Climate Change, High-Temperature Stress, Rice Productivity, and Water Use in Eastern China: A New Superensemble-Based Probabilistic Projection

FULU TAO
Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

ZHAO ZHANG
State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, China

(Manuscript received 4 April 2012, in final form 13 September 2012)

ABSTRACT

The impact of climate change on rice productivity in China remains highly uncertain because of uncertainties from climate change scenarios, parameterizations of biophysical processes, and extreme temperature stress in crop models. Here, the Model to Capture the Crop–Weather Relationship over a Large Area (MCWLA)-Rice crop model was developed by parameterizing the process-based general crop model MCWLA for rice crop. Bayesian probability inversion and a Markov chain Monte Carlo technique were then applied to MCWLA-Rice to analyze uncertainties in parameter estimations and to optimize parameters. Ensemble hindcasts showed that MCWLA-Rice could capture the interannual variability of the detrended historical yield series fairly well, especially over a large area. A superensemble-based probabilistic projection system (SuperEPPS) coupled to MCWLA-Rice was developed and applied to project the probabilistic changes of rice productivity and water use in eastern China under scenarios of future climate change. Results showed that across most cells in the study region, relative to 1961–90 levels, the rice yield would change on average by 7.5%–17.5% (from 210.4% to 3.0%), 0.0%–25.0% (from 226.7% to 2.1%), and from 210.0% to 25.0% (from 239.2% to 26.4%) during the 2020s, 2050s, and 2080s, respectively, in response to climate change, with (without) consideration of CO2 fertilization effects. The rice photosynthesis rate, biomass, and yield would increase as a result of increases in mean temperature, solar radiation, and CO2 concentration, although the rice development rate could accelerate particularly after the heading stage. Meanwhile, the risk of high-temperature stress on rice productivity would also increase notably with climate change. The effects of extreme temperature stress on rice productivity were explicitly parameterized and addressed in the study.

1. Introduction

Rice production is facing challenges from climate change, water shortages, and other factors in eastern and southern Asia, and the risk of ongoing climate change to rice production has increasingly become of key concern (e.g., Aggarwal and Mall 2002; Tao et al. 2003, 2006, 2008; Peng et al. 2004; Yao et al. 2007; Lobell et al. 2008; Xiong et al. 2008; Shen et al. 2011; Liu et al. 2012). The effects of climate change on rice productivity have been documented on the basis of historical long-term field experiment records (Peng et al. 2004; Tao et al. 2006), controlled-environmental experiments, such as controlled-environment chamber experiments (e.g., Cheng et al. 2009), and free-air carbon dioxide (CO2) enrichment experiments (e.g., Kim et al. 2003; Ainsworth and Long 2005; Yang et al. 2006). Additionally, a number of studies have used process-based crop models, driven by climate change scenarios output from global climate models (GCMs) or regional climate models (RCMs), to simulate the effects of climate change on rice production in Asia (e.g., Kropff et al. 1993; Horie et al. 1997; Matthews et al. 1997; Aggarwal and Mall 2002; Masutomi et al. 2009; Iizumi et al. 2011) and, specifically, in China (e.g., Yao et al. 2007; Tao et al. 2008; Xiong et al. 2008; Chavas et al. 2009). However, the projected changes in rice yields have a quite large range, depending on the crop model, greenhouse gas emission (GHG) scenario, and climate change scenario used. The uncertainties mainly originate

Corresponding author address: Fulu Tao, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China.
E-mail: taofl@igsnrr.ac.cn

DOI: 10.1175/JAMC-D-12-0100.1

© 2013 American Meteorological Society
from many physical, biological, and socioeconomic processes (Tebaldi and Lobell 2008; Tao et al. 2009a,b; Rötter et al. 2011; Lobell et al. 2012).

Recent studies have attempted to develop new crop models suitable over a large area or/and ensemble prediction approaches to deal with these uncertainties (Challinor et al. 2005, 2009; Tao et al. 2008, 2009a,b; Tao and Zhang 2013; Iizumi et al. 2009, 2011). For example, Tao et al. (2008) developed a probabilistic assessment of the effect of climate change on future rice production in China using probabilistic climate scenarios generated by a Monte Carlo technique. Challinor et al. (2009) estimated the uncertainties in simulating the groundnut yield in India associated with biophysical parameters in a crop model and physical parameters in a GCM. Iizumi et al. (2009) inferred the probability distributions of biophysical and empirical parameter values in a crop model through Bayesian inversion analysis and quantified the uncertainty in simulating the paddy rice yield in Japan. Tao et al. (2009a,b) developed a new process-based Model to Capture the Crop–Weather Relationship over a Large Area (MCWLA) and a new superensemble-based probabilistic projection system (SuperEPPS) to account for uncertainties not only from CO2 emission scenarios and climate change scenarios, but also from biophysical parameters of crop models, and further assessed the effects of climate change (variability) on regional maize productivity and water use in a probabilistic framework. The climate change impact studies were improved by accounting for more sources of uncertainties.

In the present study, we focused on rice (Oryza sativa L.) production in eastern China, specifically Anhui Province, Jiangsu Province, and Zhejiang Province in the lower reaches of the Yangtze River; these provinces are a primary rice-cultivation area in China (Fig. 1). The typical cultivation system in Anhui and Jiangsu Provinces is rotation between winter wheat and rice. In Zhejiang Province, the typical cultivation system is double rice, although there are growing areas of single-rice cultivation. For single-rice cultivation in the region, rice is generally transplanted in mid-June and harvested in late September. Here, we aimed to 1) develop a new crop model MCWLA-Rice by adapting and validating the crop model MCWLA to simulate rice growth, development, and productivity over a large area; 2) address the uncertainties in projecting the impacts of climate change on rice productivity and water use using the SuperEPPS coupled to MCWLA-Rice; and 3) develop a new superensemble-based probabilistic projection for the responses of rice productivity and water use to climate change temporally and spatially in eastern China in the twenty-first century.

2. Methods and data

The general framework of the study was given in Fig. 2. It was described in more details as follows.

a. Description of crop model MCWLA-Rice

In the present study, the crop model MCWLA-Rice was developed by adapting the process-based general crop model MCWLA (Tao et al. 2009a) to simulate the growth, development, and productivity of the rice crop. MCWLA model development, parameter optimization,
and uncertainty analysis had been detailed by Tao et al. (2009a). Based on the MCWLA, MCWLA-Rice simulates rice phenological development, leaf development, and the effects of high- and low-temperature stresses on the harvest index following the Simulation Model for Rice-Weather Relationship (SIMRIW) (Horie et al. 1995). Specifically, rice phenological development is simulated using the development index (DVI), following Horie et al. (1995). The value of DVI ranges from 0.0 to 2.0; the values of 0.0, 1.0, and 2.0 indicate transplanting, heading, and maturity, respectively. The DVI at day \( i \) after transplanting, \( \text{DVI}_i \) (day\(^{-1}\)), is given by

\[
\text{DVI}_i = \sum_{j=0}^{i} \text{DVR}_j,
\]

where \( \text{DVR}_j \) is the developmental rate on day \( j \) (day\(^{-1}\)). The daily value of the developmental rate is given by the daily mean temperature and day length depending on the crop stage:

\[
\text{DVR} = \begin{cases} 
\frac{1}{G_v \{1 + \exp[-A_T(T - T_h)]}\}, & \text{DVI} = \text{DVI}^* \\
\frac{1 - \exp[K_r(L - L_c)]}{G_v \{1 + \exp[-A_T(T - T_h)]\}}, & \text{DVI} = \text{DVI}^* \quad \text{and} \quad L \leq L_c \\
0, & \text{DVI}^* < \text{DVI} \leq 1 \quad \text{and} \quad L > L_c \\
\frac{1 - \exp[-K_r(T - T_{cr})]}{G_r}, & 1 < \text{DVI} < 2
\end{cases}
\]
where \( G_r \) is the minimum number of days required from transplanting to heading (days), \( A_T \) is the sensitivity of the developmental rate to air temperature \((^\circ C^{-1})\), \( T \) is the daily mean air temperature \((^\circ C)\), \( T_h \) is the air temperature at which DVR is half the maximum rate at the optimum temperature \((^\circ C)\), DVI* is the value of DVI at which the crop becomes sensitive to photoperiod \((day^{-1})\), \( L \) is the day length (h), \( L_c \) is the critical day length (h), and \( G_r \) (day) is the minimum number of days from heading to maturity (in the study, \( G_r = 28.8 \) days; Horie et al. 1995). The quantities \( K_1 (h^{-1}) \), \( K_r (^{\circ}C^{-1}) \), and \( T_{cr} (^{\circ}C) \) are empirical constants (in the study, \( K_r = 0.118^{\circ}C^{-1}; \) Horie et al. 1995).

The leaf area index \( L_{AI} \) on day \( t \), \( L_{AI,t} \), is described as a summation of the daily growth rate of \( L_{AI} \): \( \Delta L_{AI} \):

\[
L_{AI,t} = \sum_{j=0}^{\infty} \Delta L_{AI,t-j},
\]

where \( \Delta L_{AI} \) is estimated following Horie et al. (1995). For the period before heading,

\[
\Delta L_{AI,t} = L_{AI,t} R_m \{1 - \exp[-K_f(T - T_{ct})]\} \times \left[1 - \left(\frac{L_{AI_t}}{L_{AI_{max}}}\right)^h\right] Y_{gp} \min\left(\frac{s}{s_{cr}}, 1\right),
\]

where \( R_m \) is the maximum relative growth rate of \( L_{AI} \) under an optimum condition \((day^{-1})\), \( T_{ct} \) is the minimum temperature for \( L_{AI} \) growth (in the study, \( T_{ct} = 11.5^{\circ}C \)), \( L_{AI_{max}} \) is an asymptotic value of \( L_{AI} \) when the temperature is nonlimiting (in the study, \( L_{AI_{max}} = 10.0 \text{ m}^2 \text{ m}^{-2} \)), \( K_f (^{\circ}C^{-1}) \) and \( h \) are empirical constants (in the study, \( h = 1.1 \)), and \( Y_{gp} \) is the yield gap parameter representing the ratio of actual yield to theoretical yield. The soil water stress factor \( S \) is given by

\[
S = \frac{T_T}{T_{T pot}},
\]

which begins to affect growth as values less than the critical threshold value \( S_{cr} \) (in the study, \( S_{cr} = 0.6 \)). Here \( T_T \) and \( T_{T pot} \) are the rates of transpiration and potential transpiration, respectively. For the period from just after heading to maturity \( \Delta L_{AI} \) is given as an empirical function of the developmental rate:

\[
\Delta L_{AI,t} = - L_{AI,t} (1 - c) DVR_{\text{max}} \left\{1 + \left(1 - \frac{S}{S_{cr}}\right)\right\},
\]

where \( c \) is an empirical constant (\( c = 0.5; \) Horie et al. 1995).

Extreme high and low temperatures can affect rice yield notably in a number of ways (Matsui and Horie 1992; Imin et al. 2004). The effects of high- and low-temperature stresses on yield formation are simulated through their effects on the daily harvest index \( H_i \), which is given by

\[
H_i = \min(h_{c_i}, h_{h_i}),
\]

where \( h_{c_i} \) and \( h_{h_i} \) are the harvest index under low- and high-temperature stress, respectively. Another quantity, \( h_{h_i} \), accounts for the stress due to two types of cool-summer damage: the damage due to floral impotency, which is the increase in the number of sterile grains resulting from low temperature at the booting and flowering stage, and the damage due to delayed growth, which is the premature cessation of growth due to low temperature in summer. It is given by

\[
DVI_i \leq 1.22
\]

\[
DVI_i > 1.22
\]

where \( H_{l_{max}} \) is the maximum harvest index under optimum climatic conditions \((H_{l_{max}} = 0.40 \) in this study), \( K_h \) is an empirical constant \((day) \) \((K_h = 5.57; \) Horie et al. 1995), and \( \gamma_c \) is the percent of

---

**Table 1. Model names and expansions.**

<table>
<thead>
<tr>
<th>Climate model name</th>
<th>Expansion</th>
</tr>
</thead>
<tbody>
<tr>
<td>CGCM2</td>
<td>Coupled General Circulation Model, version 2</td>
</tr>
<tr>
<td>CSIRO2</td>
<td>Commonwealth Scientific and Industrial Research Organisation, version 2</td>
</tr>
<tr>
<td>ECHAM4</td>
<td>No expansion</td>
</tr>
<tr>
<td>GFDL GCM</td>
<td>Geophysical Fluid Dynamics Laboratory GCM</td>
</tr>
<tr>
<td>GISS GCM</td>
<td>Goddard Institute for Space Studies GCM</td>
</tr>
<tr>
<td>HadCM3</td>
<td>Third climate configuration of the Met Office Unified Model</td>
</tr>
<tr>
<td>PCM</td>
<td>Parallel Climate Model</td>
</tr>
<tr>
<td>PRECIS RCM</td>
<td>Providing Regional Climates for Impacts Studies RCM</td>
</tr>
<tr>
<td>RegCM3 RCM</td>
<td>Regional Climate Model 3 RCM</td>
</tr>
<tr>
<td>UKMO GCM</td>
<td>Met Office GCM</td>
</tr>
</tbody>
</table>
sterile spikelet due to low temperature. It is estimated as

\[ \gamma = \gamma_0 + K_q Q_{\text{cool}}, \]

where \( \gamma_0 \) (dimensionless) and \( K_q \) (\( ^{\circ}\text{C}^{-1} \)) are empirical constants (\( \gamma_0 = 4.6 \) and \( K_q = 0.054 \); Horie et al. 1995), \( Q_{\text{cool}} \) is the curvature factor of spikelet sterility due to low temperature, and \( Q \) is the cooling degree-days (\( ^{\circ}\text{C} \)). The quantity \( Q \) is calculated as

\[ Q = \sum (T^* - T), \]

where \( T^* \) is the base temperature for calculating cooling degree-days. The summation of cooling degree-days is for the period in which the rice panicle is sensitive to low temperature. The period is defined by the development index as \( 0.75 \leq \text{DVI} \leq 1.20 \) (Horie et al. 1995).

Experiments have increasingly suggested that there is damage to pollen at the flowering stage when the temperature is above approximately 35\( ^{\circ}\text{C} \) (Matsui and Horie 1992). The rice-yield index under high-temperature stress \( h_{hi} \) is parameterized as (Nakagawa et al. 2003; Iizumi et al. 2009)

\[
\begin{align*}
\left\{ h_{hi} &= 0, \\
 h_{hi} &= H_{\text{max}} \{1 - \exp[-K_h(DVI - 1.22)]\}(1 - 0.95 \gamma_h), \quad \text{DVI} > 1.22 \\
\end{align*}
\]

and

\[
\begin{align*}
\gamma_h &= \left[ \frac{T_{\text{max}} - T_b}{T_o - T_b} \right] \left(\frac{T_c - T}{T_c - T_o}\right)^{T_c - T_o} (T_c - T_o) T_{\text{hot}} , \\
\gamma_h &= 0, \quad \text{DVI} \leq 1.22 \\
\end{align*}
\]

\[ T_{\text{max}} > T_o, \]

\[ T_{\text{max}} < T_o. \]

\[ \gamma = \gamma_0 + K_q Q_{\text{cool}}, \]

where \( \gamma_0 \) (dimensionless) and \( K_q \) (\( ^{\circ}\text{C}^{-1} \)) are empirical constants (\( \gamma_0 = 4.6 \) and \( K_q = 0.054 \); Horie et al. 1995), \( Q_{\text{cool}} \) is the curvature factor of spikelet sterility due to low temperature, and \( Q \) is the cooling degree-days (\( ^{\circ}\text{C} \)). The quantity \( Q \) is calculated as

\[ Q = \sum (T^* - T), \]

where \( T^* \) is the base temperature for calculating cooling degree-days. The summation of cooling degree-days is for the period in which the rice panicle is sensitive to low temperature. The period is defined by the development index as \( 0.75 \leq \text{DVI} \leq 1.20 \) (Horie et al. 1995).

Experiments have increasingly suggested that there is damage to pollen at the flowering stage when the temperature is above approximately 35\( ^{\circ}\text{C} \) (Matsui and Horie 1992). The rice-yield index under high-temperature stress \( h_{hi} \) is parameterized as (Nakagawa et al. 2003; Iizumi et al. 2009)

\[
\begin{align*}
\left\{ h_{hi} &= 0, \\
 h_{hi} &= H_{\text{max}} \{1 - \exp[-K_h(DVI - 1.22)]\}(1 - 0.95 \gamma_h), \quad \text{DVI} > 1.22 \\
\end{align*}
\]

and

\[
\begin{align*}
\gamma_h &= \left[ \frac{T_{\text{max}} - T_b}{T_o - T_b} \right] \left(\frac{T_c - T}{T_c - T_o}\right)^{T_c - T_o} (T_c - T_o) T_{\text{hot}} , \\
\gamma_h &= 0, \quad \text{DVI} \leq 1.22 \\
\end{align*}
\]

\[ T_{\text{max}} > T_o, \]

\[ T_{\text{max}} < T_o. \]

\[ \gamma = \gamma_0 + K_q Q_{\text{cool}}, \]

where \( \gamma_0 \) (dimensionless) and \( K_q \) (\( ^{\circ}\text{C}^{-1} \)) are empirical constants (\( \gamma_0 = 4.6 \) and \( K_q = 0.054 \); Horie et al. 1995), \( Q_{\text{cool}} \) is the curvature factor of spikelet sterility due to low temperature, and \( Q \) is the cooling degree-days (\( ^{\circ}\text{C} \)). The quantity \( Q \) is calculated as

\[ Q = \sum (T^* - T), \]

where \( T^* \) is the base temperature for calculating cooling degree-days. The summation of cooling degree-days is for the period in which the rice panicle is sensitive to low temperature. The period is defined by the development index as \( 0.75 \leq \text{DVI} \leq 1.20 \) (Horie et al. 1995).

Experiments have increasingly suggested that there is damage to pollen at the flowering stage when the temperature is above approximately 35\( ^{\circ}\text{C} \) (Matsui and Horie 1992). The rice-yield index under high-temperature stress \( h_{hi} \) is parameterized as (Nakagawa et al. 2003; Iizumi et al. 2009)

\[
\begin{align*}
\left\{ h_{hi} &= 0, \\
 h_{hi} &= H_{\text{max}} \{1 - \exp[-K_h(DVI - 1.22)]\}(1 - 0.95 \gamma_h), \quad \text{DVI} > 1.22 \\
\end{align*}
\]

and

\[
\begin{align*}
\gamma_h &= \left[ \frac{T_{\text{max}} - T_b}{T_o - T_b} \right] \left(\frac{T_c - T}{T_c - T_o}\right)^{T_c - T_o} (T_c - T_o) T_{\text{hot}} , \\
\gamma_h &= 0, \quad \text{DVI} \leq 1.22 \\
\end{align*}
\]

\[ T_{\text{max}} > T_o, \]

\[ T_{\text{max}} < T_o. \]

\[ \gamma = \gamma_0 + K_q Q_{\text{cool}}, \]

where \( \gamma_0 \) (dimensionless) and \( K_q \) (\( ^{\circ}\text{C}^{-1} \)) are empirical constants (\( \gamma_0 = 4.6 \) and \( K_q = 0.054 \); Horie et al. 1995), \( Q_{\text{cool}} \) is the curvature factor of spikelet sterility due to low temperature, and \( Q \) is the cooling degree-days (\( ^{\circ}\text{C} \)). The quantity \( Q \) is calculated as

\[ Q = \sum (T^* - T), \]

where \( T^* \) is the base temperature for calculating cooling degree-days. The summation of cooling degree-days is for the period in which the rice panicle is sensitive to low temperature. The period is defined by the development index as \( 0.75 \leq \text{DVI} \leq 1.20 \) (Horie et al. 1995).

Experiments have increasingly suggested that there is damage to pollen at the flowering stage when the temperature is above approximately 35\( ^{\circ}\text{C} \) (Matsui and Horie 1992). The rice-yield index under high-temperature stress \( h_{hi} \) is parameterized as (Nakagawa et al. 2003; Iizumi et al. 2009)

\[
\begin{align*}
\left\{ h_{hi} &= 0, \\
 h_{hi} &= H_{\text{max}} \{1 - \exp[-K_h(DVI - 1.22)]\}(1 - 0.95 \gamma_h), \quad \text{DVI} > 1.22 \\
\end{align*}
\]

and

\[
\begin{align*}
\gamma_h &= \left[ \frac{T_{\text{max}} - T_b}{T_o - T_b} \right] \left(\frac{T_c - T}{T_c - T_o}\right)^{T_c - T_o} (T_c - T_o) T_{\text{hot}} , \\
\gamma_h &= 0, \quad \text{DVI} \leq 1.22 \\
\end{align*}
\]

\[ T_{\text{max}} > T_o, \]

\[ T_{\text{max}} < T_o. \]
where $\gamma_h$ is the spikelet sterility due to high temperature, 
$T_{\text{max}}$ is the average daily maximum temperature over
the flowering period, defined by $0.96 \leq \text{DVI} \leq 1.20$, and
$C_{\text{hot}}$ is the curvature factor of spikelet sterility due
to high temperature. The empirical constants $T_{o}$, $T_{c}$,
and $T_{b}$ represent the optimum temperature, critical up-
per limit, and critical bottom limit for crop growth, and
are set at $33^\circ$, $43^\circ$, and $10^\circ$C, respectively, following
Nakagawa et al. (2003).

b. Data

The MCWLA-Rice model requires daily weather in-
puts for maximum and minimum temperatures, pre-
cipitation, vapor pressure (or relative humidity), and
fractional sunshine hours (or solar radiation). In this
study, MCWLA-Rice was run for each $0.5^\circ \times 0.5^\circ$ cell
with a rice-cultivation fraction (the ratio between rice-
cultivation area and total area in a cell) $\geq 0.05$ across
three major production provinces; that is, Anhui,
Jiangsu, and Zhejiang Provinces (Fig. 1). In total, there
were 44 cells in Anhui Province, 37 cells in Jiangsu
Province and 28 cells in Zhejiang Province. Monthly
data on maximum and minimum temperatures, precip-
itation, vapor pressure, wet days, and fractional sunshine
hours for the $0.5^\circ \times 0.5^\circ$ cells from 1901 to 2002 were
obtained from the Climatic Research Unit, University of
East Anglia, United Kingdom (Mitchell and Jones 2005).

The 10 future climate change scenarios for monthly
values of maximum and minimum temperatures, precip-
itation, vapor pressure, and fractional sunshine hours
for each $0.5^\circ \times 0.5^\circ$ cell from 2001 to 2100 were also
taken from the Climatic Research Unit, University of
East Anglia (Mitchell et al. 2004). The scenarios com-
prise all 10 combinations of two emission scenarios
(A1FI and B1) and five GCMs (HadCM3, PCM, CGCM2, CSIRO2, and ECHAM4; see Table 1 for list
of full model names), using GCMs outputs from the In-
tergovernmental Panel on Climate Change (IPCC) Data
Distribution Centre. Details on the GCMs can be found
at http://www.ipcc-data.org/. The complete method of
dataset construction was described by Mitchell et al.
(2004).

![Fig. 3. Time series of the modeled and detrended statistical yields (kg ha$^{-1}$) at the crop model grid scale for rice in the cells of (a) Nanjing and (b) Wuxi in Jiangsu Province, (c) Bengbu and (d) Xuancheng in Anhui Province, and (e) Hangzhou and (f) Shaoxing in Zhejiang Province. The locations of the cells are shown in Fig. 1.](image-url)
As in our previous studies (Tao et al. 2009a,b), the monthly means of maximum and minimum temperature, vapor pressure, and fractional sunshine hours were interpolated to daily values using spline interpolation (Press et al. 1992). Daily precipitation is disaggregated using a stochastic weather generator, with monthly total precipitation and wet days as inputs (Gerten et al. 2004).

Soil texture and hydrological properties data, such as soil percolation characteristic, soil volumetric water holding capacity at field capacity minus volumetric water holding capacity at wilting point as fraction of soil layer depth, were based on the Food Agriculture Organization soil dataset (Zobler 1986; FAO 1991). Yearly district-, county-, subprovince- (usually including from five to

Fig. 4. Time series of the modeled and detrended statistical yields (kg ha\(^{-1}\)) at the province scale for (a) Anhui Province, (b) Jiangsu Province, and (c) Zhejiang Province.
FIG. 5. Spatial patterns of (a) mean temperature (°C) and (b) mean monthly precipitation (mm) from June to September during 1961–90, and the projected changes in (c),(e),(g),(i) mean temperature (°C) and (d),(f),(h),(j) mean monthly precipitation (%) during the 2050s, based on the (middle) HadCM3 GCM and A1FI emission scenario, (bottom) HadCM3 GCM and B1 emission scenario, (facing-page top) CGCM2 GCM and A1FI emission scenario, and (facing-page bottom) CGCM2 GCM and B1 emission scenario.
eight counties), or provincial-level data on rice yield and growing area were obtained from the statistical yearbook of each county or province. Yearly rice phenology for the cell of Hefei, including planting, flowering, and harvest dates, were obtained from the Hefei agricultural meteorological station (Tao et al. 2006). Yearly growing-area-weighted yields for seven 0.5° × 0.5° cells including Hefei, Nanjing, Wuxi, Bengbu, Xuancheng, Hangzhou, and Shaoxing (Fig. 1) were calculated from district-level or county-level data on growing area and yield, which were taken from the available statistical yearbooks from 1981 to 2003. Yearly rice-yield series for the Anhui, Jiangsu, and Zhejiang Provinces (Fig. 1) were taken from the statistical yearbook of each province from 1981 to 2003. The yields in the 0.5° × 0.5° cells and in the provinces were detrended (a linear yield trend was assumed) to produce yield data at the management technology of the base year, and these yield series data (referred to as “detrended statistical yields”) were used in the model calibration and evaluation.

c. Parameter estimation and uncertainty analyses using Bayesian probability inversion and a Markov chain Monte Carlo technique

The Bayesian probability inversion and the MCMC technique had been detailed by Tao et al. (2009a). Here, the techniques were applied to invert and optimize the parameters of MCWLA-Rice. We inverted the parameters of MCWLA-Rice for the 0.5° × 0.5° cell of Hefei (Fig. 1) using phenological observation records (planting date, flowering date and maturity date) and detrended yield series from 1988 to 2002. Prior
knowledge of the parameters (Table 2) was taken from the literature or field experiment data, and the prior probability density function was assumed to be a normal distribution. We ran MCWLA-Rice using 55,000 sets of parameters sampled in the final run of the Metropolis–Hastings algorithm (Metropolis et al. 1953; Hastings 1970) to investigate the uncertainty in the ensemble prediction and to optimize the parameters. From the 55,000 sets of parameters, we further selected the 30 optimal parameter sets that have the minimum root-mean-square error (RMSE) between modeled and detrended historical statistical rice-yield series.

FIG. 6. (a) Cumulative probability functions and histograms of the rice yield during 1961–90 and its changes during the (b) 2020s, (c) 2050s, and (d) 2080s across the rice-cultivation cells in Anhui Province, taking CO₂ fertilization effects into account.
Table 3. Statistics of projected yield and evapotranspiration (in parentheses) changes across the rice-cultivation grids in Anhui, Jiangsu, and Zhejiang Provinces in the 2020s, 2050s, and 2080s, relative to the 1961–1990 level, with CO₂ fertilization effects considered. Here, P5 denotes the 5th percentile, P50 is the median value, and P95 is the 95th percentile.

<table>
<thead>
<tr>
<th>Province</th>
<th>Period</th>
<th>Samples</th>
<th>Probability of increase (%)</th>
<th>Mean (%)</th>
<th>Std dev</th>
<th>P5 (%)</th>
<th>P50 (%)</th>
<th>P95 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anhui</td>
<td>2020s</td>
<td>396 000</td>
<td>87.5 (16.2)</td>
<td>10.6 (−6.4)</td>
<td>23.5 (7.4)</td>
<td>−6.1 (−20.3)</td>
<td>11.1 (−4.2)</td>
<td>22.2 (2.0)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>396 000</td>
<td>68.6 (14.6)</td>
<td>7.1 (−14.4)</td>
<td>33.4 (13.4)</td>
<td>−48.9 (−36.6)</td>
<td>11.1 (−14.3)</td>
<td>40.9 (6.7)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>396 000</td>
<td>60.6 (8.1)</td>
<td>0.7 (−19.6)</td>
<td>38.8 (14.6)</td>
<td>−77.2 (−47.4)</td>
<td>9.0 (−19.2)</td>
<td>45.6 (3.0)</td>
</tr>
<tr>
<td>Jiangsu</td>
<td>2020s</td>
<td>333 000</td>
<td>93.5 (18.0)</td>
<td>11.4 (−5.9)</td>
<td>7.2 (7.3)</td>
<td>−1.3 (−20.3)</td>
<td>12.5 (−3.4)</td>
<td>21.2 (1.8)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>333 000</td>
<td>80.0 (16.3)</td>
<td>13.2 (−13.9)</td>
<td>21.8 (13.5)</td>
<td>−27.7 (−35.4)</td>
<td>16.1 (−14.1)</td>
<td>41.7 (7.9)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>333 000</td>
<td>71.2 (18.9)</td>
<td>7.8 (−19.6)</td>
<td>32.2 (14.4)</td>
<td>−67.2 (−44.1)</td>
<td>16.5 (−20.1)</td>
<td>46.6 (3.9)</td>
</tr>
<tr>
<td>Zhejiang</td>
<td>2020s</td>
<td>252 000</td>
<td>88.5 (13.4)</td>
<td>9.5 (−6.3)</td>
<td>8.6 (7.2)</td>
<td>−4.3 (−20.0)</td>
<td>10.1 (−4.9)</td>
<td>21.5 (2.4)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>252 000</td>
<td>77.5 (16.6)</td>
<td>11.3 (−11.6)</td>
<td>22.4 (12.1)</td>
<td>−30.8 (−31.9)</td>
<td>13.9 (−11.3)</td>
<td>40.6 (7.4)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>252 000</td>
<td>66.7 (10.0)</td>
<td>4.0 (−16.6)</td>
<td>33.1 (13.6)</td>
<td>−68.7 (−39.9)</td>
<td>12.0 (−16.2)</td>
<td>43.8 (4.8)</td>
</tr>
</tbody>
</table>

Table 4. As in Table 3, but without consideration of CO₂ fertilization effects.

<table>
<thead>
<tr>
<th>Province</th>
<th>Period</th>
<th>Samples</th>
<th>Probability of decrease (%)</th>
<th>Mean (%)</th>
<th>Std dev</th>
<th>P5 (%)</th>
<th>P50 (%)</th>
<th>P95 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anhui</td>
<td>2020s</td>
<td>396 000</td>
<td>77.3 (63.3)</td>
<td>−4.9 (−4.1)</td>
<td>20.5 (7.4)</td>
<td>−20.2 (−18.2)</td>
<td>−4.3 (−2.0)</td>
<td>5.1 (4.4)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>396 000</td>
<td>84.4 (76.3)</td>
<td>−18.6 (−9.9)</td>
<td>26.4 (13.0)</td>
<td>−63.9 (−31.0)</td>
<td>−15.2 (−10.0)</td>
<td>8.3 (11.4)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>396 000</td>
<td>90.0 (82.0)</td>
<td>−29.4 (−12.6)</td>
<td>29.0 (13.6)</td>
<td>−86.7 (−36.8)</td>
<td>−23.0 (−12.7)</td>
<td>5.1 (9.2)</td>
</tr>
<tr>
<td>Jiangsu</td>
<td>2020s</td>
<td>333 000</td>
<td>73.0 (56.8)</td>
<td>−3.7 (−3.5)</td>
<td>6.6 (7.3)</td>
<td>−15.5 (−18.1)</td>
<td>−2.4 (0.8)</td>
<td>4.8 (4.2)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>333 000</td>
<td>78.5 (73.8)</td>
<td>−13.4 (−9.1)</td>
<td>17.9 (13.3)</td>
<td>−48.4 (−30.0)</td>
<td>−10.7 (−9.5)</td>
<td>8.7 (12.7)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>333 000</td>
<td>87.1 (79.6)</td>
<td>−23.8 (−12.2)</td>
<td>25.5 (13.6)</td>
<td>−80.7 (−34.7)</td>
<td>−17.6 (−13.2)</td>
<td>6.0 (10.2)</td>
</tr>
<tr>
<td>Zhejiang</td>
<td>2020s</td>
<td>252 000</td>
<td>82.2 (68.7)</td>
<td>−5.9 (−3.9)</td>
<td>7.5 (7.2)</td>
<td>−18.3 (−17.6)</td>
<td>−5.2 (−2.4)</td>
<td>4.1 (4.8)</td>
</tr>
<tr>
<td></td>
<td>2050s</td>
<td>252 000</td>
<td>84.4 (71.4)</td>
<td>−15.7 (−6.9)</td>
<td>18.1 (12.0)</td>
<td>−50.8 (−26.6)</td>
<td>−13.3 (−6.8)</td>
<td>7.4 (12.4)</td>
</tr>
<tr>
<td></td>
<td>2080s</td>
<td>252 000</td>
<td>92.1 (90.0)</td>
<td>−27.1 (−9.0)</td>
<td>25.2 (12.9)</td>
<td>−81.5 (−30.1)</td>
<td>−20.2 (−8.9)</td>
<td>2.7 (12.1)</td>
</tr>
</tbody>
</table>

### d. SuperEPPS

SuperEPPS (Fig. 2) was developed to assess the effects of climate change (variability) on regional crop productivity and water use in a probabilistic framework, accounting for the uncertainties arising from CO₂ emission scenarios and climate change scenarios, as well as from biophysical processes (Tao et al. 2009a,b; Tao and Zhang 2010). In the present study, using the 30 optimal sets of parameters, MCWLA-Rice was driven by baseline climate conditions (1961–90) and 10 future climate scenarios for the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100), respectively, resulting in a superensemble-based projection. The mean [CO₂] during 1961–90 was set at 330 ppmv. The mean [CO₂] would be 436.0 (424.5) ppmv during the 2020s, 602.5 (498.5) ppmv during the 2050s, and 842.0 (541.0) ppmv during the 2080s, under the A1FI (B1) scenario (Prentice et al. 2001). Finally, for each 0.5° × 0.5° rice-cultivation cell in Anhui, Jiangsu, and Zhejiang Provinces, we calculated the changes in rice productivity and evapotranspiration (ET) using each set of simulation results during the 2020s, 2050s, and 2080s relative to the corresponding simulation for 1961–90.

Simulations were conducted with and without the CO₂ fertilization effect. The planting window was set to allow automatic planting once the soil water content was larger than half of soil water capacity or planting regardless at the end of the planting window. Since paddy fields dominated the region, irrigation was assumed in simulation settings for all cells; that is, there was automatically irrigation of 50 mm when the ratio of daily transpiration and potential transpiration (i.e., S) was less than 0.8. A wide range of crop cultivars thermal and phenological characteristics were taken into account by using multiple sets of phenological and thermal characteristics parameters, although future crop cultivars and management practices were assumed to be the same as in the baseline period.

### e. Analysis

The performance of MCWLA-Rice was evaluated by calculating the Pearson correlation coefficient $r$ and RMSE between the modeled and corresponding detrended historical yield series at both the grid scale of the crop model and province scale. We derived the probability density functions (PDFs) of rice productivity and ET changes, and analyzed the temporal and spatial changes in rice productivity and ET in a probabilistic framework, on the basis of a large number of simulation outputs from the superensemble-based projection. Specifically, across all rice-cultivation cells in a province, we derived the histogram and cumulative distribution function (CDF) of rice yields during 1961–90, and projected rice-yield changes during the 2020s, 2050s, and...
FIG. 7. Spatial patterns of (a) rice mean yield and (b) ET over the rice-growing period during 1961–90, and the projected changes in (c),(e),(g) mean yield and (d),(f),(h) ET during the (middle) 2020s, (bottom) 2050s, and (facing page) 2080s, taking CO₂ fertilization effects into account.
2080s, respectively. We analyzed the probability of a yield decrease due to climate change across the study region. We plotted the spatial changes in mean rice productivity and ET during 1961–90, and projected changes during the 2020s, 2050s, and 2080s, respectively, at the resolution of the 0.5° × 0.5° cells across the study region. Finally, we investigated the mechanisms that affect the simulated yield and ET.

3. Results

a. Inversion results of model parameters and the optimal parameter sets

The inversion results for model parameters of rice in the cell of Hefei were presented in Table 2. The selected key biophysical parameters are widely related to the processes of crop phenological and LAI development, light and water use, photosynthesis and transpiration rate, yield formation, and temperature stress. We listed the model parameters’ 97.5% highest probability intervals, mean estimates, and standard deviations, and the optimal parameter sets, based on 55 000 sets of parameters sampled in the final run of the Metropolis–Hastings algorithm. The uncertainties in the key biophysical parameters, as indicated by their intervals (Table 2), were systematically investigated and included in the simulations. Particularly, a wide range of cultivars phenological and thermal characteristics were taken into account; for example, the cultivars with \( A_T \) varying from 0.18° to 0.21°C\(^{-1}\), \( T_h \) varying from 14.19° to 15.89°C, DVI* varying from 0.93 to 0.97> day\(^{-1}\), \( G_c \) varying from 34.23 to 37.62 days, \( L_c \) varying from 13.1 to 13.56 h, \( K_t \) varying from 0.71 to 1.03 h\(^{-1}\), \( T^* \) varying from 20.06° to 22.61°C, \( C_{cool} \) varying from 1.12° to 2.35°C, and \( C_{hot} \) varying from 12.53° to 18.31°C (Table 2). Late-maturing cultivars have smaller \( A_T \) and larger \( T_h \) and \( G_c \). Cultivars with higher sensitivity to photoperiod have smaller DVI*, \( L_c \) and larger \( K_t \). High-temperature-tolerant cultivars have smaller \( C_{hot} \) and low-temperature-tolerant cultivars have smaller \( C_{cool} \) and \( T^* \).

b. Model validation at grid and province scales

At the scale of the crop model grid, the detrended statistical yield series for the cells of Nanjing from 1981 to 2002 and Wuxi from 1987 to 2002 in Jiangsu Province, Bengbu from 1987 to 2002 and Xuancheng from 1988 to 2002 in Anhui Province, and Hangzhou from 1991 to 2002 and Shaoxing from 1994 to 2002 in Zhejiang Province, were used for model evaluation. The agreement between detrended statistical yields and modeled yield series varied across cells, with \( r \) ranging from 0.12 to 0.58 (\( p < 0.05 \)), and the RMSE ranging from 200 to 573 kg ha\(^{-1}\) (Fig. 3).

At province scale, \( r \) and RMSE in comparison of the modeled and detrended statistical yield series from 1981 to 2002 were 0.62 (\( p < 0.01 \)) and 434 kg ha\(^{-1}\), respectively, in Anhui Province (Fig. 4a). The corresponding values were 0.51 (\( p < 0.05 \)) and 266 kg ha\(^{-1}\) in Jiangsu Province (Fig. 4b), and 0.85 (\( p < 0.01 \)) and 253 kg ha\(^{-1}\) in Zhejiang Province (Fig. 4c).

The ensemble hindcasts using MCWLA-Rice captured the interannual variability of rice yield in all three investigated provinces from 1981 to 2002. Among other things, the relative performance of the model within an individual grid or province could be attributed to the heterogeneous features of agricultural cultivation system and management practices across the grids. The
agricultural management practices might be better represented in simulations for some grids than others. Over a large area, agricultural management practices could generally be more homogeneous and the relationships between crop yields and weather could be better captured.

c. Climate change scenarios of temperature and precipitation

During the period 1961–90, the mean temperature during the single-rice-growing period (i.e., June–September) ranged generally from 22.5°C to 26.5°C in the study region, with the temperature being highest in the southwestern part of Anhui Province (Fig. 5a) and lowest in the mountainous areas between Anhui and Zhejiang Provinces. Mean monthly precipitation from June to September ranged generally from 135 to 180 mm, with precipitation being least in the northwestern part of Anhui Province (Fig. 5b). During the period 2041–70, both temperature and precipitation were projected to increase generally across the region. As examples, from the 10 climate change scenarios used in the study, we illustrated the spatial patterns for four scenarios as follows. In the case of the HadCM3 GCM and A1FI emission scenario, during the period 2041–70, the mean temperature from June to September would increase generally from 3.0°C to 4.25°C relative to the value for 1961–90, with the largest increase at the areas between Anhui and Jiangsu Provinces (Fig. 5c). Mean monthly precipitation from June to September would increase generally by up to 30%, with the smallest increase in the northern part of Zhejiang Province (Fig. 5d). In the case of the HadCM3 GCM and B1 emission scenario, the mean temperature from June to September would increase generally from 1.9°C to 3.0°C (Fig. 5e) and the mean monthly precipitation from June to September would increase generally by up to 25% relative to 1961–90 levels (Fig. 5f). In the case of the CGCM2 GCM and A1FI emission scenario, during the period 2041–70, the mean temperature from June to September would increase generally from 2.7°C to 3.2°C relative to the 1961–90 level, with the largest increase in the southwestern part of Anhui Province (Fig. 5g). Mean monthly precipitation from June to September would increase generally by up to 25%, with the smallest increase in the central part of Zhejiang Province (Fig. 5h). In the case of the CGCM2 GCM and B1 emission scenario, the mean temperature from June to September would increase generally from 1.5°C to 1.9°C (Fig. 5i) and the mean monthly precipitation from June to September would increase generally by up to 17.5% relative to 1961–90 levels, with the smallest increases in the southwestern part of Anhui Province (Fig. 5j).

Fig. 8. Probability of a rice-yield decrease relative to the 1961–90 level during the (a) 2020s, (b) 2050s, and (c) 2080s across the rice-cultivation cells in the study region, taking CO2 fertilization effects into account.
For all rice-cultivation cells across Anhui Province, the histogram and CDF of rice-yield changes from a large number of superensemble simulations (44 grids × 30 sets of parameters × 30 yr × 10 scenarios = 396,000 simulations) showed that if CO2 fertilization effects were not taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–90 level (Fig. 6a) was respectively 87.5% (Fig. 6b), 68.6% (Fig. 6c), and 60.0% (Fig. 6d), and the simulated rice yield increased on average by 10.6%, 7.1%, and 0.7%, respectively, owing to climate change (Table 3). If CO2 fertilization effects were taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–90 level was respectively 88.5%, 77.5%, and 66.7%, and the simulated rice yield increased on average by 9.5%, 11.3%, and 4.0%, respectively, owing to climate change (Table 3). If CO2 fertilization effects were not taken into account, the probability of the rice yield decreasing during the 2020s, 2050s, and 2080s relative to the 1961–90 level was respectively 82.2%, 84.4%, and 92.1%, and the simulated rice yield decreased on average by 5.9%, 15.7%, and 27.1%, respectively, owing to climate change (Table 4). In addition, in all three provinces, the yield variability, as indicated by the standard deviation of the simulated yields during the 2020s, 2050s, and 2080s, increased with climate change (Tables 3 and 4).

e. Temporal and spatial changes in rice yields and ET

The spatial patterns of simulated rice yields and ET during 1961–90, and their changes during the 2020s, 2050s, and 2080s, taking CO2 fertilization effects into account, are presented in Fig. 7. For each cell, the results were computed from 30 sets of parameters × 30 yr × 10 scenarios = 9000 simulations. Across most cells in the study region, relative to 1961–90 levels, rice yields would change on average by 7.5% to 17.5% (Fig. 7c), 0.0% to 25.0% (Fig. 7e), and −10.0% to 25.0% (Fig. 7g); ET during the rice-growing period would decrease by 3.0% to 8.0% (Fig. 7d), 6.0% to 16.0% (Fig. 7f), and 8.0% to 22.0% (Fig. 7h) during the 2020s, 2050s, and 2080s, respectively, owing to climate change. Rice yields were projected to increase most in areas of northern Jiangsu Province (Figs. 7c,e,g), where the mean temperature during 1961–90 was lower (Figs. 5a). In contrast, in areas of southwestern Anhui Province and northwestern Zhejiang Province, with higher mean temperature during 1961–90 (Fig. 5a), rice yields were projected to increase less (Figs. 7c,e,g), and ET during the rice-growing period was projected to decrease moderately (Figs. 7d,f,h). The spatial patterns of the probability of rice yield decreasing across the study region during the 2020s, 2050s, and 2080s, relative to the 1961–90 level, are presented in Fig. 8. The results showed that the probability of rice yield decreasing could be higher in southwestern Anhui Province, where the probability could be about 25%, 45%, and 50% for some cells during the 2020s (Figs. 8a), 2050s (Fig. 8b), and 2080s (Fig. 8c), respectively.

If CO2 fertilization effects were not taken into account, the spatial patterns of simulated yields and ET changes during the 2020s, 2050s, and 2080s were generally as same as when CO2 fertilization effects were taken into account. However, rice yields were projected to change on average by from −10.4% to 3.0%, from −26.7% to 2.1%, and from −39.2% to −6.4%, and ET was projected to change on average by from −5.9% to 0.1%, from −11.8% to −0.1% and from −14.6% to −2.5%, relative to the 1961–90 level, during the 2020s, 2050s, and 2080s, respectively. Across the cells, the probability of a decrease in the rice yield could be 26.4% to 90.4%, 44.3% to 91.3%, and 62.1% to 95.1% during the 2020s, 2050s, and 2080s, respectively, relative to the 1961–90 level.

f. Mechanisms of changes in rice yield and water use

Among major factors that may affect yield, we found that climate change was projected to reduce the duration...
Fig. 9. Spatial patterns of (a) projected changes in the duration of the rice-growing period and (b) the mean daily ratio of transpiration and potential transpiration over the growing period during the 2050s, relative to 1961–90 levels. Probabilities of high-temperature stress during (c) 1961–90 and (d) the 2050s. Probabilities of low-temperature stress during (e) 1961–90 and (f) the 2050s. Projected changes in fractional sunshine hours during the (g) 2050s and (h) 2080s relative to the 1961–90 level. The simulated effects of rising atmospheric [CO₂] on (i) rice yield and (j) ET during the 2050s.
of the rice-growing period by up to 7.0% across the study area during the 2050s (Fig. 9a). The largest reduction could be in the southwestern part of Anhui Province, where the mean temperature was relatively high during 1961–90 and was projected to have a relative large increase during the 2050s. In addition, the projected changes in the ratio of daily transpiration and potential transpiration over the growing period during the 2050s would increase by up to 10% across the study area (Fig. 9b). The patterns of temperature and its change (Fig. 5), as well as the change in duration of the rice-growing period, were consistent with the pattern of yield (Fig. 7c), suggesting temperature and its change should play key important roles in affecting rice yield. The occurrence probability of high-temperature stress on rice could increase notably during the 2050s (Fig. 9d), relative to the probability for the period 1961–90 (Fig. 9c), particularly in Anhui Province and the northwestern part of Zhejiang Province, suggesting high-temperature stress could reduce rice yield substantially in those areas. By contrast, the occurrence probability of low-temperature stress on rice could decrease notably during the 2050s (Fig. 9f), relative to the probability for the period 1961–90 (Fig. 9e), particularly in the southern part of Anhui Province. We found the projected fractional sunshine hours would increase generally by 6% to 12.5% during the 2050s (Fig. 9g) and by 10%–15% during the 2080s (Fig. 9h), taking the HadCM3 GCM and A1FI emission scenario as an example. Increases in solar radiation, as indicated by changes in fractional sunshine hours (Figs. 9g,h), together with rising mean temperature and [CO₂], could contribute to greater photosynthesis. CO₂ fertilization effects were projected to generally increase rice yield by an additional 23.9%–30.4% (Fig. 9i) and reduce ET during the

**Fig. 9. (Continued)**
Rising atmospheric \([\text{CO}_2]\) was projected to contribute notably to an increase in rice yield. Our simulations on the effects of rising atmospheric \([\text{CO}_2]\) were generally consistent with previous findings of various controlled-environmental experiments, including Free-Air Carbon Dioxide Enrichment (FACE) experiments (e.g., Kimball 1983; Kimball et al. 2002; Tubiello and Ewert 2002; Ainsworth and Long 2005; Tubiello et al. 2007; Easterling et al. 2007). The complex interactions between climate variables and \([\text{CO}_2]\) resulted in distinct spatial patterns of \(\text{CO}_2\) fertilization effects on rice-yield increases across the simulations, with the largest effect in the southeastern part of Zhejiang Province (Figs. 9g,i), where both temperature and precipitation were projected to increase less (Fig. 4).

Our results showed that if taking \(\text{CO}_2\) fertilization effects into account, there was a relatively high probability of the rice yield increasing and water use decreasing. The rice photosynthesis rate and biomass could increase substantially owing to increases in temperature, solar radiation and \([\text{CO}_2]\), although rice development could accelerate and the duration of the growing period could be shortened. Meanwhile, the probability of high-temperature stress could increase notably with climate change, reducing the harvest index and yield substantially. An increase in temperature could offset the benefits of rising \([\text{CO}_2]\) on rice yield (Tao et al. 2008; Cheng et al. 2009). And climate change eventually could reduce rice yield in areas of eastern China during the 2080s (Fig. 7g) where the mean temperature and especially the probability of extreme high temperatures were projected to be higher. The decrease in rice water use could be ascribed to the stomatal response of plants to rising atmospheric \([\text{CO}_2]\) and a decrease in the duration of the rice-growing period. When \(\text{CO}_2\) fertilization effects were ignored, the yield would decrease substantially and this crop response could be partly ascribed to the high-temperature stress on net \(\text{CO}_2\) assimilation (Morison and Lawlor 1999). In addition, increases in temperature could also accelerate grain growth could accelerate grain growth rate, reduce the duration of grain filling, and thus reduce grain weight (Morison and Lawlor 1999). Furthermore, high-temperature stress at the flowering stage, which could increase with climate warming, could induce floret sterility and reduce rice yield substantially (Matsui and Horie 1992). Our study provided empirical evidences on the combined effects of climate change, high-temperature stress, and rising \([\text{CO}_2]\) on rice yield.

The results were generally applicable to single or late rice in the region; in contrast, early rice in the region would be less affected by high-temperature stress in summer. Additionally, although the most severe climate changes and yield losses were found at lower elevations such as southwestern Anhui Province, the potential for greater climate sensitivity at higher elevations should also be worthy of concern.

4. Discussion

a. The complex interactions between climate change, high-temperature stress, and rising \([\text{CO}_2]\) on rice productivity and water use

Rising atmospheric \([\text{CO}_2]\) was projected to contribute to an increase in rice yield. Our simulations on the effects of rising atmospheric \([\text{CO}_2]\) were generally consistent with previous findings of various controlled-environmental experiments, including Free-Air Carbon Dioxide Enrichment (FACE) experiments (e.g., Kimball 1983; Kimball et al. 2002; Tubiello and Ewert 2002; Ainsworth and Long 2005; Tubiello et al. 2007; Easterling et al. 2007). The complex interactions between climate variables and \([\text{CO}_2]\) resulted in distinct spatial patterns of \(\text{CO}_2\) fertilization effects on rice-yield increases across the simulations, with the largest effect in the southeastern part of Zhejiang Province (Figs. 9g,i), where both temperature and precipitation were projected to increase less (Fig. 4).

Our results showed that if taking \(\text{CO}_2\) fertilization effects into account, there was a relatively high probability of the rice yield increasing and water use decreasing. The rice photosynthesis rate and biomass could increase substantially owing to increases in temperature, solar radiation and \([\text{CO}_2]\), although rice development could accelerate and the duration of the growing period could be shortened. Meanwhile, the probability of high-temperature stress could increase notably with climate change, reducing the harvest index and yield substantially. An increase in temperature could offset the benefits of rising \([\text{CO}_2]\) on rice yield (Tao et al. 2008; Cheng et al. 2009). And climate change eventually could reduce rice yield in areas of eastern China during the 2080s (Fig. 7g) where the mean temperature and especially the probability of extreme high temperatures were projected to be higher. The decrease in rice water use could be ascribed to the stomatal response of plants to rising atmospheric \([\text{CO}_2]\) and a decrease in the duration of the rice-growing period. When \(\text{CO}_2\) fertilization effects were ignored, the yield would decrease substantially and this crop response could be partly ascribed to the high-temperature stress on net \(\text{CO}_2\) assimilation (Morison and Lawlor 1999). In addition, increases in temperature could also accelerate grain growth could accelerate grain growth rate, reduce the duration of grain filling, and thus reduce grain weight (Morison and Lawlor 1999). Furthermore, high-temperature stress at the flowering stage, which could increase with climate warming, could induce floret sterility and reduce rice yield substantially (Matsui and Horie 1992). Our study provided empirical evidences on the combined effects of climate change, high-temperature stress, and rising \([\text{CO}_2]\) on rice yield.

The results were generally applicable to single or late rice in the region; in contrast, early rice in the region would be less affected by high-temperature stress in summer. Additionally, although the most severe climate changes and yield losses were found at lower elevations such as southwestern Anhui Province, the potential for greater climate sensitivity at higher elevations should also be worthy of concern.

b. Uncertainties in climate change impact studies and the superensemble-based probabilistic projection approach

Previous estimates of the effects of climate change on rice yield in China varied widely (Table 5). The comparisons of these estimates were quite difficult because they were quite different in terms of study regions, study period, climate change scenarios and crop models used (Table 5). Nevertheless, based on these studies, we could conclude that rice yield could decrease with high probability in future if \(\text{CO}_2\) fertilization effects were not taken into accounted. Rice yield could increase in future with moderate warming if \(\text{CO}_2\) fertilization effects were taken into accounted, however an increase in temperature may offset the benefits of rising \([\text{CO}_2]\) on rice yield and the final yield change should be subjected largely to the complex interactions between \(\text{CO}_2\) and climate, the impacts of extreme climate events, as well as the adaptations such as cultivars turnover. Unfortunately, the three crucial issues were relatively poorly understood and remained uncertain. In the present study, the uncertainties from both climate change scenarios and biophysical parameters of crop model were taken into account; the effects of extreme temperature stress on rice productivity were explicitly parameterized. Furthermore, a wide range of crop cultivars phenological and thermal characteristics were taken into account through the use of multiple sets of cultivar parameters, instead of adopting a single cultivar as in some previous studies. Thus, the responses and adaptations of different crop cultivars to climate change were relatively better accounted for in comparison with some of previous studies that used only one set of cultivar parameters, although the parameters were calibrated on the basis of current crop datasets.

5. Conclusions

The crop model MCWLA-Rice was developed by adapting the MCWLA, a general crop model, to the rice...
TABLE 5. Comparisons of estimates on the effects of climate change on rice yield in China. Here, CERES is the Crop Environment Resource Synthesis model, EPIC is the Environmental Policy Integrated model, and “ORYZA” is the name of a rice model.

<table>
<thead>
<tr>
<th>Study region</th>
<th>Study period</th>
<th>Climate change scenario</th>
<th>Crop model</th>
<th>Projected yield changes with CO₂ fertilization effects</th>
<th>Projected yield changes without CO₂ fertilization effects</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Four agroecological zones across China</td>
<td>When [CO₂] is doubled</td>
<td>GFDL GCM and 2×[CO₂], GISS GCM and 2×[CO₂], UKMO GCM and 2×[CO₂]</td>
<td>ORYZA1</td>
<td>from −7.4% to 5.8%, from −21.7% to 5.8%, from −27.6% to 3.1%</td>
<td></td>
<td>Matthews et al. (1997)</td>
</tr>
<tr>
<td>Four agroecological zones across China</td>
<td>When [CO₂] is doubled</td>
<td>GFDL GCM and 2×[CO₂], GISS GCM and 2×[CO₂], UKMO GCM and 2×[CO₂]</td>
<td>SIMRIW</td>
<td>from −10.0% to 9.7%, from −30.7% to 9.7%, from −17.2% to −1.4%</td>
<td></td>
<td>Matthews et al. (1997)</td>
</tr>
<tr>
<td>Some stations in southern China</td>
<td>2071–90</td>
<td>PRECIS RCM and B2 emission scenario</td>
<td>CERES-Rice</td>
<td>5%–20% from −7% to −0.25%</td>
<td></td>
<td>Yao et al. (2007)</td>
</tr>
<tr>
<td>Rice cultivation areas across China</td>
<td>2010–19</td>
<td>PRECIS RCM and A2 emission scenario</td>
<td>CERES-Rice</td>
<td>15.1%, 7.9%, −0.8%, −20.9%</td>
<td></td>
<td>Xiong et al. (2008)</td>
</tr>
<tr>
<td>Rice cultivation areas across China</td>
<td>2040–49</td>
<td>PRECIS RCM and B2 emission scenario</td>
<td>CERES-Rice</td>
<td>2.2%, −1.8%, −2.6%, −19.1%</td>
<td></td>
<td>Xiong et al. (2008)</td>
</tr>
<tr>
<td>Rice cultivation areas across China</td>
<td>2070–79</td>
<td>Probabilistic climate scenarios generated by a Monte Carlo technique</td>
<td>CERES-Rice</td>
<td>from −10.1% to 3.3%, from −16.1% to 2.5%, from −19.3% to 0.18% from −18.6% to −6.1%, from −31.9% to −13.5%, from −40.2% to −23.6%</td>
<td></td>
<td>Tao et al. (2008)</td>
</tr>
<tr>
<td>Six representative stations across China</td>
<td>When global mean temperature changes by 1°C, 2°C, 3°C</td>
<td></td>
<td></td>
<td>6.5%</td>
<td></td>
<td>Chavas et al. (2009)</td>
</tr>
<tr>
<td>Eastern China</td>
<td>2071–2100</td>
<td>RegCM3 RCM and A2 emission scenario</td>
<td>EPIC</td>
<td>≤−14%</td>
<td></td>
<td>Shen et al. (2011)</td>
</tr>
<tr>
<td>The middle and lower reaches of Yangtze River</td>
<td>2021–50</td>
<td>PRECIS RCM and B2 emission scenario</td>
<td>ORYZA2000</td>
<td>9.5%–11.4%, 7.1%–13.2%, 0.7%–7.8% from −5.9% to −3.7%, from −18.6% to −13.4%, from −29.4% to −23.8%</td>
<td></td>
<td>This study</td>
</tr>
<tr>
<td>Eastern China</td>
<td>2011–40, 2041–70, 2071–2100</td>
<td>Combinations of five GCMs (HadCM3, PCM, CGCM2, CSIRO2, and ECHAM4) and two emission scenarios (A1FI and B1)</td>
<td>MCWLA-Rice</td>
<td>9.5%–11.4%, 7.1%–13.2%, 0.7%–7.8% from −5.9% to −3.7%, from −18.6% to −13.4%, from −29.4% to −23.8%</td>
<td></td>
<td>This study</td>
</tr>
</tbody>
</table>
crop. Bayesian probability inversion and an MCMC technique were applied to MCWLA-Rice to analyze the uncertainties in parameter estimations, and to optimize the parameters. Ensemble hindcasts showed that MCWLA-Rice could capture the interannual variability of rice yield fairly well, especially over a large area.

The MCWLA-Rice and SuperEPPS were applied to project the probabilistic changes in rice productivity and water use in eastern China due to future climate change. The results showed that across most of cells in the study region, relative to 1961–90, there was a relatively high probability of the rice yield increasing and water use decreasing in near future, although the probability of high-temperature stress would increase notably with climate change, reducing the harvest index and yield substantially.

Our study represented explicitly the effects of extreme weather events and represented better the responses of different rice cultivars with contrasting phenological and thermal characteristics. The resultant probabilistic changes could provide more robust information for adaptations.

Acknowledgments. This study is supported by the National Science Foundation of China (Project Number 41071030) and National Key Programme for Developing Basic Science (Project Number 2010CB950902), China. F. Tao acknowledges the support of the “ Hundred Talents” Program of the Chinese Academy of Sciences.

REFERENCES


Matthews, R. B., M. J. Kropff, T. Horie, and D. Bachelet, 1997: Simulating the impact of climate change on rice production in


