Decreasing wheat yield stability on the North China Plain: Relative contributions from climate change in mean and variability

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Abstract

There has been increasing interest in understanding climate change impacts on crop yield stability, including interannual yield variability and lower yield extremes, in addition to mean yield. In this study, we evaluated these impacts on wheat yield and investigated the contribution of changes in climate mean and variability, and their interaction, on the North China Plain (NCP). Wheat yield simulation experiments with control groups were conducted using the Crop Environment Resource Synthesis (CERES) model, with multiple general circulation model ensembles under two representative concentration pathways (RCPs), namely 4.5 and 8.5. Climate change was projected to reduce mean yield by 15 and 17%, increase yield interannual variability by 5 and 11%, and reduce 10-year return period lower yield extremes by 31 and 34% under RCPs 4.5 and 8.5, respectively. When analysed, changes in climate mean proved the main cause for changes in mean yield (62–71%), followed by the interactive changes in climate mean and variability (26–33%). As for the impact on yield variability, the interaction of the changes in climate mean and variability proved the main cause (48–54%), followed by changes in climate mean (33–41%). Surprisingly, climate change in variability contributed the least in both cases. Our results pertaining to the decrease in both availability and stability of wheat yield on the NCP presents a greater challenge for building a resilient food system for local areas than before. They also highlighted the importance of separating the impacts of changes in climate mean and variability on crop yield stability in a holistic framework, with particular attention paid to the tangible and interactive effects.

KEYWORDS
changes in climate mean and variability, crop model, North China Plain, wheat yield stability
INTRODUCTION

Global climate change presents a serious challenge to sustainable development and human security (IPCC, 2014a) and has led to an important consensus to conduct global change risk assessments and to take risk-informed actions (IPCC, 2014b; UNDRR, 2019). The risk to food security is particularly important among the various types of risks (O’Neill et al., 2017) because of the stress on food production that is imposed by climate change and the projected rapid increase in demand with global population growth (Tilman et al., 2011). Previous studies have mostly focused on the variation in the mean global population growth (Ruane et al., 2011; Rosenzweig et al., 2014; Liu et al., 2016b; Ruane et al., 2018; Van Meijl et al., 2018), addressing the issue of availability in food security. Climate change impacts on food stability, however, remains as a key research gap (IPCC, 2019). Increases in the yield interannual variability and the likelihood of lower yield extremes can affect the livelihoods of farmers (Morton, 2007), increase pressure on inter-temporal food reserves (Bobenrieth et al., 2013), induce large price changes in the global market, or even destabilize regions of the world (Sternberg, 2011).

Recent studies have preliminarily evaluated climate change impacts on yield stability from the angle of yield interannual variability and lower yield extremes. Yield interannual variability has been reported to increase over 9–22% global crop sown areas during the period 1981–2010, and over 21% of yield variability change could be explained by the change in variability of the agroclimatic index (Iizumi and Ramankutty, 2016). In the future, along with global warming, yield interannual variability and the probability of lower yield extremes have been projected to increase simultaneously in tropical wheat production regions (Liu et al., 2019) and major maize production regions worldwide (Tigchelaar et al., 2018). Evidence of the impact has also been found at regional/country scales. For instance, the probability of lower maize yield extremes was projected to increase by 10–30% in the United States (Leng and Hall, 2020).

When analysing yield interannual variability and lower yield extremes responses to climate change, present studies have followed three main hypotheses: (1) yield variability changes in response to climate variability change (Osborne et al., 2013; Iizumi and Ramankutty, 2016); (2) yield extremes change in response to climate extremes (Trnka et al., 2014) and (3) yield variability changes in response to climate mean changes (Urban et al., 2012; Tigchelaar et al., 2018). However, as climate change contains simultaneous changes in mean, variability and skewness (IPCC, 2012), and consequently in extremes, climate change impacts on crop yield, in response, must be evaluated through a holistic framework. Previous studies have mostly omitted either mean or variability in analyses and have largely ignored their interactive effects (Wang et al., 2018). Further discussions on the impacts of changes in climate mean and variability, and their interactive changes on yield changes (mean, interannual variability and lower extremes), including the direct and interactive impacts, and quantifying the relative contributions of these impacts, are critically important for a complete understanding of the impacts of climate change on crop yield.

In this study, wheat yield changes on the North China Plain (NCP) was evaluated in the context of future climate change. Two key questions were addressed: (1) How do wheat mean yield and yield stability (including yield interannual variability and lower yield extremes) change in response to climate change? (2) In what ways do changes in the climate components (mean and variability) contribute to mean yield and yield stability? To simulate the changes in wheat yield from 1981 to 2099 under two representative concentration pathways (RCPs 4.5 and 8.5), a process-based crop model, the Crop Environment Resource Synthesis (CERES) model for wheat in the Decision Support System for Agrotechnology Transfer (DSSAT; DSSAT-CERES wheat) (Jones et al., 2003), was used with five general circulation models (GCMs) (Warszawski et al., 2014). The simulated mean yield, interannual yield variability (standard deviation), and lower yield extremes (10th percentile of the yield distribution) over each 25-year period were used to analyse the changes in wheat yield. Controlled simulation experiments were designed by holding either the climate mean or variability as a constant from the baseline, and the differences in the yield change were measured to determine the contributions of the changes in climate mean and variability, and their interaction. Finally, the implications of adaptation and further analysis on the impacts of climate change on wheat yield were examined.

MATERIALS AND METHODS

2.1 Study area

The NCP is located within 32°–40°N and 114°–121°E. The NCP is the largest wheat production area in China (Zhao et al., 2016), contributing more than 60% of China’s total harvest and is critical not only for the Chinese population but also for international wheat trade (Tao and Zhang, 2013). Geographically, the NCP includes the Hebei, Henan, Shandong, and Shanxi provinces...
(Yin et al., 2015). The average elevation of the NCP is 20 m. The major climate type is the temperate monsoon climate, with an annual mean temperature of 8–15°C, and annual cumulative precipitation of 500–900 mm. The NCP has a crop rotation system; winter wheat is planted in September or October and harvested in June, and maize is planted in summer and harvested in fall (Wang et al., 2012). The fields are well irrigated with flood or furrow irrigation, and fertilization is sufficient.

Considering the crop model input data requirements, eight agrometeorological stations (AMSs) were selected on the NCP: Zunhua and Bazhou in Hebei Province; Xinxiang, Nanyang and Zhumadian in Henan Province; and Huimin, Juxian and Liaocheng in Shandong Province. All stations were in typical wheat production areas, and the climatic and geographic differences among the stations were sufficiently large to represent the study area. Descriptions of the exact locations, climate conditions, wheat phenology, and field experimental data that were used to validate the crop model are provided in Table S1 and Figure S1. There are also other stations in the study area. However, they were not included in the analysis due to frequent changes in cultivars or missing management information.

2.2 | Data

2.2.1 | Historical wheat field experimental data

Historical wheat field experimental data, including the observed wheat sowing date, anthesis date, maturity date, harvest date, fertilization, irrigation and yield, were obtained from the China Meteorological Administration (CMA; http://data.cma.cn/). The soil surface and profile conditions were obtained from the Harmonized World Soil Dataset (Nachtergaele et al., 2008). The soil profile was divided into two layers: 0–30 cm and 30–100 cm. For each layer, information was provided on the soil properties, including the organic carbon, Ph, water capacity and the proportions of clay, sand and stone (Table S1).

2.2.2 | Climate data

Historical climate observations from eight national reference meteorological stations were used for crop model calibration and validation. Climatic data for the daily maximum temperature (\(T_{\text{max}}\)), daily minimum temperature (\(T_{\text{min}}\)), sunshine hours and precipitation (\(Pr\)) from 1981 to 2005 were obtained from the CMA. The daily sunshine hours were converted to daily solar radiation (\(SR\)) using the empirical Angstrom function (Angstrom, 1924).

The climate projections for 1981–2099 were obtained from the Intersectoral Impact Model Intercomparison Project (ISI-MIP). Five general circulation models (GCMs, including Hadgem2-ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M) that have been used most commonly in climate change impact on crop yield studies (Rosenzweig et al., 2014; Yin et al., 2015; Iizumi et al., 2017) were selected as the climate forcing inputs. The five GCMs were developed by ISI-MIP to span the space of global mean temperature change and relative precipitation changes as best as possible (Warszawski et al., 2014). The data were interpolated into 0.5° resolution, and bias was corrected to ensure agreement with Water and Global Change (WATCH) climate forcing data (Hempel et al., 2013).

Before the GCMs were used, tests for consistency between the projected data and historical observations were conducted. Large disagreements were found between the two datasets. The ISI-MIP bias correction was based on a global gridded dataset, and therefore might have retained biases on the NCP local areas. Further bias corrections were conducted with the bias correction methodology described by Hempel et al. (2013) to improve consistency between the observed and projected data over the historical period. This correction effectively reduced the root mean square error (RMSE) between GCMs and the observed data (Table S2, Figure S2).

2.3 | Methods

Four steps of analyses were followed (Figure 1): (1) calibrate and validate the DSSAT-CERES wheat model with the experimental field data, and the corresponding meteorological observations and soil data; (2) set up climate scenarios on the basis of the bias-corrected ISI-MIP projection data to separate the changes in climate mean and variability; (3) simulate the wheat yield using the calibrated model, prepare the climate forcing scenarios, and measure the yield change and (4) evaluate the impacts and relative contributions of the changes in the climate mean and variability, and their interactions.

2.3.1 | DSSAT-CERES wheat model calibration and validation

DSSAT-CERES wheat is one of the most frequently used process-based crop models for the analysis of the impacts of climate change on wheat yields (Jones et al., 2003; White et al., 2011). In this study, DSSAT version 4.7
(Hoogenboom et al., 2017) was calibrated and validated with historical field experimental data, and the corresponding meteorological observations and consistent soil properties obtained from the national reference meteorological stations. The calibration procedure followed the standard approach of cultivar-specific calibration (Xiao and Tao, 2014). Our experimental records spanned over a long period (1981–2009) but suffered from frequent cultivar changes, as has occurred in many other studies (Ruane et al., 2016). As a result, for each station, years of observation that had identical cultivars were used for model calibration. The observation of 1 year was used for calibration with the generalized likelihood uncertainty estimation (GLUE) (He et al., 2010), while the observations for the rest of the years were used for validation. The validation performances were evaluated by $R^2$, predicted deviation (PD) and relative root mean square error (RRMSE) between the observed and simulated yields, anthesis dates and maturity dates as follows:

$$PD = \frac{(S_i - O_i)}{O_i}$$

and

$$RRMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \times 100\%$$

where $O_i$ is the observed value, $S_i$ is the simulated value and $n$ is the sample size. In general, a PD within ±15% indicates that the calibration process has reached an agreement between the simulated and observed values (Timsina and Humphreys, 2006). If the $RRMSE$ is less than 10%, the model performance is considered perfect (Rinaldi et al., 2003).

2.3.2 Climate change scenarios

To evaluate the impact of climate change on yield and unravel the contributions of changes in climate mean and variability, one baseline scenario and three climate change scenarios were considered (Figure 1). Scenario 0 (S0), the baseline scenario, used climate data from the historical period (1981–2005). Scenario 1 (S1), which was the scenario for the change in climate mean alone, allowed changes in the climate mean but not in climate variability, and used the climate mean of the future period and climate variability from the historical period. Scenario 2 (S2), which was the scenario for the change in climate variability alone, allowed changes in the climate variability but not in the climate mean, and used the cli-
mate variability of the future period and the climate mean from the historical period. Scenario 3 (S3), which was the scenario for changes in both climate mean and variability, used the climate mean and variability projected for the future period.

With these scenarios, for S1 and S2, the changes in the mean and variability first had to be separated to create a new series in which either the climate mean or variability was controlled (assuming no change). In this study, empirical mode decomposition (EMD) was used to separate four climate factors, namely the maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), solar radiation (SR) and precipitation (Pr), into several intrinsic mode functions (IMFs). EMD is a nonstationary method that is widely used for the decomposition of time series (Huang et al., 1998) in meteorological analyses. The results of the EMD can be divided into several IMFs, with periods that are constant, and a residue term, which has a period that is infinite. In this study, the residue term with infinite frequency was used to denote the change in climate mean, and the IMFs together represented the change in climate variability.

A schematic chart is provided that used $T_{\text{min}}$ as an example (Figure S3). The baseline scenario used the historical period (baseline: 1981–2005) of the bias-corrected ISI-MIP climate data. Scenario 3 used the data for the future period (2006–2099) of the bias-corrected ISI-MIP climate data. We further used three sub-periods from the future period: the 2030s (2011–2035), the 2050s (2041–2065), and the 2080s (2071–2095). Then, each of the climate components (mean and variability) for each of the future periods was replaced with its corresponding historical component. For example, in S1, climate forcing was reassembled by replacing the climate variabilities of each of the three future periods (the 2030s, 2050s and 2080s) with historical ones (the baseline). After the components of climate change (changes in means and variabilities) of all four climate factors were obtained, the climate data were prepared for all four scenarios for the controlled experiment (Figure 1).

2.3.3 | Wheat yield simulation and yield change metrics

The calibrated DSSAT was then used to simulate the wheat yield with the driving of five GCMs under RCP 4.5 and RCP 8.5. We kept the region-specific soils, current cultivars, and crop management consistent among the baseline period and the 2030s, 2050s and 2080s. Two of the stations, Nanyang and Zhumadian, used rainfed cultivation. The other stations were classified as irrigated cultivation, which was reflected using the average irrigation levels in the calibration and validation.

To fully describe the yield change, the conventional approach was to derive the probability distribution or cumulative distribution of the yield (Coble et al., 2010; Ye et al., 2015). In this study, we computed the changes in mean yield (multi-year average), yield interannual variability (multi-year standard deviation), and lower yield extremes (multi-year 10th percentile) across different 25-year periods. To account for the uncertainty associated with the projected input climate data (Tao and Zhang, 2013), the computation was conducted for simulated yield series derived independently with each GCM, and the statistics of the multi-model ensemble were reported.

The changes in yield $Y^c$ relative to the baseline under each GCM and station were determined as follows:

$$\Delta Y^c = \frac{Y^c_t - Y^c_0}{Y^c_0} \times 100\%$$

where $c = m, v, e$, which indicate the mean yield, yield interannual variability, and 10-year return period lower yield extremes, respectively; $i = 1, 2, 3$ represents the scenarios of changes in climate components (Figure 1); and $t$ = the 2030s, 2050s and 2080s. The subscript 0 indicates the baseline (S0).

2.3.4 | Relative contribution analysis

The impacts of the changes in climate mean and variability on the yield were measured by the difference $\Delta Y^c$ of the corresponding scenarios under each GCM and at each station ($i = 1$ for change in climate mean and $i = 2$ for change in climate variability). The interaction effect was then the change in the yield associated with the changes in the climate mean and variability together, minus the sum of the changes associated with changes in either the climate mean or variability, which was calculated as follows:

$$\Delta_{\text{int},t} = \Delta_{t} - \left( \Delta_{1,t} + \Delta_{2,t} \right)$$

Based on these separated impacts, the relative contribution of a specific climate change component $k$ to the yield change component $c$ was derived using the following conventional method (Hu et al., 2017; Zhu et al., 2019):

$$R_{k,t}^c = \frac{\Delta Y^c_{k,t}}{\Delta Y^c_{\text{int},t}} \times 100\%$$

where $k = m, v, \text{int}$, which represent the relative contributions from the changes in the climate mean and variability, and their interaction, respectively.
3 | RESULTS

3.1 | Model validation and evaluation

After calibration and validation, our model could effectively capture the anthesis and maturity dates and wheat yield (Figure S4). The $R^2$ values of the anthesis date, maturity date, and wheat yield were 0.99, 0.96 and 0.65, respectively, while the PDs were all less than 12%, and the RRMSE values were 0.93, 1.84 and 8.78%, respectively, indicating that the model performance reached an agreement between the simulated and observed values (Timsina and Humphreys, 2006).

3.2 | Projected climate changes in the mean and variability

The changes in the mean values of SR, $T$ (mean of daily maximum and minimum temperature), and the total $Pr$ during the growing season in the 2030s, 2050s and 2080s compared with the baseline are shown in Figure 2. Our study area was projected to have a considerable increase in the growing season mean $T$ (1–5.4°C, median values) and the magnitude of warming was projected to increase in the more distant future. The growing season total precipitation was projected to experience reductions in the 2030s (7.3–7.6%, or 9.8–8.6 mm, median values) but then increased after that (5.4–8.8%, or 6.3–12.5 mm, median values). A very modest change in the growing season mean $SR$ was found (−1.6 to 2.7%, or −0.22 to 0.43 MJ/m², median values). The changes in climate variability were substantially smaller than those in the mean. The variability of $T$ was projected to modestly change by −0.08 to 0.08°C (median values). The $Pr$ variability was predicted to change from −15.8 to 3% (or −6.6 to 1.1 mm, median values). The $SR$ was noted to increase by 8.9–25.8% (or 0.04–0.11 MJ/m², median values).

At the station level, the magnitudes of the increases in temperature and solar radiation were similar across the eight stations in the study area (Figure S5). The growing season total precipitation increased in the southern parts of the study area, which were also the locations of the two rainfed stations, Nanyang and Zhumadian, while at the irrigated stations, the precipitation was predicted to decrease under RCP 4.5, with the reduction smaller

FIGURE 2 Changes in the means (top) and variabilities (bottom) of the mean $T$, total $Pr$ and mean $SR$ during the growing season in the 2030s, 2050s and 2080s compared with baseline under RCPs 4.5 and 8.5 using biascorrected projection results from five GCMs (box: 0.25 and 0.75 quartile; black line: median). Each box contains 40 results (eight stations under five GCMs)
under RCP 8.5. At most stations, the T variability was predicted to decrease, such as Huimin, Liaocheng, Juxian, Nanyang and Zhumadian. Similarly, the Pr variability was predicted to be reduced at all stations, except Bazhou and Xinxiang. The pattern of the change in SR variability was also very small across all stations.

### 3.3 Wheat yield changes

The changes in yield are summarized in Figure 3. The results indicated a clear pattern of reducing mean yield by 5.7–29.4% (median values), increasing yield interannual variability by 0.4–21% (median values) (except for the 2050s in RCP 4.5, −4.6%) and reducing the 10-year return period lower yield extremes by 25.9–39.8% (median values). In general, a larger increase or reduction was associated with a larger magnitude of warming (either in the more distant future or under RCP 8.5).

At station level (Figure S6), the simulated yield time series showed a clear downward trend at all stations except Zunhua, which is located in the northern part of the study area. This trend was not consistent with the reported increase in wheat production in China over the past decades. The critical reason for such a difference is the improvement in cultivar and management (Liu et al., 2010; Zhang et al., 2013), which was assumed to be constant in the simulation. In Zunhua, the mean yield was predicted to increase, and the yield interannual variability would decrease until the 2050s, indicating the initial beneficial impact of warming on the colder regions, but the change would reverse after that time period. For other stations south of Zunhua, the mean yield would decrease, and the yield interannual variability in most southern stations would increase.

### 3.4 Contribution of climate change to yield changes

Notably, when change was only assumed in the climate mean (S1, Figure 4), the mean yield decreased gradually by 5.3–6.3%, 12.8–17.3% and 16.4–26.5% (median values) during the 2030s, 2050s and 2080s, respectively. The yield reduction under RCP 8.5 was larger than that under RCP 4.5. The change in the climate mean also induced a reduction of 1.7–6.1% in the yield interannual variability. The median change in the 10-year return period lower yield extremes was negative, from −46.3 to −6.2%. Because the lower yield extremes (10th percentile) could be to the left of the mean by several standard deviations (two for a normal distribution), the increase in the 10-year return period lower yield extremes could be explained by the changes in the mean yield and interannual variability.

Climate change in variability alone (S2) brought only modest changes in the mean yield (Figure 5). The impact on yield interannual variability was positive, with changes of 0.5–2.5% (median values), except for in the 2030s under RCP 4.5. The 10-year return period lower yield extremes also increased as a result of the modest changes in the mean and variability. Therefore, the impacts of the changes in climate variability alone were modest at the median values across the stations. Nevertheless, the differences in the yield interannual variability
across the stations and GCMs were still larger than that of the mean yield.

When measured as the relative contributions (Figure 6), a large effect was found to be due to changes in the climate mean, which accounted for 62–71% of the total changes in the mean yield and 33–41% of changes in the yield interannual variability. The interactive effect was the second largest contributor to changes in the mean yield (26–33%) and the largest contributor to the yield interannual variability (48–54%). Changes in climate variability had the smallest relative contribution to changes in the mean yield and yield interannual variability, with less than 15% for both.

4 | DISCUSSION

4.1 | Future wheat yield changes on the NCP

Our results indicated that reduced mean yield, decreased yield stability with increased interannual variability, and smaller 10-year return period lower yield extremes occurred at seven out of the eight stations (with Zunhua being the exception). Our results echo earlier reports in many respects.

For wheat mean yield, our result of reduced mean yield at seven out of the eight AMS stations was highly consistent with previous reports: global warming is likely to induce wheat yield loss at lower and mid latitudes but could benefit yield production at higher latitudes (Rosenzweig et al., 2014). A detailed analysis of China based on global gridded crop model outputs has also reported a 10–30% reduction in the mean yield (without CO₂ fertilization) in future on the NCP, except for its northern border (Yin et al., 2015). Another simulation driven by 30 GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) reported that the wheat mean yield would decrease by 2–8.9% under RCP 4.5, and 2.4–12.3% under RCP 8.5 (Yang et al., 2014). This result was somewhat more optimistic than ours.

As for yield stability, there have been rather limited reports pertaining to wheat in the NCP. In a global analysis covering 1981–2010, both a significant increase and decrease in the interannual variability of wheat yield has been found in the NCP (Iizumi and Ramankutty, 2016). For the future period, a global station-based evaluation of climate change impacts on wheat yield interannual variability and lower yield extremes can be found in Liu et al. (2019). Due to their consideration of the CO₂ fertilization effect, their results are more optimistic than ours: a 5% increase and a 10% reduction in the yield

At the station level, there were large differences in the relative contributions (Figure S7). In general, the stations in the southern part (warmer) and closer to the coast (wetter) were predicted to have a larger contribution from the interactive effects of changes in climate mean and variability. For instance, contributions from the interactive effect on the mean yield and variability were both larger than 50% in Juxian, Xinxiang and Zhumadian. The stations in the northern areas were predicted to have a larger contribution from the change in climate mean. A typical example was Zunhua, for which the contributions of climate mean change reached 60% on average.
coefficient variance (CV) at Luancheng (204 km northwest of LiaoCheng) and Xuchang (134 km north of ZhuMadian), respectively. Correspondingly, our results showed a 4–6.6% increase for LiaoCheng (the 2050s, RCP 4.5, equivalent to 2°C warming) and a 20–80% increase for ZhuMadian. Their results also suggested a smaller probability (2.5–5%) of experiencing the fifth percentile of yield (Liu et al., 2019) in Luancheng and Xuchang.

### 4.2 Relative contributions from climate change in mean and variability

In our results, climate change mean has a relatively strong impact on mean yield and yield interannual variability, accounting for 62–71% of the total changes in the mean yield and 33–41% of changes in the yield interannual variability. Its impact on mean yield has been extensively discussed in the literature, and the largest share of relative contribution is expected. The impact on yield interannual variability echoes the third hypothesis mentioned in the introduction, that yield variability changes in response to climate mean changes, as proposed by Urban et al. (2012). In our results, all stations except Zunhua were found to have increased yield interannual variability as warming is driving the growing season mean temperature further away from the optimal thermal condition.

The impact of climate variability change was relatively large on yield interannual variability, contributing 11–13% of the total change. There is no direct evidence available for the NCP for comparison. The global estimate from Iizumi and Ramankutty (2016) suggested that over 21% of global yield interannual variability change can be explained by climate variability changes. Their results indicate a statistically significant linkage between yield and climate variability changes, which is consistent with our results. However, their figure, the $R^2$ derived from single-variate regression is not directly comparable with ours, as the impact of climate change in mean was not considered simultaneously.

However, existing theory would suggest that climate variability change is the major driver of yield variability change. Our results did not reject such a hypothesis. The limited contribution of climate variability change in our results was mainly due to minor changes in climate variability. For instance, the magnitude of the growing season temperature change in variability (−0.08 to 0.08°C) is substantially smaller than that in mean (1–5.4°C; Figure 2). Consequently, the contribution of climate variability change was low, even if the marginal impact of climate variability change on yield variability is large.

In our results, the interactive effect of climate mean and variability contributed considerably to mean yield changes (26–33%) and yield interannual variability changes (48–54%). This point has rarely been discussed in earlier studies. Based on this evidence, the interactive effect of changes in the climate mean and climate variability must be highlighted in future studies on the impacts of climate change on crop yield. This recognition is very important because climate change, by definition, includes climate change in the means and variabilities (IPCC, 2012). When constant climate variability in crop simulations is assumed, or the interactive effects of the changes in the climate mean and variability are ignored, in regressions, biased estimates of climate impacts on crop yields are highly likely.

In order to further explore the mechanism of impacts, we investigated the effects of temperature change in mean and variability on mean yield and yield interannual variability. We did not consider SR and Pr for this analysis as (1) temperature dominated the impact of climate change on yield (Figure S8) and (2) six out of the eight stations were irrigated. For two stations in the south (Figure S9), Xinxiang and ZhuMadian, the changes in the mean temperature alone would reduce the mean yield and increase the yield interannual variability, aligned with previous reports of Tigchelaar et al. (2018). This implies that the growing season temperature for those locations moved further away from the thermal optimum. The change patterns at the rest of the stations were less clear, indicating higher-order impacts from temperature or interactive effects with other components.

### 4.3 Implications

From a risk management perspective, the eight stations in the NCP will need an improved crop yield risk management system, given its reduced stable food system. There are two related systems: the grain reserve system, which levels interannual fluctuations in grain production (Schewe et al., 2017), and the crop insurance system, which indemnifies producers from crop losses due to extreme events. China has a long-established grain reserve system (Tilman et al., 2011) and a recently established agricultural insurance program (Wang et al., 2011). For the grain reserve system, the increasing yield interannual variability requires increasing the reserve levels and stock capacities for individual reserves. In light of this, the recent policy of grain reserve destocking, which moves more grains into the market, should be reevaluated carefully. It is also important to consider inter-reserve diversification, that is, among
different reserves on the NCP or even all reserves across China, in preparation for possible synchronized wheat yield failure (Tigchelaar et al., 2018). Our results suggested a moderate correlation between the yield series across the stations (Pearson correlation coefficients of −0.2 to 0.56), and therefore such inter-regional diversification seems feasible. For the crop insurance system, the increasing yield interannual variability suggests rising insurance premium rates for producers and corresponding rises in government expenditure in the form of premium subsidies (Tack et al., 2018).

From an adaptive perspective, there are two issues that require special attention. Firstly, the contribution of rising temperatures topped climate factors on wheat yield. It emphasizes the extreme importance of relieving heat stress from an adaptive point of view. This could be achieved by adopting new cultivars and advancing the sowing date (Lobell, 2014) to avoid heat during grain filling (Lobell et al., 2013), or introducing heat-resistant cultivars to stabilize the length of the vegetative period against the shortening effects of warming (Liu et al., 2010). Secondly, water availability as an adaptive factor should be considered. In our results, due to the irrigation assumption, the precipitation change did not induce a significant change in the yield at the six stations in the north. Nevertheless, considering the decreasing growing-season precipitation, non-recharging ground water (Zhao et al., 2019), and growing irrigation demand (Elliott et al., 2014), water shortages for wheat would become more severe on the NCP under climate change than it has been previously. Even when applying minimum irrigation strategies, the ground water table would decrease and lead to mean yield reduction and increased yield interannual variability (Sun et al., 2015). Therefore, improving water-use efficiency and developing water-efficient cultivars should be considered a part of adaptation in irrigated areas. For rainfed areas, precipitation changes in the future shows an ascending trend, and water availability might not be an emergent issue as wheat yield could benefit from increasing precipitation.

4.4 Limitations

This study had several limitations. Firstly, although multiple GCMs were considered as inputs, multiple crop models were not used. The lack of a multi-model ensemble may have caused uncertainties in the results arising from the crop model (Asseng et al., 2013; Liu et al., 2016b; Tao et al., 2018). Fortunately, the DSSAT-CERES wheat model has been frequently applied in crop assessments of the NCP and has been employed two- to three-fold more often than other models (White et al., 2011) and occasionally outperformed other models (Ahmed et al., 2016).

Secondly, the focus of the study was to specifically address the contributions of climate change in mean and variability to changes in yield, without considering the contribution of climate change in extremes. There are two obstacles to incorporating climate change extremes into our framework. On the one hand, the decomposition of daily values into IMFs can distinguish climate mean and variability by frequency, but it can hardly capture extreme events such as droughts (Liu et al., 2016a). On the other hand, it remains a challenge for current process-based crop models to simulate the impacts of extreme events, particularly those causing physical and permanent damage (Schauberger et al., 2017).

Many other factors were not considered in the simulation experiments to avoid distraction from our focus—climate change—such as cultivars, management practices, CO₂ and nitrogen fertilization or adaptation practices. Interactions between climate factors, such as evapotranspiration at high temperatures, were not considered. Other potential sources of risks were not considered either. Because these factors could favourably affect wheat yield (Liu et al., 2010; Zhang et al., 2013), the adverse effects of climate change on wheat yield could have been overestimated in this study.

Third, the comparison between the simulated and observed yield interannual variability was critical for analysing the changes in yield interannual variability (Liu et al., 2019). However, as in many other studies, our crop field experimental data were subjected to frequent cultivar changes (Ruane et al., 2016) and could not support the comparison between the simulated and observed yield interannual variability. Therefore, the simulation results were compared with those of earlier studies to investigate the uncertainty. For the same reason, it was difficult to measure the spatial representativeness of the station-based simulation results, and an up-scaling to the entire study area by aggregating station results was not conducted.

5 Conclusion

Yield stability is critically important, in addition to the mean yield, in describing food system resilience to climate change. This study evaluated wheat yield changes in response to climate change on the NCP and measured the relative contributions of changes in climate mean and variability. Using decomposed and reassembled climate change scenarios, we found a reduction in the mean yield (5.7–29.4%), decreasing yield stability with
increased yield interannual variability (0.4–21.0%), and reduced lower yield extremes (25.9–39.8%). Our efforts to explain the changes indicated that the interaction of climate mean and variability changes explained 26–33% and 48–54% of the mean yield and yield interannual variability, respectively. The change in climate mean contributed the largest share in the change in mean yield, with 62–71%, and the second largest share in the yield interannual variability change, with 33–41%. The relative contribution of climate variability change was surprisingly low, even in explaining yield variability changes. Our results highlight the importance of considering the interactive effect of changes in climate mean and variability in future crop yield analyses. Considering our projected increase in yield interannual variability and projected decrease in the 10-year return period, lower yield extremes should also remind the Chinese government to reconsider policy adjustments regarding the grain reserve system and agriculture insurance as a part of risk governance under climate change.

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