how farmers adapted to drought (Chen et al., 2014; Huang et al., 2015; Wang et al., 2009; Yan et al., 2016). Empirical models have been applied to analyze the statistical relations among meteorological factors and yields (Huang et al., 2013; Qin et al., 2014; Zhang & Huang, 2012; Zhang et al., 2017). More research efforts have focused on evaluating drought risks based on meteorological (Das et al.,

2016; Li et al., 2016; Naresh Kumar et al., 2009), hydrological (Abebe & Foerch, 2008; Shukla & Wood, 2008), or composite (Ellis et al., 2010; Huang et al., 2011; Palmer, 1965) drought indices (Zargar et al., 2011). Piao et al. (2010) used precipitation and runoff data together with the Palmer Drought Severity Index (PDSI) to show that north and northeast China have experienced significant increases in hydrometeorological drought since the 1960s (Piao et al., 2010). They also noted that it is difficult to produce a clear assessment of the impacts of drought on Chinese agriculture and food security under climate change. Such difficulty embodies the knowledge gap between the physical characteristics of extreme hydrometeorological events and their actual and potential impacts as recently emphasized by the World Meteorological Organization (2015).

Realistic crop growth models (Di Paola et al., 2016; Kroes et al., 2000; Mearns et al., 1999; Morgan et al., 1980; Steduto et al., 2009; van Diepen et al., 1989) are arguably one of the best tools to quantify the influences of short- and long-term variations in weather conditions and human management on soil moisture availability, crop growth, and harvest yields (Jin et al., 2016; Niyogi et al., 2015; Singh et al., 2013) at regional (Yu et al., 2014) and global (Asseng et al., 2015) scales. In China, for example, the Environmental Policy Integrated Climate model was applied to evaluate the impacts of drought on yields of cereal crops in China (Jia et al., 2012; Li et al., 2017). The Crop Environment Resource Synthesis model was used to assess the effects of future climate change on crop yields (Tao & Zhang, 2011; Ye et al., 2013). The AquaCrop model was utilized to estimate the effects of irrigation on winter wheat yields on the Loess Plateau (Wang et al., 2013). And the Decision Support System for Agrotechnology Transfer model was used to simulate drought impacts on wheat and maize yields in North China Plain (Hu et al., 2014). In spite of such progress, the following issues need to be improved for enhancing our understanding of agricultural drought risks in China. First, a recent study by Martre et al. (2015) reveals that multimodel ensemble mean (or median) generates more accurate results than using any single crop model due to compensation of the limitations in individual models' structure and parameterization (Martre et al., 2015). Second, the complex cropping systems have not been well considered when modeling the nationwide food production. Third, the contribution of irrigation, especially groundwater irrigation, to the food productivity has not yet been well understood. Fourth, the potential consequences of extreme droughts in light of yield losses and water availability are not well quantified. Finally, none of the reported research has truly built the linkage between drought impacts and a clearly defined food security levels for the country (e.g., as shown in Figure 1).

We aim to present a comprehensive analysis of agricultural drought impacts in China, integrating climate change, water resource, and socioeconomic factors using multiple models. The multimodel ensemble simulations performed in this study include complex cropping system and provide long historical series for probability calculation. Based on a supercomputer system, the research objectives are to provide quantitative evaluation of (1) the current agricultural drought risk of the major grain crops, (2) the contributions of irrigation to the reduction of agricultural droughts, (3) the potential drought risks under extreme droughts in the scenario of groundwater depletion, (4) the impacts of future climate change on agricultural drought risk, and (5) other social economic effects (e.g., market and policies) on major reductions of grain production, including rice, maize, and wheat.

## 2. Methods and Material

### 2.1. Agricultural Drought Risk Assessment

Drought impact on crop yields represents the combined effects of reduced precipitation, increased temperature, increased solar radiation, decreased soil moisture, and human management in an event. It is also related to the frequency of drought events when evaluating the long-term impacts on food production in a specific place because the concept of risk consists of damage ( $D$ ) and probability ( $p$ ). Agricultural drought risk in a given place therefore is defined as the following equation:

$$R = \int_0^1 D(p) dp \quad (1)$$

where  $R$  represents risk.  $D$  represents drought-induced yield loss in a given drought event relative to a target yield. And  $p$  represents probability of this drought event.  $R$  can be understood as integral of annual yield losses caused by all possible drought events in this place.  $D$  is a combined result from the effects of climate, soil, technology, irrigation, fertilization, and other management on crop growth. Choosing the maximum yield or the average yield as the target yield does not change the probability distribution when evaluating

drought risk based on a consistent input data set. In the current research, we use the achievable maximum yield from history to define  $D$ .

## 2.2. Drought Frequency Analysis

We use 60-year historical climate data to simulate daily crop growth and yield formation and derive time series of drought-induced yield losses relative to local maximum yields (Yu et al., 2014). We have tested a variety of distribution types for goodness of fit tests using the  $\chi$ -square statistic, including the Weibull, Pearson Type III, Generalized Logistic, Gumbel, Generalized Additive Model, and Generalized Extreme Value (GEV) distributions, and find that the GEV is the best distribution for drought frequency analysis. The historical time series yield loss data are then used to generate the parameters of GEV distributions for each county, each province, and the country as a whole. Damage-probability curves are then generated for China and its subregions. An identical set of GEV parameters is also used for drought frequency analysis in each location for future climate change scenarios.

## 2.3. Crop Model Setting

We evaluate drought impacts on major cereal crops in China based on yield loss and probability as simulated by multiple crop models at the county level. We build agricultural databases containing the parameters required by these models to simulate the daily growth of three main cereal crops (rice, maize, and wheat, or RMW; Figure S3) in the 2403 counties of China (Figure S4). The data include 1,510 counties with rice, 1,704 counties with maize, and 2,007 counties with wheat. The baseline for crop modeling is defined with the identical (2007–2011 mean) conditions for land use, soil, crop rotations, and fertilization. We use observed daily climate data from 1955 to 2014 to simulate county-level daily growth and assess historical drought impacts on yields. We then examine potential future changes in drought impacts using projected daily climate data for 2006–2100 from nine global climate models (GCMs).

There are multiple cropping systems in China. Most of the northeastern, northwestern, and Tibetan Plateau regions only have single-cropping systems. Double cropping is dominating in other major agricultural regions. Some places in the south have triple cropping systems. Balancing the water and nutrient budgets in crop modeling can become challenging if only studying a single crop without considering the actual rotation systems. We apply 11 crop rotation systems commonly used in China: rice, maize, spring wheat, winter wheat, maize/winter wheat, rice/winter wheat, rice/rice, rice/vegetable, rice/rice/vegetable, vegetable/winter wheat, and vegetable/maize. The assumed distribution of these crop rotation systems is based on geographical information and county-level archives for all three crop models.

## 2.4. Irrigation Scenarios

Irrigation is crucial for evaluating drought risk in China, but there is a lack of reliable information on when, how, and to what extent farmers irrigated their crops. Our baseline simulations assume that irrigation demands can always be fully met, although water resources may not be sufficient to meet irrigation demands during drought years. Such overestimation of irrigation water use can be reduced through optimizing the parameters to minimize the gap between the modeled and observed yields. Three core irrigation scenarios are considered: baseline irrigation (2007–2011 mean), 1958 irrigation (irrigation is reduced to levels recorded for 1958), and rainfed (no irrigation). The 1958 scenario is used to evaluate the climate and socioeconomic impacts on the reduction of grain production in the following 3 years (Figure 1) with the irrigation level in 1958. We also perform sensitivity studies to evaluate the potential impacts of sustainable groundwater use or total groundwater depletion in northern China on national cereal crop yields. The method is to reduce irrigation areas in each province by an amount consistent with the ratio of groundwater overuse to all groundwater use. Groundwater overuse is defined as groundwater consumption that exceeds annual recharge.

## 2.5. Model Calibration and Validation

We conducted simulations of the three major crops in China on the Sunway Taihu Light Supercomputer hosted by the National Supercomputing Center in Wuxi City, China. Considering energy, water, and fertilization as the primary drivers of grain yield variations, we chose the following crop models in this research: the nitrogen-oriented DNDC (DeNitrification and DeComposition) (Li et al., 1994; Yu et al., 2014), the water-oriented AquaCrop (Steduto et al., 2009), and the radiation-oriented SWAP (soil-water-atmosphere-plant, using WOFOST (WOrld FOod STudies) for crop growth modeling, Kroes et al., 2000). Another reason of

**Table 1**  
The Parameters Used for Model Calibration (GDD: Growing Degree Day)

| Crop model | Parameter                                    | Definition  | Unit                                  |
|------------|--|---|---------------------------------------|
| DNDC       | MaxB   | Maximum biomass   | kgC/ha                                |
|            | $T_{opt}$                                    | Optimal temperature   | °C                                    |
|            | WD   | water requirements  | Kg                                    |
| AquaCrop   | G-CN   | Carbon/nitrogen ratios of grain   | kg/kg                                 |
|            | $WP_0$                                       | Water productivity normalized for evapotranspiration and CO <sub>2</sub>  | g/m <sup>2</sup>                      |
|            | $HI_0$                                       | Reference harvest index   | %                                     |
|            | CGC  | Canopy growth coefficient   | Fraction per GDD                      |
|            | CDC  | Canopy decline coefficient  | Fraction per GDD                      |
|            | $T_1$  | Time from sowing to flowering   | °C/d                                  |
|            | $T_2$  | Time from sowing to maturity  | °C/d                                  |
|            | $K_1$  | Upper threshold of soil water depletion for canopy expansion  | -                                     |
| SWAP       | $K_2$  | Upper threshold of soil water depletion for stomatal control  | -                                     |
|            | $WP_0$                                       | Water productivity normalized for evapotranspiration and CO <sub>2</sub>  | g/m <sup>2</sup>                      |
|            | $TSUM_1$                                     | Time from emergence to anthesis   | °C/d                                  |
|            | $TSUM_2$                                     | Time from anthesis to maturity  | °C/d                                  |
|            | $AMAXTB_1$                                   | Maximum leaf CO <sub>2</sub> assimilation rate at the first development stage of crop maturity                    | kg·ha <sup>-1</sup> ·hr <sup>-1</sup> |
|            | EFFTB  | Initial light-use efficiency for CO <sub>2</sub> assimilation by single leaves as a function of daily temperature | %                                     |
|            | PERDL  | Maximum relative death rate of leaves due to water stress   | %                                     |
|            | CFET   | Correction factor transpiration rate  | -                                     |
| RGRLAI     | Maximum relative increase in leaf area index | d <sup>-1</sup>   |                                       |

Note. SWAP = soil-water-atmosphere-plant; DNDC = DeNitrification and DeComposition.

choosing these models is that the source codes can be transferred to fit the special hardware structure of the supercomputer with relatively less efforts than using other models. We use observed yields from 1998 to 2007 to calibrate the parameters in all three models and observed yields from 2008 to 2010 to validate the resulting configurations. The sensitive parameters selected for optimization are listed in Table 1. For DNDC and AquaCrop, the prior ranges of these parameter are set as  $100 \pm 20\%$  of the defaulted values (Li, 2016; Raes et al., 2017). For SWAP, we use the recommended parameter range in the user manual (Kroes et al., 2009). All the other crop-related parameters are set as the defaulted values.

We perform Markov chain Monte Carlo simulation for parameter optimization for all three crop models in each of the 2,403 counties using DREAM (DiffeRential Evolution Adaptive Metropolis) algorithm (Vrugt et al., 2009). We run the models on the supercomputer 2000–3500 samples in each county. With the convergence achieved after the first 1,200–1,800 samples, we use the last 600 postconvergence samples for analysis. These postconvergence samples are then used to estimate uncertainty and determine the optimal parameter sets (defined here as the parameter sets that produce the maximum posterior probability).

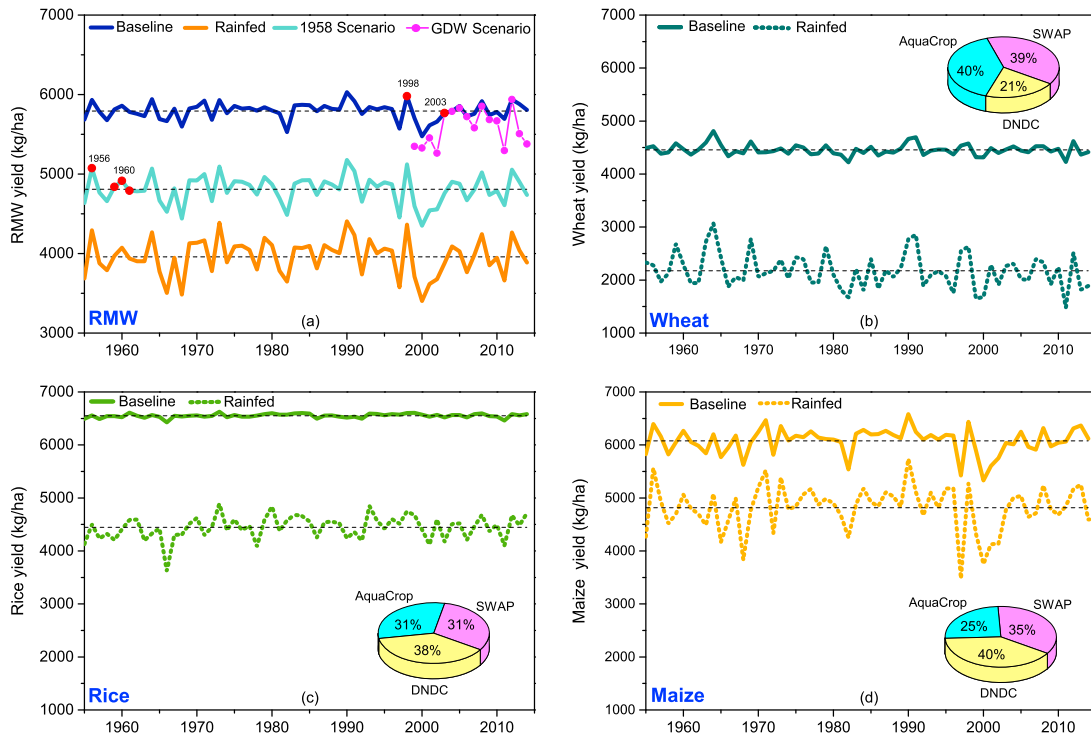
## 2.6. Ensemble of Multiple Crop Models

To reduce the predictive uncertainty of model structure, we use the Bayesian Model Averaging (BMA) method to obtain the multimodel ensemble by the linear combination of individual model predictions (Huang et al., 2017). The DREAM algorithm is also used to derive the weights and variance for the individual ensemble members. Figure S5 shows the results in the calibration and validation periods, including statistics that summarize model performance relative to recorded data from all 2,043 counties ( $r^2$ , root-mean-square error, and biases). After model calibration, the observed or statistical data were applied to validate the modeling results from the site level, the provincial level to the national level.

## 2.7. Uncertainty Estimation

Three sources of uncertainty are considered: model-specific uncertainties estimated using the DREAM algorithm, statistical uncertainties in time mean quantities, and potential measurement errors in national planting area. Uncertainties in model-generated yield loss rates and drought risks are estimated as a 95% confidence interval constructed from postconvergence Markov chain Monte Carlo samples. Statistical errors in time mean quantities are estimated as twice the standard error of the time mean with the number of degrees of freedom adjusted to account for temporal autocorrelations. Potential measurement errors in national





**Figure 2.** Simulated Bayesian model average (BMA) grain yields in mainland China during 1955–2014 based on observed meteorological variations under different irrigation scenarios. (a) Integrated RMW yields under the baseline, rainfed, and 1958 scenarios during 1955–2014. Yields under the 1958 scenario prescribe irrigation areas at 1958 values. The GDW scenario shows expected national RMW yields if groundwater had been unavailable for irrigation in the northern plains during 1999–2014. The green dot represents the national maximum RMW yield, which occurred in 1990, and the red dots are used to highlight model results for 2003 and 1959–1961 (see text for details). BMA yields of (b) wheat, (c) rice, and (d) maize under the baseline and rainfed scenarios. The relative contributions of each crop model to the weighted BMA are also shown. RMW = rice, maize, and wheat; SWAP = soil-water-atmosphere-plant; GDW = groundwater.

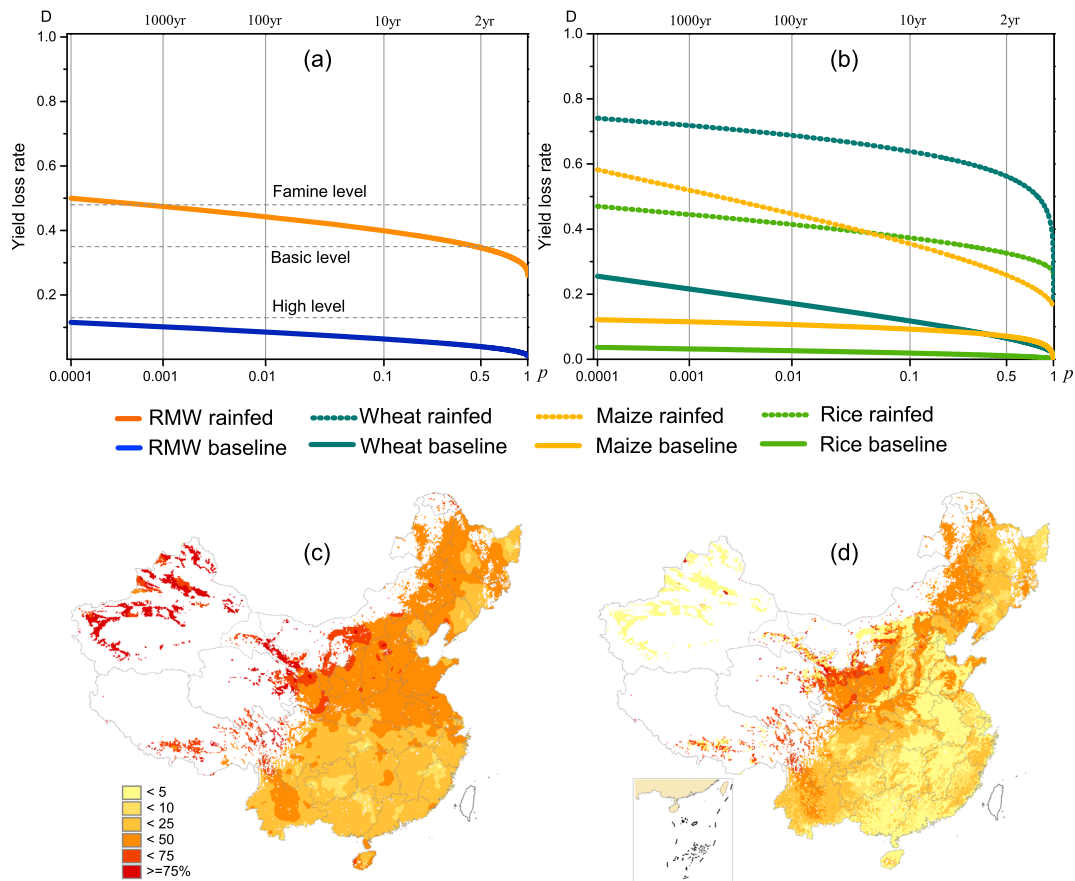
planting area are estimated as the time mean relative difference (5%) between the national planting area reported by the National Bureau of Statistics of China and the sum of the provincial planting areas reported by the Ministry of Agriculture during 1970–2006. Standard error propagation rules are used to combine and propagate the uncertainties, under the assumption that the three sources of uncertainty are mutually independent.

### 3. Results

#### 3.1. Impacts of Irrigation on Agricultural Drought Risk

To quantify the contributions of irrigation to reducing agricultural drought risks in China, we simulate daily growth of RMW under a baseline scenario (assuming irrigation fully meets the crop demand) and a rainfed scenario (zero irrigation). We also study other permutations to these limiting case scenarios, such as sensitivity simulations in which baseline irrigation rates are adjusted to match 1958 levels (the “1958 scenario”) or to exclude unsustainable groundwater consumption (the “GDW scenario”). Land use, soil conditions, crop rotations, and fertilizer use for all scenarios are based on average records from 2007 to 2011. Figure 2a shows variations in national RMW yields under the baseline irrigation and rainfed scenarios, which are summarized from daily simulated crop growth in all 2,403 counties between 1955 and 2014. Figures 2b–2d show yields for wheat, rice, and maize, along with the weights assigned to the DNDC, AquaCrop, and SWAP models in the BMA ensemble for each crop. In these simulations, crop parameters are held constant at their calibrated values for 1955–2014, neglecting changes in breeding and agricultural practice that have contributed to the observed yield increases shown in Figure 1. Simulated yield variability thus mainly reflects the national-scale impacts of climatological and meteorological droughts (Figure 2).

Figure 2a shows that irrigation substantially reduces the risks of yield loss associated with meteorological droughts and therefore plays a central role in ensuring national food security. The maximum simulated



**Figure 3.** Agricultural drought risks ( $R$ ) in mainland China. (a) Damage-probability curves for RMW under the rainfed and baseline irrigation scenarios. Damage ( $D$ ) is quantified as integrated yield loss rates of RMW relative to maximum yields (vertical axis) in a given probability ( $p$ , horizontal axis) of a drought event.  $p = 0.5$  corresponds to a 2-year drought event,  $p = 0.01$  to a 100-year event, and so on. The values of the famine-, basic-, and high-level food productions can be read in Figure 1a. (b) Damage-probability curves for rice, maize, and wheat individually under the rainfed (dotted) and baseline (solid) scenarios. (c) Spatial distribution of agricultural drought risk map (expressed as annual expected yield loss ratio in percent) for RMW under the rainfed scenario. (d) Agricultural risk map for RMW under the baseline irrigation scenario. The spatial resolution of the land use map is 10 km, with gridded values interpolated from model results in 2,403 counties (Figure S4). RMW = rice, maize, and wheat.

national RMW yield for the past 60 years occurred in 1990 under both the rainfed and baseline scenarios (Figure 2a). Applying the simulated maximum yield, we find that the agricultural drought risk  $R$  for RMW (Figure 3a) is much larger under the rainfed scenario (average yield losses of  $35 \pm 2\%$ ) than under the baseline irrigation scenario ( $4 \pm 2\%$ ). These results indicate that approximately one third of current RMW production in China ( $31 \pm 2\%$ ) can be attributed to irrigation (Figures 2a and 3a). Drought risks and the contributions of irrigation to reducing these risks vary by crop. Estimated drought yield losses during 1955–2014 are  $55 \pm 2\%$  for wheat,  $27 \pm 2\%$  for maize, and  $33 \pm 2\%$  for rice under the rainfed scenario compared to  $7 \pm 2\%$  for wheat,  $7 \pm 2\%$  for maize, and  $2 \pm 2\%$  for rice under the baseline scenario (Figures 2b–2d and 3b). Figures 3a and 3b summarize agricultural drought risks for integrated RMW and rice, maize, and wheat individually under the baseline irrigation and rainfed scenarios as a function of agricultural drought severity.

The probability curves for the yield losses of RMW (Figure 3a) indicate that China can maintain its current high-level food supply (3,000 kcal per person per day) even during extreme drought events so long as agricultural technology, water supplies for irrigation, and planting areas are maintained at the baseline levels. By contrast, without irrigation, basic level food supply (2,250 kcal per person per day) would be threatened approximately every other year (i.e., every year with agricultural drought exceeding the 50th percentile; Figure 3a).

The northern and northeastern parts of China have grown drier over the past 60 years, with increasing frequencies of meteorological drought (Dai, 2013; Piao et al., 2010). Without irrigation, we estimate that



this signal of increased drought severity during 1995–2014 would have reduced average yields by ~5% for wheat and maize relative to 1955–1994 (Figures 2b and 2d). Irrigation has reduced these rises in drought-related losses after 1995 to less than 1.5% for maize and wheat. Rice yields were negligibly affected (<0.5%) since rice is mainly grown in southern China (Figures 2c and S3) where droughts were less severe. Therefore, irrigation has thus far prevented recent increases in the frequency and severity of meteorological droughts from significantly affecting agricultural productivities.

The maximum simulated yields for different counties may occur in different years. County-level agricultural drought risks are derived from model results using maximum county-level yields, local planting areas for each crop, and local irrigation areas. Figures 3c and 3d show 10-km gridded spatial distributions of agricultural drought risk interpolated from county-level results. Spatial distributions of agricultural drought impacts on RMW yields under the baseline and rainfed scenarios confirm that drought risks and the effects of irrigation in reducing these risks are larger in northern China, particularly in northwestern China. Corresponding spatial distributions of drought risks for each crop (Figure S8) show that drought risks are larger for wheat than for maize or rice. Simulated drought risks for all three crops compare well with the results of site-level irrigation/nonirrigation experiments (Figure S7). The longest of these experiments, which has been conducted in Liuan County of Anhui Province, in the transitional zone between north and south China, indicates that irrigation has improved rice yields by 34% between 1959 and 2013 relative to control plots without irrigation (Shi, 2015). This observed improvement is consistent with our simulated drought risk for rice in this county (i.e.,  $33 \pm 2\%$ ).

### 3.2. Water Resources and Extreme Droughts

Our simulations indicate that the severest national agricultural drought between 1955 and 2014 (a 165-year drought event) occurred in 2000 under both the baseline and rainfed scenarios. This event caused simulated RMW yield losses of  $44 \pm 2\%$  under rainfed conditions and  $9 \pm 2\%$  under baseline irrigation. The magnitude of this difference indicates that irrigation was crucial for food production during this drought. The shift in the center of food production in China from the water-abundant south to the water-scarce north has been facilitated in large part by unsustainable consumption of groundwater resources by agriculture in northern China (Figure S1). Reducing this unsustainable groundwater consumption is one of the most pressing grand challenges to agricultural drought management in China (Yu et al., 2011). We treat groundwater resources as the sum of a long-term storage component and an annual recharge component and then define *groundwater overuse* as consumption that exceeds the annual recharge component. We construct a groundwater depletion scenario that assumes the elimination of long-term storage due to unsustainable water management, such that water for domestic, industrial, and agricultural use can only be withdrawn from surface water sources (streams, lakes, and reservoirs) and the annual recharge component of ground water. We use detailed groundwater use statistics from provincial records (Ministry of Water Resources, China) to estimate groundwater overuse during 1999–2014 (Figure S1c) and then reduce the prescribed irrigation rates by this amount in the crop model simulations (the groundwater depletion scenario, or GDW). Simulated yield reductions under this groundwater depletion scenario are shown in Figure 2a (pink line). Our simulations indicate that eliminating groundwater overuse in northern China would have reduced national RMW yields by  $3 \pm 2\%$  on average during 1999–2014 and by as much as  $7 \pm 2\%$  during drought years.

The impacts of recent extreme droughts at the provincial scale illustrate the importance of sustainable groundwater management. The 2002 agricultural drought was relatively mild nationally (an ~8-year return period) but was much more severe in northern China with a 20-year return period in Hebei Province and a 122-year return period in Shandong Province. Our simulations indicate that this drought would have only reduced RMW productivities by  $6 \pm 2\%$  in Hebei Province and by  $10 \pm 2\%$  in Shandong Province relative to the nondrought year 1998 if irrigation demands were fully met. Recorded yield data from statistical yearbooks show that cereal crop yields in 2002 were 7% less than those in 1998 in Hebei Province and 9% less than those in 1998 in Shandong, in agreement with our estimates. These relatively mild losses stand in stark contrast to simulated RMW yield losses in these provinces ( $51 \pm 2\%$  in Hebei and  $52 \pm 2\%$  in Shandong) under the GDW scenario, which assumes zero long-term groundwater storage at the beginning of the year 2002. Table 2 shows annual water resources (surface water plus groundwater recharge from precipitation during 1 year) as recorded by the Ministry of Water Resources. Annual water resources during 2002 were more than 60% less than normal even though annual precipitation in these provinces was only about 30% less than its

**Table 2**

*Recorded Values of Precipitation, Annual Water Resources Received From Precipitation, Groundwater Use, and Total Water Use (billion m<sup>3</sup>, Bm<sup>3</sup>) During an Average Year and During the 2002 Drought in Hebei and Shandong Provinces*

| Provinces | Year    | Annual precipitation     |             | Annual water resources from precipitation (Bm <sup>3</sup> ) |               |                          | Actual water use (Bm <sup>3</sup> ) |                 |                  |
|-----------|---------|--------------------------|-------------|--|---------------|--------------------------|-------------------------------------|-----------------|------------------|
|           |         | Total (Bm <sup>3</sup> ) | Anomaly (%) | Total  | Surface water | Groundwater <sup>a</sup> | Total water use                     | Groundwater use | Agricultural use |
| Hebei     | Average | 144.1                    | /           | 20.3   | 9.9           | 10.4                     | 21.5                                | 15              | 14.5             |
|           | 2002    | 104.9                    | −27.2%      | 8.6  | 2.0           | 6.6                      | 21.1                                | 17.1            | 16.1             |
| Shandong  | Average | 236.2                    | /           | 30.6   | 18.8          | 11.8                     | 23.9                                | 10.8            | 15.5             |
|           | 2002    | 146.6                    | −37.9%      | 9.8  | 3.7           | 6.1                      | 25.2                                | 13.3            | 18.8             |

<sup>a</sup>Represents only fast turnover ground water pools recharged from annual precipitation. Data source: Ministry of Water Resources of China (Ministry of water Resources, China). Annual water resources here include incoming surface water and groundwater recharge from precipitation within the boundaries of the specified region during the specified year. Water use includes domestic, industrial, and agricultural uses.

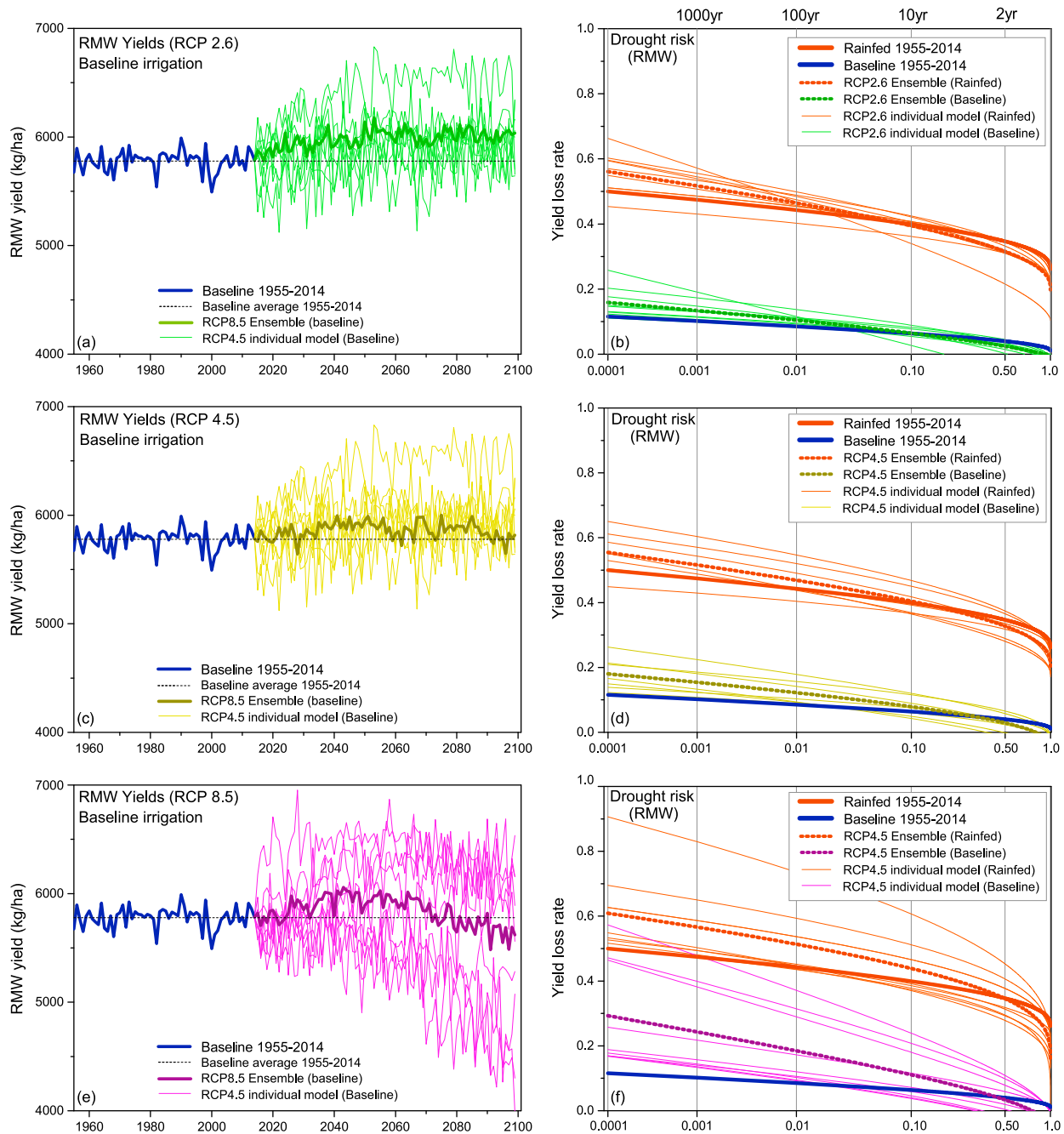
average value (Ministry of water Resources, China). Surface water was dangerously reduced to only one fifth of its long-term average value in both Hebei and Shandong. This type of situation arises during droughts because the combined effects of reduced precipitation and enhanced temperature during these events intensify total evapotranspiration. The data listed in Table 2 illustrate that groundwater depletion could lead to the development of severe water crises in regions with high population densities under drought conditions. Even if water resources received from precipitation in 2002 could have been collected entirely for human use, they would only have met about 40% of the water demand in Hebei and Shandong Provinces, which are collectively home to 157 million people.

Hebei Province experienced a continuous multiyear drought from 1999 to 2002. The average annual RMW yields recorded during these four years were 6% less than yields during the nondrought year 1998. Our simulations indicate that annual mean RMW yields during these four drought years would have declined by  $66 \pm 2\%$  relative to 1998 without any irrigation, by  $46 \pm 2\%$  if irrigation water had been strictly limited to annual water resources (i.e., no groundwater overuse), and by  $4.5 \pm 2\%$  if irrigation water demand had been fully satisfied. These model results explain why extreme droughts often resulted in widespread famine and social unrest in China before the 1950s, when technologies for accessing groundwater resources were first deployed. In modern society, pressures associated with regional food shortages can be relieved by grain stocks and international food markets. However, water shortages in large geographic regions such as these cannot be easily resolved. Such shortages could result in serious conflicts, particularly under extreme or prolonged drought conditions. This potential for social conflict and unrest highlights the importance of sustainable water management and the need to maintain long-term strategic groundwater reserves.

### 3.3. Impacts of Future Climate Change

The increased drought severity observed in the past two decades over northern China is not the norm in climate model simulations, which project generally wetter conditions as the monsoon rain belt is displaced northward under global warming (Yang et al., 2015). The observed trend in northern China could be caused by local climate feedbacks that are not captured by climate models (Seneviratne et al., 2006), or it could result from decadal variability that is not representative of trends during the next century. It is in any case important to consider projections from different climate models in assessing the potential future evolution of drought risks in crop production, rather than to rely on a single climate model. We therefore run the three crop models and evaluate the potential impacts of future climate change on agricultural drought risks in China using output from nine GCMs acquired from the Intergovernmental Panel on Climate Change Climate Model Intercomparison Project Phase 5 archive (Taylor et al., 2012). Potential CO<sub>2</sub> fertilization effects and other changes in boundary conditions are not considered within the crop models to maintain the focus on the agricultural impacts of meteorological drought. BMA weights for each crop model in all future (2015–2100) scenarios are identical to those derived for the historical (1955–2014) simulations (Figure 2). As it is not possible to make realistic projections of future changes in technologies, soils, irrigation areas, and crop rotations, these parameters are fixed at values appropriate for 2007–2011.

Figures 4a, 4c, and 4e show the projected evolution of RMW yields from 2015 to 2100 in response to climate change alone assuming baseline irrigation under the Representative Concentration Pathway (RCP) scenarios



**Figure 4.** Impacts of climate change on agricultural drought risks for integrated productivities of rice, maize, and wheat (RMW) in mainland China. Simulated RMW yields for 2015–2100 under the (a) Representative Concentration Pathway (RCP) 2.6, (c) RCP 4.5, and (e) RCP 8.5 future emissions scenarios developed for the Intergovernmental Panel on Climate Change Climate Model Intercomparison Project Phase 5 assuming baseline irrigation. Damage-probability curves for 2015–2100 under the (b) RCP 2.6, (d) RCP 4.5, and (f) RCP 8.5 future emissions scenarios under rainfed and baseline irrigation conditions. Damage-probability curves for 1955–2014 (thick solid lines as in Figure 3a) are included for context. Thin solid lines indicate agricultural drought risk based on individual climate models during 2015–2100, while thick dotted lines represent ensemble average agricultural drought risk during 2015–2100. Damage is expressed as RMW yield loss ratio relative to maximum yields of the given time series data for each model. Data for 1955–2014 are simulated baseline yields (Figures 4a, 4c, and 4e) based on weather station observations. Future scenario data are normalized against historical yields by matching average yields based on each set of global climate model output during 2006–2014 to average historical yields based on climate observations during 2006–2014.

RCP 2.6, RCP 4.5, and RCP 8.5 (Taylor et al., 2012). All GCM-based RMW yields have been normalized so that average 2006–2014 yields based on GCM output match average yields based on observed climate data during 2006–2014. Simulated RMW yields from seven of the nine GCMs (78%) indicate that overall grain

productivities will increase through at least the first half of the 21st century under all three scenarios (Figures 4a, 4c, and 4e) due to increases in precipitation and temperature (Figure S9). Mean baseline RMW yields during the decade 2040–2050 are projected to be larger than mean baseline yields during 1955–2014 by 3.3% under RCP 2.6, by 3.2% under RCP 4.5, and by 2.5% under RCP 8.5. After 2050, RMW yields are projected to stay roughly constant under RCP2.6, drop back toward historical levels under RCP 4.5, and decrease to 2.7% below historical mean under RCP 8.5 (during the decade 2090–2100). These simulations indicate that future climate change will likely be at least temporarily beneficial to grain production in China and also indicate that the duration and magnitude of these potential benefits are reduced for scenarios with larger future greenhouse gas emissions. By contrast, damage-probability curves (Figures 4b, 4d, and 4f) indicate that the risks associated with extreme agricultural droughts will increase in the future under all three emission pathways. For example, assuming baseline irrigation, the expected yield loss associated with a 100-year agricultural drought under the current climate is equivalent to the expected yield loss associated with a 30-year drought under RCP2.6, a 13-year drought under RCP 4.5, and a 5-year drought under RCP 8.5. Figure 4f shows that the increasing drought frequency would double the rate of drought-induced yield losses under the RCP 8.5 scenario even if water resources can fully meet irrigation demands (cf. purple dotted and blue solid lines in Figure 4f). These findings highlight the urgency of developing and maintaining an accessible strategic groundwater reserve that can help to mitigate the risks associated with the increasing frequency and severity of extreme droughts.

### 3.4. Impacts of Other Socioeconomic Factors

As shown above, the calibrated model simulations presented here accurately reproduce yield losses during severe droughts. However, these simulations do not reproduce the sharpest actual drops in food production during the past six decades, suggesting that these drops cannot be explained by extreme droughts alone. The Great Leap Forward for rapid industrialization and collectivization (1958–1961) is an informative example. National census data show that domestic supplies of RMW dropped by 17% in 1959, 25% in 1960, and 36% in 1961 relative to the nondrought year 1956 (Figure 1a). These large decreases contrast sharply with simulations assuming irrigation at levels consistent with that time (the 1958 scenario). Simulated RMW yields per unit area during 1959–1961 are comparable with average simulated productivity under this scenario (Figure 2a) and only 3–6% less than the simulated yield for 1956. The Great Leap Forward led to sharp reductions in planting area (Figure S1b); however, simulated total yield losses after accounting for changes in planting area are still only  $17 \pm 2\%$  (1959),  $12 \pm 2\%$  (1960), and  $16 \pm 2\%$  (1961) relative to 1956. Other socioeconomic factors (such as mismanagement fueled by exaggerated production estimates) were also influential in reducing domestic grain supplies. These factors are not quantifiable using available data.

More recently, the total domestic production of RMW dropped by 18% in 2003 relative to the nondrought year 1998 (Figure 1a). Our baseline ensemble indicates that drought stresses in 2003 can only explain a  $3.5 \pm 2\%$  drop in RMW production per unit area relative to 1998 (Figure 2a). Socioeconomic factors were the major drivers that caused a 13% reduction in planting area between 1998 and 2003 (Figure S1b). First, grain prices fell substantially between 1996 and 2003 because no price protection policy for grain production. These market changes resulted in a sharp decrease in profitability, with the net profit to cost ratio even dipping below zero in 2000 (Figure 1b). Second, agricultural taxes and fees remained high as discussed by Tso (2004). Giving up grain production was an inevitable option in such circumstance. We assess that losses of 13% in food production are about 1.3 times the expected yield losses associated with a 1,000-year drought under baseline irrigation (Figure 3a). If irrigation water during 2000–2002 was not sufficient, socioeconomic pressures can compound the effects of agricultural droughts. New agricultural policies were formulated in response to the food shortages after 2003 with the intention of stabilizing income in farming households. These policies include agricultural tax exemptions, direct cash subsidies, and grain price protections.

## 4. Conclusions and Discussion

China has made tremendous strides toward increased food productivity and security over the past 60 years without expanding planting area. Developing irrigation systems has played an important role in improving food productivity. The following conclusions from our modeling results may be helpful for future sustainable drought management. First, sustainable water use can maintain the high-level domestic food supplies (3,000 kcal per person per day) even in extreme droughts. Otherwise, extreme droughts can cause large

food reduction and severe water crisis. Second, groundwater overuse is not necessary during nondrought years because its contribution to the national food productivity is limited. Third, the worst drought damage on individual crops (e.g., maize 1997, rice 1963, and wheat 2011 in Figures 2b and 2c) does not necessarily result in the largest grain loss in the nation due to the characteristics of the spatiotemporal distributions of RMW. Therefore, maintaining a reasonable plantation structure for maize, rice, and wheat can be helpful for reducing the overall agricultural drought risk. Fourth, given the contribution of irrigation to food productivity, the largest food reductions in the past 60 years were caused by socioeconomic drivers, rather than by droughts. Finally, the increased extreme droughts in the recent decades may continue in the future and cause higher agricultural risks, even though climate change is likely to bring more precipitation in the north. Preparing water resources for extremes therefore has to be fully considered in drought management.

Policymaking should address two major challenges in future agricultural drought management. The first challenge is that the frequency and severity of agricultural droughts in China are projected to increase under climate change (Figure 4). More frequent droughts may have a cumulative effect on the availability of groundwater for irrigation, progressively reducing the margins for water management. More severe droughts that have no analogs in recent history may likewise challenge the water management and adaptation strategies that are currently in place. Our results emphasize the need for a strategic groundwater reserve in northern China. Yet the areas of groundwater irrigation continue to expand, especially in the north and northeast. Achieving sustainable water use requires an integrated national policy that regulates provincial responsibilities in food production in accordance with local land and water resources. For example, grain planting area in the south has declined by 22.4% since 1978. Our model results suggest that recultivating one quarter of the abandoned planting area in the south could replace the food production that currently relies on groundwater overuse in the north. Sustainable intensification should be prioritized in policy making because technological developments for improving harvest ratios and water-use efficiency are more effective at increasing yields than further increases in irrigation areas in the north. For example, in the predominantly rainfed Jilin Province, which produced 13% of the total maize for China in 2013, maize productivity has increased by 163% from 1980 (3134 kg/ha) to 2013 (7,933 kg/ha) despite a provincial irrigation rate of less than 20%. Enhancing farmers' adaption capacities is helpful for reducing drought risks in the north, such as early warning, adjusting seeding or harvesting dates (Wang et al., 2015), and compensating insurance fees. Monitoring actual groundwater extraction is a must for effective water management, such as water saving (Wang et al., 2014), prevention of overpumping during nondrought years, and compensation of local stakeholders to minimize their losses due to reduced groundwater use and increased drought risks. Storing floodwaters underground by developing and deploying groundwater recharge technologies and dedicated detention basins could also help to restore and maintain a strategic groundwater reserve for drought years, especially given the expectation of more extreme events (both droughts and floods) under future climate change.

The second challenge is that socioeconomic changes can destabilize food planting area and become one of the major uncertainties affecting domestic food security. Despite the subsidy policy that followed the reduction of food production in the early 2000s, the domestic profitability of RMW production has dropped again in recent years (Figure 1b). The fundamental causes are the high costs in small-sized farming, which result in the domestic costs higher than the international food prices. Improving the efficiency of food production is essential to increase the benefit-cost ratio in food production and maintain food planting area. Diet change is another socioeconomic driver that affects agricultural water use. The decrease of human grain consumption allows adjusting the current crop structure. A previous field study suggests that replacing the current double-cropping system in northern China (winter wheat/summer maize) with a three-crops-per-two-years system (winter wheat/summer maize/spring maize) could reduce groundwater use by 23% while maintaining total productivity at current levels (Gao et al., 2015). However, increased meat consumption would likely amplify overall water demands because the water footprint for livestock is about 3–5 times that of cereal grains (Mekonnen & Hoekstra, 2010). A careful reconfiguration of crop planting structures and diet-related water footprint would help to balance regional water resources and food production.

Lessons learned from China about drought adaptation policies in the face of climate change can be helpful for agricultural development in other countries with fast population growth (Bongaarts, 2016). First, large and continuous government investments in irrigation infrastructure are crucial for enhancing drought adaptation



### Acknowledgments

We thank Peng Gong, Guangwen Yang, Xiaomeng Huang, Haohuan Fu, Wei Xue, and Xinghua Han for their support in this research. The Sunway Taihu Light Supercomputer was tremendously helpful in completing the computational tasks. This research was supported by the Ministry of Science and Technology of the People's Republic of China (MOST) grant 2017YFA0603602 and National Natural Science Foundation of China grant 41371491. The data sources include the following. Historical data of crop yields, food production, planting costs, market prices, per capita consumption, fertilizer use, planting area, and irrigation area at the provincial and national levels since the 2000s are compiled from statistical yearbooks published by National Bureau of Statistics of China (NBS of China, 2000–2015, <http://www.stats.gov.cn/tjsj/ndsj>). The provincial and national data before the 2000s are from the book of "China Compendium of Statistics 1949–2008" (NBS of China, 2010). The source of the county-level data is from the Department of Crop Production in the Ministry of Agriculture (<http://www.zzys.moa.gov.cn/>). Soil properties are derived from "soil database of China for land surface modeling" (Shangguan et al., 2014, <http://globalchange.bnu.edu.cn/research/soil2>). Water resource and usage information are based on records compiled from Ministry of Water Resources (1997–2015, <http://www.mwr.gov.cn/zwzc/hygb>). Historical weather (temperature and precipitation) data are provided by China Meteorological Administration (<http://cdc.nmic.cn>). Surface radiation fluxes are from Sheffield et al. (2006). Surface air relative humidity and wind speed are from Zhang et al. (2014). Land use data are from Gong et al. (2013). Crop distribution maps are from Ramankutty et al. (2008). GCM output for future climate scenarios under IPCC CMIP5 is acquired from the archive maintained by the Program for Climate Model Diagnosis and Intercomparison at Lawrence Livermore National Laboratory (<https://pcmdi.llnl.gov/search/cmip5/>). The climate models include BNU-ESM (from Beijing Normal University); CNRM-CM5 (from Centre National de Recherches Météorologiques at Météo France); GFDL-CM3, GFDL-ESM2G, and GFDL-ESM2M (from the National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory); IPSL-CM5A-MR (from the Institut Pierre Simon Laplace); and MIROC5, MIROC-ESM, and MIROC-ESM-CHEM (from the Japan Agency for Marine-Earth Science and Technology, the University of Tokyo, and the

capacity. For example, investment in building and maintaining infrastructure for agricultural water resources accounted for 6.6–8.0% of total investment in infrastructure in China between 1955 and 1980 (Ministry of Water Resources, 1988); this ratio remained at 3% (about 488.1 billion Chinese yuan) in 2014. Second, a long-term sustainability plan is needed based on a full evaluation of the availability of water resource, technology, and food demands to avoid unbalanced development. Third, it needs a clear definition of safe boundaries of water use for preparing the worst case in terms of extreme events. Finally, improving water-use efficiency through technology development and policymaking is important when expanding irrigation systems.

Overall, this research advances the study of broad-scale drought risk assessment in multiple ways. We quantify agricultural drought impacts by building integrated data-driven connections among climate, water resource, irrigation, technology, and agricultural management. We propose a generic metric for agricultural drought impact assessment that goes beyond drought indices and statistical approaches in accounting for both drought-induced damage and drought probability and establish that this metric is robust across multiple crop models in a supercomputer platform. Our results address the knowledge gap identified by Piao et al. (2010) to provide a quantitative assessment of agricultural risks in light of climate change, irrigation, and water resources in China's complex cropping systems. The modeling results reveal the contributions of groundwater to food production in normal and extreme drought situations and distinguish the causes between the drought effects and socioeconomic drivers in the largest food reductions during the 1960s and the 2000s. This research in particular provides a holistic view of the quantitative relations among climate, water, and food security in the past and the possible changes in future climate change.

Further study is needed in the next-step improvement. First, it is unclear individual farmers' water use when irrigating their croplands in different space and time. More investigation is required to monitor the actual water use and the availability of current water resources. Second, we are unable to fully consider how climate change will affect the future availability of water resources. Future work should address this limitation by integrating hydrological and crop models, thereby facilitating a more realistic representation of the evolution of water resource availability during extreme droughts. Third, none of the three crop models applied in this work include the effects of pests, storms, or flooding. More case studies with well-understood historical data are required to assess the biases that propagate systematically into the results of all three models. Fourth, historical and future crop parameters are changing, and these changes should be considered in modeling to reduce the uncertainty caused in parameterization. Fifth, geographical scales present an important source of uncertainty when applying crop models to large regions. County-level data represent the finest resolution available for historical records of yields and planting areas, but the soil, terrain, climate, and other relevant factors can vary substantially within a single county. The number of weather stations is also limited, particularly in earlier years, with multiple counties sharing data from a single station in some cases. These limitations may affect the accuracy of the model output. Drought risk maps interpolated from county-level results therefore may not accurately represent drought risks at finer resolutions. Future work will attempt to constrain the potential impacts of these limitations using alternative data sources (such as remote sensing data) and integrated modeling systems that combine climate, water, crop, and socioeconomic models.

### References

- Abebe, A., & Foerch, G. (2008). Stochastic simulation of the severity of hydrological drought. *Water Environment Journal*, 22, 2–10.
- Asseng, S., Ewert, F., Martre, P., Tter, R. R., & Lobell, D. B. (2015). Rising temperatures reduce global wheat production. *Nature Climate Change*, 5(2), 143–147.
- Bongaarts, J. (2016). Slow down population growth. *Nature*, 530(7591), 409–412.
- Chen, H., Wang, J., & Huang, J. (2014). Policy support, social capital, and farmers' adaptation to drought in China. *Global Environmental Change*, 24, 193–202.
- Dai, A. (2013). Increasing drought under global warming in observations and models: *Nature Climate Change*, 52–58.
- Das, P. K., Dutta, D., Sharma, J. R., & Dadhwal, V. K. (2016). Trends and behaviour of meteorological drought (1901–2008) over Indian region using standardized precipitation–evapotranspiration index. *International Journal of Climatology*, 36, 909–916.
- Di Paola, A., Valentini, R., & Santini, M. (2016). An overview of available crop growth and yield models for studies and assessments in agriculture. *Journal of the Science of Food and Agriculture*, 96, 709–714.
- Edgerton-Tarpley, K. (2008). *Tears from iron: Cultural responses to famine in nineteenth-century China*. Berkeley: University of California Press.
- Ellis, A. W., Goodrich, G. B., & Garfin, G. M. (2010). A hydroclimatic index for examining patterns of drought in the Colorado River Basin. *International Journal of Climatology*, 30, 236–255.
- Gao, B., Ju, X., Meng, Q., Cui, Z., Christie, P., Chen, X., & Zhang, F. (2015). The impact of alternative cropping systems on global warming potential, grain yield and groundwater use. *Agriculture, Ecosystems & Environment*, 203, 46–54.



National Institute for Environmental Studies). Three future climate change scenarios (Representative Concentration Pathways) are considered: RCP 2.6, RCP 4.5, and RCP 8.5. The three crop models are run independently using the individual model outputs from each of these climate change scenarios. To assess future trends in agricultural yields, GCM-based RMW yields for 2006–2014 based on each GCM and RCP scenario are normalized to match average 2006–2014 yields from the historical baseline irrigation or rainfed scenarios.

- Gong, P., Wang, J., Yu, L., Zhao, Y. C., Zhao, Y. Y., Liang, L., et al. (2013). Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing*, *34*(7), 2607–2654.
- Hu, Y., Liu, Y., Tang, H., Xu, Y., & Pan, J. (2014). Contribution of drought to potential crop yield reduction in a wheat-maize rotation region in the North China Plain. *Journal of Integrative Agriculture*, *13*, 1509–1519.
- Huang, J., Wang, Y., & Wang, J. (2015). Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. *American Journal of Agricultural Economics*, *97*, 602–617.
- Huang, M., Zhang, W., Jiang, L., & Zou, Y. (2013). Impact of temperature changes on early-rice productivity in a subtropical environment of China. *Field Crops Research*, *146*, 10–15.
- Huang, S., Dahal, D., Young, C., Chander, G., & Liu, S. (2011). Integration of Palmer Drought Severity Index and remote sensing data to simulate wetland water surface from 1910 to 2009 in Cottonwood Lake area, North Dakota. *Remote Sensing of Environment*, *115*, 3377–3389.
- Huang, X., Huang, G., Yu, C., Ni, S., & Yu, L. (2017). A multiple crop model ensemble for improving broad-scale yield prediction using Bayesian model averaging. *Field Crops Research*, *211*, 114–124.
- Jia, H., Wang, J., Cao, C., Pan, D., & Shi, P. (2012). Maize drought disaster risk assessment of China based on EPIC model. *International Journal of Digital Earth*, *5*, 488–515.
- Jin, Z., Zhuang, Q., Tan, Z., Dukes, J. S., Zheng, B., & Melillo, J. M. (2016). Do maize models capture the impacts of heat and drought stresses on yield? Using algorithm ensembles to identify successful approaches. *Global Change Biology*, *22*, 3112–3126.
- Kroes, J. G., Van Dam, J. C., Groenendijk, P., Hendriks, R., & Jacobs, C. (2009). SWAP version 3.2. Theory description and user manual, Alterra.
- Kroes, J. G., Wesseling, J. G., & Van Dam, J. C. (2000). Integrated modeling of the soil-water-atmosphere-plant system using the model SWAP 2-0 an overview of theory and an application. *Hydrological Processes*, *14*, 1993–2002.
- Lesk, C., Rowhani, P., & Ramankutty, N. (2015). Influence of extreme weather disasters on global crop production. *Nature*, *529*, 84–87.
- Li, B., Liang, Z., Zhang, J., & Wang, G. (2016). A revised drought index based on precipitation and pan evaporation. *International Journal of Climatology*, *37*(2), 793–801.
- Li, C. (Ed.) (2016). *Biogeochemistry: Scientific basis and modeling approach*. Beijing: Tsinghua University Press.
- Li, C., Frolking, S., & Harriss, R. (1994). Modeling carbon biogeochemistry in agricultural soils. *Global Biogeochemical Cycles*, *8*, 237–254. <https://doi.org/10.1029/94GB00767>
- Li, R., Tsunekawa, A., & Tsubo, M. (2017). Assessment of agricultural drought in rainfed cereal production areas of northern China. *Theoretical and Applied Climatology*, *127*, 597–609.
- Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J. W., Rötter, R. P., et al. (2015). Multimodel ensembles of wheat growth: many models are better than one. *Global Change Biology*, *21*, 911–925.
- Mearns, L. O., Mavromatis, T., Tsvetinskaya, E., Hays, C., & Easterling, W. (1999). Comparative responses of EPIC and CERES crop models to high and low spatial resolution climate change scenarios. *Journal of Geophysical Research*, *104*, 6623–6646. <https://doi.org/10.1029/1998JD200061>
- Mekonnen, M. M., & Hoekstra, A. Y. (2010). The green, blue and grey water foot-print of farm animals and animal products, Value of Water Research Report Series No. 48, UNESCO-IHE, Delft, the Netherlands.
- Ministry of Water Resources (1988). The rates water conservancy investment in the national infrastructure and agricultural investments. *China Water Conservancy*, *8*, 31.
- Ministry of Water Resources (1997–2015). *China water resource bulletin*. Beijing: China Water & Power Press.
- Ministry of water Resources, China (2011). *China water statistical yearbook 2011*. Beijing: China Water & Power Press.
- Ministry of water Resources, China (2014). Groundwater bulletin for northern plains. Retrieved from <http://www.mwr.gov.cn/zwzc/hygb/>
- Morgan, T. H., Biere, A. W., & Kanemasu, E. T. (1980). A dynamic model of corn yield response to water. *Water Resources Research*, *16*, 59–64. <https://doi.org/10.1029/WR016i001p00059>
- Naresh Kumar, M., Murthy, C. S., Sessa Sai, M. V. R., & Roy, P. S. (2009). On the use of Standardized Precipitation Index (SPI) for drought intensity assessment. *Meteorological Applications*, *16*, 381–389.
- NBS of China (2000–2015). China statistical yearbook (2000–2015). Retrieved from <http://www.stats.gov.cn/tjsj/ndsj/>
- NBS of China (2010). *China compendium of statistics 1949–2008*. Beijing: China Statistics Press.
- Niyogi, D., Liu, X., Andresen, J., Song, Y., Jain, A. K., Kellner, O., et al. (2015). Crop models capture the impacts of climate variability on corn yield. *Geophysical Research Letters*, *42*, 3356–3363. <https://doi.org/10.1002/2015GL063841>
- Palmer, W. C. (1965). *Meteorological drought, Research Paper* (Vol. 45). Washington, DC: Thornthwaite, U.S. Weather Bureau.
- Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., et al. (2010). The impacts of climate change on water resources and agriculture in China. *Nature*, *467*, 43–51.
- Qian, Z. (2009). The 60-year history of water-resource management in China (in Chinese). *Dushu*, *10*, 101–108.
- Qin, Z., Tang, H., Li, W., Zhang, H., Zhao, S., & Wang, Q. (2014). Modeling impact of agro-drought on grain production in China. *International Journal of Disaster Risk Reduction*, *7*, 109–121.
- Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2017). AquaCrop, version 6.0 reference manual. FAO: Land and Water Division, Rome, Italy.
- Ramankutty, N., Evan, A. T., Monfreda, C., & Foley, J. A. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, *22*, GB1003. <https://doi.org/10.1029/2007GB002952>
- Seneviratne, S. I., Lüthi, D., Litschi, M., & Schär, C. (2006). Land-atmosphere coupling and climate change in Europe. *Nature*, *443*(7108), 205–209.
- Shangguan, W., Dai, Y., Duan, Q., Liu, B., & Yuan, H. (2014). A global soil data set for earth system modeling. *Journal of Advances in Modeling Earth Systems*, *6*, 249–263. <https://doi.org/10.1002/2013MS000293>
- Sheffield, J., Goteti, G., & Wood, E. F. (2006). Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *Journal of Climate*, *19*, 3088–3111.
- Shi, G. (2015). The annual contributions of irrigation to rice yields in the Pi-Shi-Hang irrigation region during 1959–2013. *Jianghuai Water Resources Science and Technology*, 7–8.
- Shukla, S., & Wood, A. W. (2008). Use of a standardized runoff index for characterizing hydrologic drought. *Geophysical Research Letters*, *35*, L02405. <https://doi.org/10.1029/2007GL032487>
- Singh, A., Saha, S., & Mondal, S. (2013). Modeling irrigated wheat production using the Fao Aquacrop model in West Bengal, India, for sustainable agriculture. *Irrigation and Drainage*, *62*, 50–56.
- Steduto, P., Hsiao, T. C., Raes, D., & Fereres, E. (2009). AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal*, *101*, 426–437.

- Tao, F., & Zhang, Z. (2011). Impacts of climate change as a function of global mean temperature: Maize productivity and water use in China. *Climatic Change*, *105*, 409–432.
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*, 485–498.
- Tso, T. C. (2004). Agriculture of the future. *Nature*, *428*, 215–217.
- van Diepen, C. A., Wolf, J., van Keulen, H., & Rappoldt, C. (1989). WOFOST: A simulation model of crop production. *Soil Use and Management*, *5*, 16–24.
- Vrugt, J. A., ter Braak, C. J. F., Diks, C. G. H., Robinson, B. A., Hyman, J. M., & Higdon, D. (2009). Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling. *International Journal of Nonlinear Sciences and Numerical Simulation*, *3*, 273–290.
- Wang, J., Huang, J., Zhang, L., & Huang, Q. (2014). Do incentives still matter for the reform of irrigation management in the Yellow River Basin in China? *Journal of Hydrology*, *517*, 584–594.
- Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., & Zhang, L. (2009). The impact of climate change on China's agriculture. *Agricultural Economics*, *40*, 323–337.
- Wang, J., Yang, Y., Huang, J., & Chen, K. (2015). Information provision, policy support, and farmers' adaptive responses against drought: An empirical study in the North China Plain. *Ecological Modeling*, *318*, 275–282.
- Wang, X., Wang, Q., Fan, J., & Fu, Q. (2013). Evaluation of the AquaCrop model for simulating the impact of water deficits and different irrigation regimes on the biomass and yield of winter wheat grown on China's Loess Plateau. *Agricultural Water Management*, *129*, 95–104.
- World Meteorological Organization (2015). WMO guidelines on multi-hazard impact-based forecast and warning services, WMO-No.1150.
- Yan, H., Wang, S., Wang, J., Lu, H., Guo, A., Zhu, Z., et al. (2016). Assessing spatiotemporal variation of drought in China and its impact on agriculture during 1982–2011 by using PDSI indices and agriculture drought survey data. *Journal of Geophysical Research: Atmospheres*, *121*, 2283–2298. <https://doi.org/10.1002/2015JD024285>
- Yang, S., Ding, Z., Li, Y., Wang, X., Jiang, W., & Huang, X. (2015). Warming-induced northwestward migration of the East Asian monsoon rain belt from the Last Glacial Maximum to the mid-Holocene. *Proceedings of the National Academy of Sciences of the United States of America*, *112*, 13,178–13,183.
- Ye, L., Xiong, W., Li, Z., Yang, P., Wu, W., Yang, G., et al. (2013). Climate change impact on China food security in 2050. *Agronomy for Sustainable Development*, *33*, 363–374.
- Yu, C., Gong, P., & Ying, Y. (2011). China's water crisis needs more than words. *Nature*, *307*.
- Yu, C., Li, C., Xin, Q., Chen, H., Zhang, J., Zhang, F., et al. (2014). Dynamic assessment of the impact of drought on agricultural yield and scale-dependent return periods over large geographic regions. *Environmental Modeling and Software*, *62*, 454–464.
- Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, *19*, 333–349.
- Zhang, D. E. (2005). Severe drought events as revealed in the climate records of China over the last thousand years. *Acta Meteorologica Sinica*, *485*–491.
- Zhang, D. E., & Liang, Y. (2010). A long lasting and extensive drought event over China in 1876–1878. *Advances in Climate Change Research*, *1*, 91–99.
- Zhang, Q., Zhang, J., & Wang, C. (2017). Risk assessment of drought disaster in typical area of corn cultivation in China. *Theoretical and Applied Climatology*, *128*, 533–540.
- Zhang, T., & Huang, Y. (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, X., Tang, Q., Pan, M., & Tang, Y. (2014). A long-term land surface hydrologic fluxes and states dataset for China. *Journal of Hydrometeorology*, *15*, 2067–2084.