Introducing a drought index to a crop model can help to reduce the gap between the simulated and statistical yield

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ABSTRACT
A well-established and pre-calibrated crop model can normally represent the overall characteristics of crop growth and yield. However, it can hardly include all relevant factors that affect the yield, and usually overestimates the crop yield when extreme weather conditions occur. In this study, the authors first introduced a drought index (the Standardized Precipitation Evapotranspiration Index) into a process-based crop model (the Agro-C model). Then, the authors evaluated the model’s performance in simulating the historical crop yields in a double cropping system in the Huang-Huai-Hai Plain of China, by comparing the model simulations to the statistical yields. The results showed that the adjusted Agro-C model significantly improved its performance in simulating the yields of both maize and wheat as affected by drought events, compared with its original version. It can be concluded that incorporating a drought index into a crop model is feasible and can facilitate closing the gap between simulated and statistical yields.

1. Introduction
China’s agricultural production has increased rapidly during the past several decades (FAOSTAT 2017), due mainly to technological developments such as crop variety improvement and the adoption of fertilization and irrigation (Fan et al. 2012). Meanwhile, it has been reported that excessive irrigation has resulted in the cessation of river flows and the depletion of underground water sources (Wang et al. 2008). The overuse of irrigation is not sustainable, and agricultural production will be threatened by water shortages sooner or later.

It has also been reported that the current climate change background, characterized mainly by global warming, is expected to have negative impacts on food production and thus a threat to food security (Schlenker and Lobell 2010). In facing such a future whereby food security may be affected by climate change, our knowledge in this area needs to be advanced and our tools of assessment sharpened. Over the past several years, numerous efforts have already been taken to explore the directions and/or magnitudes in the impacts of droughts on crop yields (Vicente-Serrano et al. 2012; Wang et al. 2016; Zhang, Zhang, and Wang 2017). Most studies have adopted a statistical approach, which normally requires relatively less detailed information but is hard to apply at finer or larger spatiotemporal scales. A process-based crop model, however, has the advantage of estimating the spatiotemporal variations in crop productions under various environmental conditions and management practices. The disadvantages of a process-based model, meanwhile, are also clear: (1) several uncertain model parameters usually exist (Lobell, Torney, and Field 2011); and (2) it is difficult to include all relevant factors in model development. Consequently, existing process-based crop models often overestimate observed crop yields when extreme weather conditions occur (Ewert et al. 2002; Doltra, Lægdsmand, and Olesen 2011; Liu et al. 2011; Miguez et al. 2012; Rötter et al. 2012). Efforts to close this gap are essential; however, considerable challenges exist because of the complexity of agricultural systems and because crop yields are regulated by too many factors.
Among the extreme conditions traditionally neglected by a crop model, drought occurrence is recognized as one of the world’s most widespread climatic disaster types against the current climate change background (Helmer and Hilhorst 2006; Quiring and Ganesh 2010). Globally, the intensity and frequency of drought events have increased under global warming over the past several decades (Dai 2011, 2013), and crop yield reduction is significantly and positively correlated with drought (Li et al. 2009; Bo et al. 2015; Zhang, Zhang, and Wang 2017). In one of China’s foremost agricultural regions, the Huang-Huai-Hai (HHH) Plain (Figure S1), water shortage is also a critical stress factor for agricultural production (Wang, Liu, and Zhang 2002; Wang et al. 2008). Over the past several decades, this area has experienced enhanced intensity and frequency of drought occurrence (Bo et al. 2015). Nevertheless, the impacts of drought on crop yield variations has seldom been successfully characterized by a process-based modeling approach. In the present study, we first adjusted a biogeophysical model that contains a crop growth module (i.e., Agro-C) by introducing a drought index into the model. Then, we constrained the model against a historical county-level statistical yield dataset and compared the performance of the adjusted and original model.

2. Materials and methods

The spatial boundaries of the HHH Plain (Figure S1) were acquired from Liu et al. (2015). The spatial distribution of croplands was computed on the basis of the National Land Cover Data Sets of China, as developed from Landsat TM digital images in approximately 2000 (Liu et al. 2003). The agricultural model, Agro-C (Text S1), was used to model the yields of the winter wheat and summer maize system in the HHH Plain from 1991 to 2010 on a county scale. We selected the Agro-C model because it was developed based on observations conducted in China’s agro-ecosystems and has been frequently and successfully used to quantify agricultural production and carbon and nutrient dynamics at both regional and national scales in China (Huang et al. 2009; Wang et al. 2014; Zhang et al. 2017). A description of the spatial model inputs for Agro-C, such as climatic and edaphic conditions, as well as the agricultural management and crop phenology data, are also presented in Text S1. A yearly county-level database (Huang and Tang 2010) including the annual cultivation acreage and yield for each crop in China was used to determine the annual statistical crop yields of both winter wheat and summer maize in the HHH Plain over the study period. These statistical yield data were used to adjust the model simulated yield, based on the drought condition as characterized by the Standardized Precipitation Evapotranspiration Index (SPEI). We chose SPEI because it has been proved to be advantageous for drought monitoring in northern China owing to its multiscalarity and effective characterization of agricultural droughts (Wang et al. 2016). The R SPEI package (http://cran.r-project.org/web/packages/SPEI) was used to compute the monthly SPEI for wheat and maize growing seasons, and the evolution of cumulative moisture conditions from 1- to 12-month lags was selected to identify the impact of the SPEI interannual variability on crop yield (Potopová et al. 2015). In general, drought occurs when the SPEI value is negative; and the smaller the SPEI, the higher the drought intensity (Table 1).

Based on the compiled county-level soil, climate, crop, and management model input data, the crop yields from 1991 to 2010 in each county were simulated by Agro-C in daily increments. The simulated and statistical crop yields were further categorized according to the average SPEI values in the associated growing seasons. Here, crop growing seasons were assumed under no drought to have an SPEI value of more than 0, under slight drought to have an SPEI from −0.99 to 0, moderate drought an SPEI from −1.49 to −1, and severe and extreme drought an SPEI less than −1.5 (Table 1).

In the model simulations, we found that the simulated crop yields were generally higher than the associated county statistical yields, regardless of the SPEI categories. Such a general overestimation could be attributed to other factors not considered in the model, and the overall bias needed to be eliminated before analyzing the impacts of drought on yield reduction. By doing this, we firstly calculated the average bias between the original simulations and statistics (i.e., overall bias) in each county for the years without droughts (i.e., SPEI > 0). Then, the simulated crop yields for all years in a county were further determined by subtracting the above-calculated overall bias from the yield of the original model simulations.

Under different SPEI ranges, we then calculated the average proportion between the statistical and

| Category                | SPEI value |
|-------------------------|------------|
| Extremely wet           | > 2.0      |
| Severe wet              | 1.50 to 1.99|
| Moderate wet            | 1.0 to 1.49|
| Near normal             | 0.99 to −0.99|
| Moderate drought        | −1.49 to −1.00|
| Severe drought          | −1.99 to −1.50|
| Extreme drought         | < −2.00    |
simulated crop yields (Table 2). In the model adjustment, these ratios were used to multiply the simulated crop yields and improve the model’s performance under different drought conditions. All analyses were performed with the statistical and graphical software R 3.4.2 (R Development Core Team 2017).

### 3. Results and discussion

In general, the original version of the Agro-C model overestimated the yields for both crops associated with a drought-affected growing season, particularly under higher drought intensities, e.g., SPEI < −1 (Table 1). For slight drought (SPEI from −0.99 to 0, also characterized as near-normal conditions in Table 1), the ratios between the statistics and simulations were 0.98 and 0.99 for wheat and maize, respectively (Table 2). For moderate drought (SPEI from −1.49 to −1), the ratios decreased to 0.91 for both wheat and maize (Table 2). The ratios were even lower at 0.86 for wheat and 0.89 for maize when severe and extreme drought events occurred (SPEI < −1.5, Table 2).

Adjusting the model by multiplying the simulated yields under different SPEI categories with the associated ratios (Table 2) improved the model’s performance in representing the observed crop yields as affected by drought (Figure 1). Figure 1 shows the statistical and Agro-C (adjusted and original versions) simulated crop yields of maize and wheat under drought growing seasons (SPEI < 0) over the study period. Both the simulated maize and wheat yields were better represented by the adjusted model than its previous version. In general, of the drought growing seasons, the adjusted Agro-C model could explain 51% and 63% of the variations in observed maize and wheat yields, respectively (Figure 1). The relative mean deviation (RMD) decreased from around 5% under original simulations to less than 1% with adjusted model simulations for both crops (Figure 1).

In addition, based on the calculated SPEI values, we found that drought conditions occurred during both

### Table 2. Ratios between observed and simulated crop yields under different ranges of the Standardized Precipitation Evapotranspiration Index (SPEI).

| SPEI value | Wheat Average | Wheat SD | Maize Average | Maize SD |
|-----------|---------------|----------|---------------|----------|
| > 0       | 1.00          | 0.12     | 1.01          | 0.18     |
| −0.99 to 0| 0.98          | 0.16     | 0.99          | 0.19     |
| −1.49 to −1| 0.91        | 0.16     | 0.91          | 0.22     |
| < −1.50   | 0.86          | 0.14     | 0.89          | 0.27     |

Note: SD, Standard deviation.

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Figure 1. Yields of (a, b) maize and (c, d) wheat in the (a, c) original and (b, d) adjusted simulations. Yield data are for the drought years (Standardized Precipitation Evapotranspiration Index < 0) across counties from 1991 to 2010. The black and blue points show the original and adjusted simulations, respectively. The black and blue solid lines are the fitted linear regressions for the original and adjusted simulations, respectively.
crop growing seasons in 2002 based on the quantified average SPEI values (Figure 2(a,b)). This is consistent with the reports of the Ministry of Agriculture of the People’s Republic of China (2009), which documented that the drought-affected crop areas across Hebei, Shandong and Henan in 2002 were around 1.5-fold that in adjacent years (i.e., average of 2001 and 2003). Consequently, it can be concluded that the SPEI is a useful tool for quantifying drought-affected agricultural crop growing seasons.

Figure 2 shows the temporal changes in regionally averaged crop yields for summer maize (Figure 2(a)) and winter wheat (Figure 2(b)). In general, both the original and adjusted model simulation results were able to reasonably capture the temporal patterns of the statistical crop yields. In drought years (i.e., SPEI < 0), however, the simulations of the adjusted model were more consistent with the statistics than the original version (Figure 2(a,b)). For example, when the average SPEI in both maize and wheat growing seasons was less than −1 (i.e., drought-affected growing seasons), the adjusted simulations better represented the observations than the original model (Figure 2(a,b)). By introducing the SPEI in to the Agro-C model, the model’s overall performance in simulating the statistical yields was advanced. Nevertheless, under certain circumstances, the adjusted model (with SPEI included) degenerated the model’s performance (e.g., maize in 1999; Figure 2(a)). This may be attributable to either errors in the statistics or other factors that regulate crop yield variations but are not considered in the model.

The overall improvement in the model’s performance was also identifiable at the county scale. For example, in Luan and Ju County (Figure S2), the adjusted model bridged the gap between observations and simulations in the drought-affected maize growing seasons (Figure 3(a,b)). For the drought-affected wheat growing seasons, the results for Dacheng and Kaifeng County (Figure S2) showed that the adjusted model better captured the observations than the original model as well (Figure 3(c,d)). When pooling all the regional-scale average crop yields through the study period together, we found that the adjusted model explained around 70% of the variations in the observations (Figure 4(a,b)). The advances in the $R^2$ values for both crops were relatively small, i.e., 2% (Figure 4). The RMD values, however, were reduced significantly from 6.0% to 3.9% for maize (Figure 4(a)) and from 1.6% to −0.2% for wheat (Figure 4(b)). It should be noted that both the statistical and simulated crop yields in some years when severe drought events occurred did not decline significantly compared to normal years (e.g., maize in 1992 at Ju County (Figure 3(b)) and wheat in 2002 at Kaifeng County (Figure 3(d)). This is because water irrigation has been widely adopted to support crop production across the cropping regions in the whole HHH Plain over the past three decades, which is also configured accordingly in the model simulations. Water irrigation could of course reduce the impacts of drought on crop yield reduction.

It can be concluded that, by including the drought index, a crop model can better represent the observed crop yields. However, we acknowledge that the improvement is relatively small (Figure 4). This may be attributable to: (1) irrigation having been widely adopted in the HHH Plain during the study period, which possibly overshadowed the impacts of drought events; (2) the Agro-C model already has the capacity to simulate the dynamics of soil water and capture crop growth and yield well, meaning the room for improvement by including a drought index is limited; and (3) crop yields are influenced by complex interactions among many factors, and thus considering only drought events may be insufficient. As
such, we highlight a need for future research to include other stress factors in crop model development, like hot and dry winds, disease and pests. Moreover, it has been reported that including only a single drought index (such as SPEI in the current study) may be insufficient for describing a complete picture of the drought process, because soil moisture is also a key indicator when identifying drought propagation, coverage and strength (Adnan, Ullah, and Gao 2015). Despite having chosen to use SPEI in the present study because of its simplicity and versatility, we nonetheless highlight a need to include soil moisture data in determining drought events in future...
studies. In addition, we simply analyzed the impacts of drought conditions on crop yields without including the crop growth in response to droughts in different growing stages. We therefore highlight a further need in future work to quantify the impacts of drought on crop behavior during different phenological stages, which will provide insight into efficiently ameliorating yield reductions induced by drought disasters.

**Disclosure statement**

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