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Future increases in irrigation water requirement challenge the water-food nexus in the northeast farming region of China

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ABSTRACT

Northeast Farming Region of China (NFR) produces about one-third of the national maize output. Shortage of crop irrigation water is one of the main threat to the stable level of maize production in the NFR. Previous studies on the sensitivity of maize production to drought are typically based on field experiments and treat the maize growing season as a whole, with rare attention to the varying impacts of drought across different maize growth stages. Given the importance of NFR on China's food security, it is crucial to optimize the irrigation schedule to mitigate the adverse effects of drought. In this study, we employ Agro-ecological Zone (AEZ) model to investigate how climate change affects irrigation water requirement (IWR) of maize during different growth stages and under different climate change scenarios. Results indicate that the NFR would experience a substantial increase in the probability of extremely shortage of crop irrigation water under future climate change. The ensemble simulation under future climate projections indicates more frequent demands for irrigation with substantially increased amount in the mid-season stage (G3) when maize is more sensitive to water deficit compared with other stages. These findings indicate that earlier planning of irrigation infrastructure and development of more efficient irrigation scheme and technologies is of great importance to secure maize production in the region.

1. Introduction

Maize (Zea mays L.) production is critical in guaranteeing food and feed security for China (Gustafson et al., 2014). As the famous Golden Maize Belt, the Northeast Farming Region (NFR) is the largest rain-fed maize-producing region in China and accounted for more than one-third of the nation's total production in 2016 (National Bureau of Statistics of China, http://data.stats.gov.cn). However, with 62% of the crop water requirements (CWR) being met by precipitation (Meng et al., 2016), maize yield and production in the NFR have been vulnerable to drought due to the high sensitivity of maize to water supply and temperature as well as the spatial and temporal variability of effective rainfall in the region (Cook et al., 2015; Zhao et al., 2015). In the coming decades, the projected decrease in precipitation (Yu et al., 2014) and increase in the frequency and intensity of drought episodes (Leng et al., 2015) will further elevate the risk of maize production in the NFR (Xu et al., 2013; Meng et al., 2016; Zhao et al., 2015). The increasing competition for water from the much more profitable non-agricultural sectors will add diverting pressure on irrigation water supply and thus imposing further challenges to maize production in the region.

Water stress caused by the shortage of irrigation water at any stage of maize growth can reduce biomass production and lead to yield loss. As such, extending irrigation network and optimizing irrigation scheme

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should be one of the most efficient adaptation measures to alleviate the negative impact of drought on maize production. However, only 15% of the maize growing areas in the NFR are irrigated (Liu et al., 2005). Existing assessments of drought risk in the region are mostly based on precipitation changes in the whole growth season (e.g. Kent et al., 2017) without considering the varying sensitivity of maize growth to water stress at different growing stages (e.g., vegetative, silking and kernel-filling growth stages). For example, the maize sowing season ranges from late April to mid-May in the NFR. Spring drought can delay the sowing date, changing the corresponding relationship between hydrothermal factors and exerting influence on maize grain yields (Osman, 2015; Wang et al., 2017). The maximum reduction in grain yield results when the drought stress occurs at the vegetative growth stage (Osman, 2015). It is, therefore, crucial to understand the distribution of irrigation water requirement (IWR) in different growing stages (Song et al., 2013; Yu et al., 2013). Such distributional information will provide a scientific base for irrigation infrastructure planning and irrigation schedule designing, with the aim to mitigate the adverse effects of irrigation water shortages in the NFR under future climate change (Jiang et al., 2017; Wang et al., 2016).

Climate change will affect water availability for crop growing and increase crop water requirements as a result of changes in the magnitude and timing of precipitation at different spatial and temporal scales (Gornall et al., 2010). Warming affects irrigation water demands in two ways: First, evapotranspiration increases due to the increase in radiation, rise in temperature and uneven distribution of precipitation (Abtew and Melesse, 2013). Second, the warming climate can potentially increase the drought risk at the key growing stages. This primarily occurs through increasing crop water requirements and reducing the available crop irrigation water during the growing period with an earlier planting and harvest dates. On the other hand, climate change can advance the start date and delay the end date of the crop growing season, resulting in a longer growing season that can be utilized by farmers to increase crop yield. In fact, farmers in the NFR region have taken measures to adapt to the observed warming trend in the region during recent decades. They have typically adopted maize cultivars with longer growing-cycle which allows earlier sowing, later harvesting, and thus prolonging the maize growing length and leading to higher yield. However, such adaptation measure has significant implications for irrigation water demand because both evapotranspiration and precipitation vary seasonally (Zhang and Cai, 2013). This research will explicitly assess such implications for each growing stage of maize in the NFR.

Sustainable agricultural production also depends on the efficient use of existing water resources, for instance by increasing the efficiency of irrigation systems and adjusting crop calendar to meet the suitable climate conditions. Field experiments show that such adaptation measures can increase maize yield by 13%–38% (Liu, et al. 2012). Thus, a better understanding of the CWR and IWR is of great importance for irrigation infrastructure planning, irrigation scheduling, and agricultural water management, because of the urgent need for producing more food per unit volume of water. In other words, an enhanced ability in estimating evapotranspiration and predicting the CWR and IWR by crop growing stages can help improve crop water-use efficiency, improve crop productivity and consequently save water for other purposes (Fischer et al., 2012b).

A number of process-based crop models have been employed to assess changes in average productivity levels under future climate change (Bassu et al., 2014; Challinor et al., 2014). Nevertheless, how to effectively use them to investigate the response of rainfed agriculture to the elevated drought risk, especially for the crop water use, is not well established yet. Recent studies have focused on assessing the quantity of IWR and the impact of irrigation water shortfall on maize production over the whole growing season in the NFR, largely based on field experiments (Liu et al., 2013). There has been a lack of attention to the following important question: How does the irrigation water shortfall affect maize production at different growing stages across the region? Because the performance of process-based and site-specific models outside the place of observation would be biased due to insufficient data coverage and the inability to show spatial integrity (Tubiello and Fischer, 2007), we cannot directly use these process-based models across a large region to simulate crop growing dynamics and quantify the IWR under different climate change scenarios. In addition, previous assessments of climate change impact on maize production in China (e.g., Tao and Zhang, 2010; Xiong et al., 2007) were based on Special Report on Emission Scenarios (SRES) (Parry et al., 2004) and has been out of date. Another weakness of previous assessments is the insufficient attention to adaptation measures of crops (Gustafson et al., 2014).

In this study, we adopt a nested modeling procedure to better capture different key agricultural processes which influence maize growth and development across different spatial scales, and to improve the spatial performance of the Agro-ecological Zone (AEZ) model (Fischer et al., 2012a,b) in terms of maize growth at regional scale. At the 6 representative sites where we have detailed agro-meteorological records and agronomic information, we employ the Decision Support System for Agro-Technology Transfer (DSSAT) model to simulate the eco-physiological processes at daily steps, with the aim to calibrate and validate key eco-physiological parameters for the AEZ model based on the outputs of the DSSAT model (Tian et al., 2012, 2014). At the regional level, we employ the AEZ model to quantify the amounts of the IWR at the grid-cell level across the NFR region and analyze the impact of irrigation water shortage on maize yield and production under current and future climate conditions in the NFR. The AEZ model employs a powerful algorithm to simulate crop growth and provides standardized crop simulation and environmental matching programs to quantify the limitations of climate, soil and agro-ecological environments under specific management conditions, to determine the expected yield of related planting activities (Fischer et al., 2002). The objectives of this study are to: (1) analyze the spatial-temporal variations of the CWR and IWR with a focus on the maize growing season; (2) estimate the spatial and temporal variation of the CWR and IWR in each key growing stage under different climate scenarios; (3) investigate the risk of crop irrigation water shortage in each growing stage under different climate scenarios.

To our best knowledge, this is the first study to characterize the impacts of future climate change on irrigation water demands at a regional scale in NFR, thus providing the water demand context for regional agricultural planning and the scientific information for irrigation water resource management decision-making in the NFR of China. The AEZ model has three advantages to achieve the goals we raised above: (1) The AEZ model contains an automatic crop calendar search for adaptation to climate change; (2) the AEZ model estimates land suitability and productivity at the grid-cell level across a large region like the NFR; (3) the AEZ model can compute the CWR and IWR for each major crops and highlight the trade-offs among crop planting options and between rain-fed and irrigation uses. In addition to providing a regional-scale water requirement context for decision making, this study also lays the foundation for future efforts that can look at water supply and requirement in conjunction, and include other considerations such as competing uses, and water management (such as water rights curtailment) and human decision-making in an internally consistent manner.

The rest of the paper is structured as follows. Sections 2 provides details of the study region and datasets, and presents the approach to quantify the IWR at each growth stages across grid-cells in the NFR. Section 3 reports changes in the CWR, IWR and drought risk at different growing stages under multiple climate change scenarios. Finally, Section 4 concludes and discusses the advantages and limitation of this work.

2. Materials and methods

2.1. Study area and data

The Northeast Farming Region (NFR) is located in the Northeast China (118°50′-135°05′E, 38°43′-53°24′N), including provinces of Heilongjiang, Jilin and Liaoning. The total area of NFR is 787,300 km^2 with a population of 129.5 million in 2015. During the maize growing season (from April to October), the average precipitation ranges from 308 to 657 mm, and the ≥10 °C accumulative temperature ranges from 2200 to 3600 °C. The input data for this study includes observations of maize phenology and management information, meteorological and climate data, elevation, soil, and land-use data.

Maize phenology and management information are obtained from the National Meteorological Networks of China Meteorological Administration (CMA) (see Fig. 2 for station locations). These includes: basic site characteristics (site name, latitude, longitude and altitude), cultivation information (planting varieties, crop system, farming, etc.), the detailed date of maize growth and development (seeding, emergence, flowering and maturity, etc.), yield component (planting density, grain weight, total production potential, stem weight, etc.) and crop management (irrigation, fertilization, harvest, etc.). In this study, we focus on the maize growing period and divide it into four stages according to the AEZ model: 1) from planting date to approximately 10% ground cover as the initial growth stage (G1), 2) from 10% ground cover to effective full cover as the crop development stage (G2), 3) from effective full cover to the start of maturity as the mid-season stage (G3), 4) and from the start of maturity to harvest or full senescence as the late season stage (G4) (Fischer et al., 2012a).

Meteorological data (1981–2010) are from the Data Center of CMA, including daily observations of sunshine hours, maximum and minimum temperature, precipitation, relative humidity and wind speed. The monthly maximum and minimum air temperature, precipitation, relative humidity, wind speed and sunshine hours are required in the AEZ model. Because solar radiation is not available at the six sites but is required by the DSSAT model, we calculated it from the recorded daily sunshine hours using the empirical global radiation model (Pohlert, 2004). Other daily weather observations can be used directly in the DSSAT model. Climate projections are taken from the CMIP5 ensemble with five global climate models (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M) driven by the four representative concentration paths (RCPs) scenarios (Moss et al., 2010; Taylor et al. 2012). Future climate change data from the above 20 GCM-RCP combinations are used in this study, including surface air temperatures, precipitation, surface radiation (short and long wave down welling), surface wind speed, surface air pressure, surface relative humidity (Warszawski et al., 2014).

Soil properties, such as soil texture and organic matter content, play significant roles on soil water status and crop growth and thus affect crop yield and water productivity. The Harmonized World Soil Database (HWSD) is employed as the base for soil data. HWSD is also the base for the Global Agro-ecological Zones model. The HWSD is developed by the Land Use Change and Agriculture Program of International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization (FAO) of the United Nations, it provides reliable and harmonized soil information at the pixel level for the world (FAO/IIASA/ISRIC/ISSCAS/JRC 2009). Soil properties (soil texture, clay content, slit content, sand content, PH in water, cation exchange capacity, organic carbon, bulk density) required by the AEZ model can be extracted directly from the HWSD soil database.

The spatial distribution of cultivated land area is derived from the 2010 land use database (100 m × 100 m), which is developed by the Chinese Academy of Sciences (CAS). The primary data source for developing this land-use database is Landsat TM images, with the China-Brazil Earth Resources Satellite (CBERS) as a supplementary for places where the Landsat images do not cover. The original land use data is classified into 25 types and we further group them into six categories: cropland, woodland, grassland, water body, built-up area and unused land. These databases have been widely used in previous studies (Liu et al., 2012, 2010). In this study, we extracted the cropland data from the land-use dataset for the regional simulation. Finally, all the input data for the AEZ are bilinear interpolated into the same spatial resolution of 10 km × 10 km.

2.2. The AEZ model and the estimation of irrigation water requirement (IWR)

The IWR of maize growth in the NFR of China is estimated using the Agro-Ecological Zone (AEZ) model (Fischer et al., 2007). The AEZ model is jointly developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agricultural Organization (FAO) of the United Nations. The AEZ model employs simple and robust crop submodules and provides standardized crop modeling and environmental matching procedure to identify crop-specific limitations of prevailing climate, soil and terrain resources under assumed levels of management inputs (e.g., low, medium and high). The standardized crop-modeling and environmental matching procedure in the AEZ makes it well-suited for crop productivity assessment at regional, national and global scales (Fan et al., 2017; Fischer et al., 2012a, 2005; Fischer and Sun, 2001; Fischer et al., 2002; Tian et al., 2014, 2012; Zhong et al., 2017). The IWR in the AEZ is mainly determined by the availability of effective rainfall, radiation and temperature. The soil data are used to calculate the soil-water balance, which is then used to determine the potential and actual evapotranspiration for a reference crop and the duration of its growing period.

In this research, we run the AEZ model at a daily time step for a 30-year time frame corresponding to historical climate (1981–2010), and two 30-year time frames corresponding to future climate in the 2050s (2041–2070) and the 2080s (2071–2100), respectively, to understand the direct impacts of climate change on water deficit and crop IWR at different growing stages of maize in the NFR of China.

The crop water requirement (CWR) is the total amount of water required for compensating evapotranspiration loss from the cropped field under the well-managed condition, i.e., without water, nutrient, or pest stress. Drought occurring at any maize growth stage would reduce biomass production and cause yield loss, due to insufficient water to meet the CWR. Effects of water stress on maize include the visible symptoms of reduced growth, delayed maturity, and reduced crop yield. For instance, water stress may reduce maize canopy height, leaf area index, and root growth. The crop-specific water requirement is calculated by multiplying the crop and crop-stage specific parameters 'kc' with the reference evapotranspiration (ET_0) at different maize growing stages:

$$CWR = Kc \times ET_0$$

The calculation of the CWR for a 'reference crop' is based on the assumption that sufficient water is available for uptake in the rooting zone. CWR is linked to ET_0 through the crop coefficients for water requirements (kc). The kc factors for different growing stages (early, development, middle and late stages) are determined by phenological development and leaf area, which are obtained from previous studies (Allen et al., 1998; Kang et al., 2003; Zhao et al., 2013). The ET_0 represents the evapotranspiration from a defined reference surface which is similar to an extensive surface of green and well-watered grass of uniform height (0.12 m). The ET_0 was calculated according to the Penman-Monteith equation using the driving meteorological variables as inputs (Monteith, 1981, 1965).

The IWR is the amount of water required to meet the CWR, beyond that supplied by effective rainfall. It can be calculated using the following equation.

$$IWR = CWR - ET_a$$

The actual uptake of water for the 'reference' crop is characterized by the actual evapotranspiration (ET_a). Calculation of ET_a is differentiated between two possible cases depending on the availability of water for plant extraction: (i) adequate soil water availability (ET_a = CWR) and (ii) limited soil-water availability ($ET_a < ET_m$, i.e., maximum reference evapotranspiration) (Allen et al., 1998).

For limited water conditions, the ET_a can be calculated as the product of CWR and the variable ρ,

$$ET_a = min\left[(pre + \rho \times CWR), CWR\right]$$

Here, "pre" represents the effective precipitation, and ρ is the quotient of the current water balance (W_b) and the readily available soil water (W_{read}),

$$\rho = \frac{W_b}{W_{read}}$$

The volume of water available for plant uptake is calculated using a daily soil-water balance (W_b). The W_b accounts for the accumulated daily water inflow from precipitation (pre, mm/day) or snowmelt (snm) and the outflow from actual evapotranspiration (ET_a) and excess water loss due to runoff and deep percolation.

$$Wb_j = min(Wb_{j-1} + pre + snm - ET_a, W_{max})$$

where j is the day of the year, and $Wmax$ is the maximum soil water storage capacity.

2.3. Calibration of DSSAT and validation of maize cultivars for the AEZ model

Although the standardized crop-modeling and environmental matching procedure in the AEZ makes it well suited for crop productivity assessment and the IWR estimation at the regional scale, a disadvantage of the AEZ model is the lack of mechanisms to update the key ecophysiological parameters in its input database. The updating procedure of the AEZ is largely depedent on trial and error method. The observed warming in the last several decades in the NFR has caused the original parameters in AEZ model to be unrepresentative and outdated because farmers in the region have made innovative adaptation efforts by adopting new caltivars. To update key AEZ eco-physiological parameters in a systematic way, we adopt the model-couping procedure developed in Tian et al. (2012, 2014), which can be summarized as follows. Firstly, we employ the DSSAT model (Jones et al. 2003) to calibrate the phenological and physiological parameters of maize using detailed observations of maize growth, development and management data from six agro-meteorological stations in the NFR. The DSSAT model is developed by the International Benchmark Sites Network for Argo-technology Transfer project (IBSNAT) and it simulates the growth and development of crops within a homogeneous plot in a daily time step. The DSSAT model uses genotype coefficients to describe the genotype-by-environment interactions and simulate performance of diverse cultivars under different conditions (Penning de Vries et al., 1992). Each cultivar of a crop has specific parameters to describe the genotypic information of the cultivar within the parameter ranges of the crop. Our calibration and validation of the DSSAT is based on the attainable yield under ideal crop management conditions (no water, nutrien and pest stress). In this way, the calibration and validation can approximate field experiment conditions. The maximum attainable yield is calculated from optimum yield components, including the maximum grain number per tiller and the correspondent grain weight, maximum tiller number per plant and the optimum plant density. Tian et al. (2014, 2018) present the technical details of this calibration and validation procedure. Secondly, we convert these genotype coefficients obtained from the above calibration and validation process to the eco-physiological parameters of the AEZ to enrich and update its cultivar parameters set.

2.4. Calculation of the probability of extreme IWR under climate change

In this study, we also investigate how the probability of exceeding a critical threshold (x_c) of IWR will be altered under climate change scenarios compared to the historical period. Different from the traditional analysis focusing on the climatological mean, we are interested in the extreme case of IWR because extreme cases are useful and often provide significant insights into the particular phenomenon being studied, which also have important implications to crop yield. x_c is chosen so that the average occurrence of IWR which exceeds x_c is only 10% for both future (2041–2070) and historical (1981–2010) period in a 30-year window. We then calculated the normalized difference of this probability as follows:

$$[P(x_2 > x_c) - P(x_1 > x_c)]/P(x > x_c)$$

where x_2 refers to IWR during the future period (2041–2070) and x_1 refers to IWR during the historical period (1981–2010). The shift is normalized by P ($x > x_c$), where x refers to values during the both time periods of 1981–2010 and 2041–2070, and x_c is chosen so that P ($x > x_c$) is 10%. The results are based on 20 ensemble members for each of the five models (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M). Each model's values are first standardized to have zero mean and unit variance.

3. Results

3.1. Changes in precipitation and temperature

Table 1 reports the changes in daily mean precipitation and temperature in each growth stages of maize between the baseline of 1981–2010 and the 2050s at the six stations. We can see from the precipitation panel that there is no statistically significant reduction of daily mean precipitation in stages G3 and G4 with the only exception of Jiamusi station for G3. However, the statistically significant increases in daily mean temperature are present in stages G3 with the only exception of Haicheng, and the extent of the significant increase will be 2.12 (Dunhua) to 9.73℃ (Haerbing). Similar significant temperature increases are present in four of the six stations with the extent of significant change being 5.03 (Shuangcheng) to 7.36 (Jiamusi). Significant increase in temperature combined with the more or less unchanged precipitation means significant increase in evapotranspiration and thus irrigation water requirement in these two growth stages. The cases for G1 and G2 are sharply different. For example, at Jiamusi station, although reduction in daily mean precipitation is statistically significant, the decrease in daily mean temperature is also statistically significant and therefore, we would not expect a significant increase in the IWR at

Table 1
Change of daily mean precipitation and temperature between the baseline and 2050s in different growth stages at the six representative stations.

Site	G1	G2	G3	G4
	Precipitation (mm) and standard deviation of the change (in parentheses)			
Jiamusi	−0.50 (0.10)	−1.03 (0.17)	−0.83 (0.19)	−0.48 (0.38)
Dunhua	−0.24 (0.15)	−0.60 (0.19)	0.03 (0.43)	1.66 (0.65)
Haerbing	−0.14 (0.10)	−0.75 (0.22)	0.39 (0.36)	1.12 (0.43)
Shuangcheng	−0.34 (0.10)	−1.21 (0.22)	−0.47 (0.44)	0.37 (0.33)
Haicheng	−0.03 (0.18)	0.83 (0.49)	−0.06 (0.86)	0.48 (0.34)
Zhuanghe	−0.11 (0.18)	0.53 (0.65)	−0.23 (0.96)	0.24 (0.39)
	Temperature (℃) and standard deviation of the change (in parentheses)			
Jiamusi	−3.36 (1.20)	−2.02 (0.97)	2.41 (0.95)	7.36 (0.97)
Dunhua	−0.70 (1.19)	0.23 (0.96)	2.12 (0.76)	5.61 (0.90)
Haerbing	−0.96 (1.16)	0.32 (1.07)	9.73 (1.05)	6.00 (1.23)
Shuangcheng	−1.02 (1.13)	0.33 (0.96)	3.00 (1.09)	5.03 (1.23)
Haicheng	0.43 (0.96)	0.31 (0.69)	0.57 (0.83)	−0.26 (0.91)
Zhuanghe	3.4 (0.91)	3.04 (0.70)	8.3 (0.79)	1.32 (0.87)

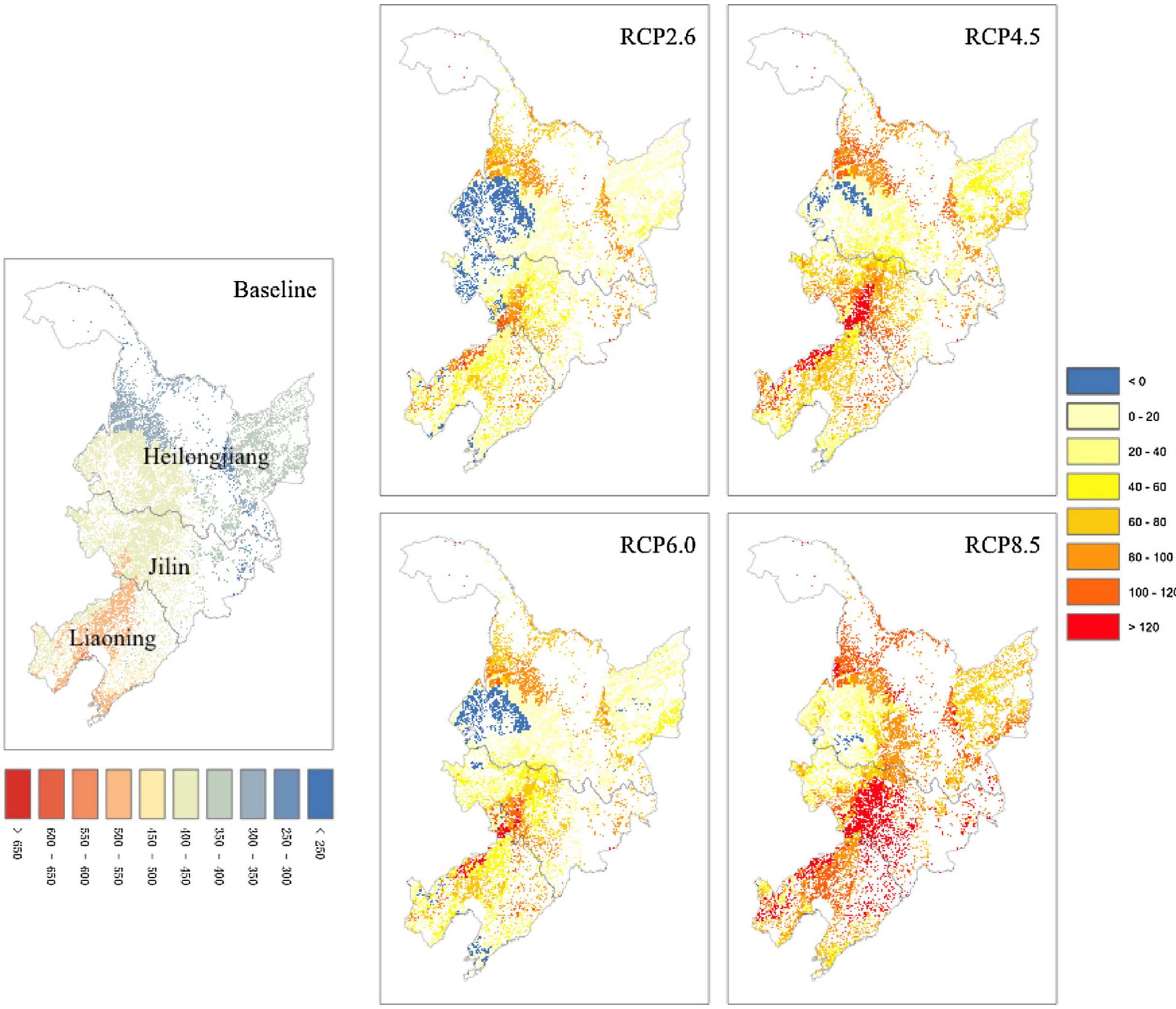

Fig. 1. Averaged total CWR of rainfed maize in the historical period (1981–2010) in the NFR and relative changes in the 2050s (2041–2070) driven by five climate models under four RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5).

this station by the 2050.

3.2. Spatial-temporal distribution of the CWR

The estimated annual averaged CWR of rainfed maize for the entire NFR in the historical period (1981–2010) is ~415 mm, with western Liaoning having the highest CWR and northern and eastern Heilongjiang province having the lowest (Fig. 1). This is due to the fact that precipitation in the NFR is unevenly distributed both seasonally and spatially with a decreasing temperature gradient from south to north. Under future climate scenarios, CWR increases significantly over the NFR by the 2050s compared to the baseline (1981–2010), with the largest increase in the middle part of Liaoning province and parts of western Jilin province (Fig. 1). More specifically, under RCP2.6, the CWR of rainfed maize decreases in western Jilin and southwestern Heilongjiang. In the medium emission pathways (RCP4.5 and RCP6.0), we observe a reduced spatial extent of the decreased CWR in southwestern Heilongjiang province compared to RCP2.6. However, with the high emissions pathway RCP8.5, the CWR increases in most parts of the NFR, especially in the middle parts of Jilin province, and decreased only in very small part of the southwestern Heilongjiang province.

3.3. Field-scale IWR under climate change

Table 2 reports the best attainable yield from observations and model simulations (including the minimum, mean, and maximum), and the average Relative Absolute Error (RAE) at the six stations in the historical period (1981–2010). It shows that the observed yield lies within the uncertainty range of the simulated yields for all six station with average RAEs between 4.54% and 7.63%. These results demonstrate that the simulated attainable yield matches observations relatively well, indicating that the AEZ model with our enriched value set of cultivar parameters is capable to simulate maize production level with relatively good accuracy.

Table 2
The observed best attainable yield, the minimum, mean, and maximum of the simulated yields, and the average RAE at the six stations (1981–2010).

Site	Average Observed yield (kg/ha)	Simulated attainted yield (kg/ha)			Average RAE (%)
		Minimum	Mean	Maximum	
Jiamusi	7670	6105	8237	9125	7.609
Dunhua	7500	7104	8032	8604	7.632
Haerbing	9000	7781	9015	9942	6.778
Shuangcheng	10147	9005	9782	10416	4.539
Haicheng	12285	11708	12667	13839	5.655
Zhuanghe	8692	7402	8084	8943	7.193

Fig. 2 presents the box plots of the simulated IWR in each growth stage under the 20 GCM-RCP combine scenarios, with reference to the

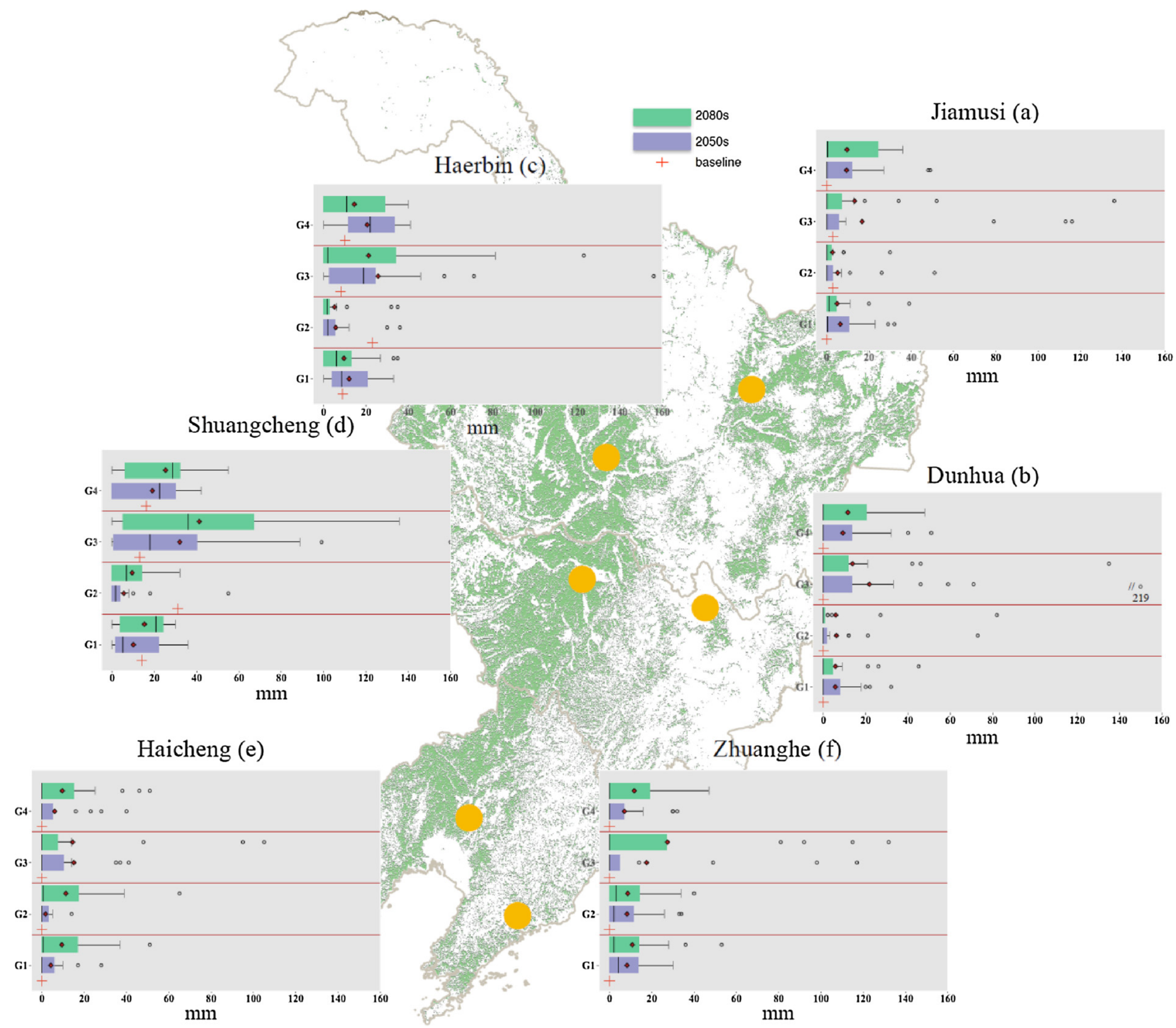

Fig. 2. Box plots showing the spread of IWR of rainfed maize in the 2050s (2041–2070, purple) and 2080s (2071–2100, green), with reference to the historical mean (1981–2010, plus symbol), for different growing stages (G1: initial growth stage; G2: crop development stage; G3: mid-season stage; G4: late season stage) at the six stations. The colored rectangle represents the 25th and 75th percentile. The vertical line and diamond symbol denote the ensemble median and mean (mm) of the 20 GCM-RCP combinations (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

historical mean of 1981–2010. Although there is no consistent IWR increases in the growth stages G1 and G2 across all six stations, uniform increases of the IWR are present in the growth stages G3 and G4. We employ the *t*-test to check the statistical significance of such IWR increase in stage G3, as crop growth in this stage is most sensitive to water stress. Five out of six stations (except Jiamusi) will experience statistically significant increase of IWR in G3 at the 5% or 10% level for both the 2050s and 2080s.

3.4. Estimation of regional IWR during the maize growth season under climate change

Fig. 3 depicts the spatial distributions of the average changes in the IWR over 5 GCMs for each RCP between the baseline 1981–2010 and the 2050s. A general increasing IWR is observed in the NFR for five GCMs. Two regions are further distinguished according to the magnitude of irrigation water shortage: (1) a large region concentrated in west Liaoning province, where IWR shortage can be very severe and would exert a greater negative impact on yield by the 2050s; and (2) west Jilin province and some southwest parts of Heilongjiang province, where shortage of the IWR would become severe as well, implying a negative impact on maize yields by the 2050s. Under RCP2.6 scenario, the ensemble averaged IWR over western Jilin province and southwest part of Heilongjiang province will decrease compared with the baseline scenario. Under RCP6.0 scenario, the ensemble averaged IWR over the southwest part of Heilongjiang province will increase compared to the baseline. Under RCP8.5 scenario, the ensemble averaged IWR show a significant and similar increase of the IWR with RCP6.0 by the 2050s.

3.5. The IWR in different growth stages under climate change

Assessment of the IWR at different growth stages is crucial because different maize cultivars have different growth length and because climate change may alter the seasonal variability of precipitation. The spatial variation of the IWR at different growth stages of maize in the NFR is shown in Fig. 4. The change of IWR in the early maize growth stage (G1) ranges from −30 to 10 mm, with a general decreasing IWR across the NFR under RCP2.6 and RCP4.5, and more or less unchanged level under RCP6.0 and RCP8.5 (Fig. 4-a). The range of IWR change is from −30 to 40 mm in development stage (G2), with the most significant increase in western Liaoning and southwest Jilin (Fig. 4-b). Consistent with the station-level findings, water deficit becomes the highest in the middle stage (G3), with a gap of up to 100 mm in the maize belt under RCP8.5 (Fig. 4-c). During G3, maize is at the critical stage of plant

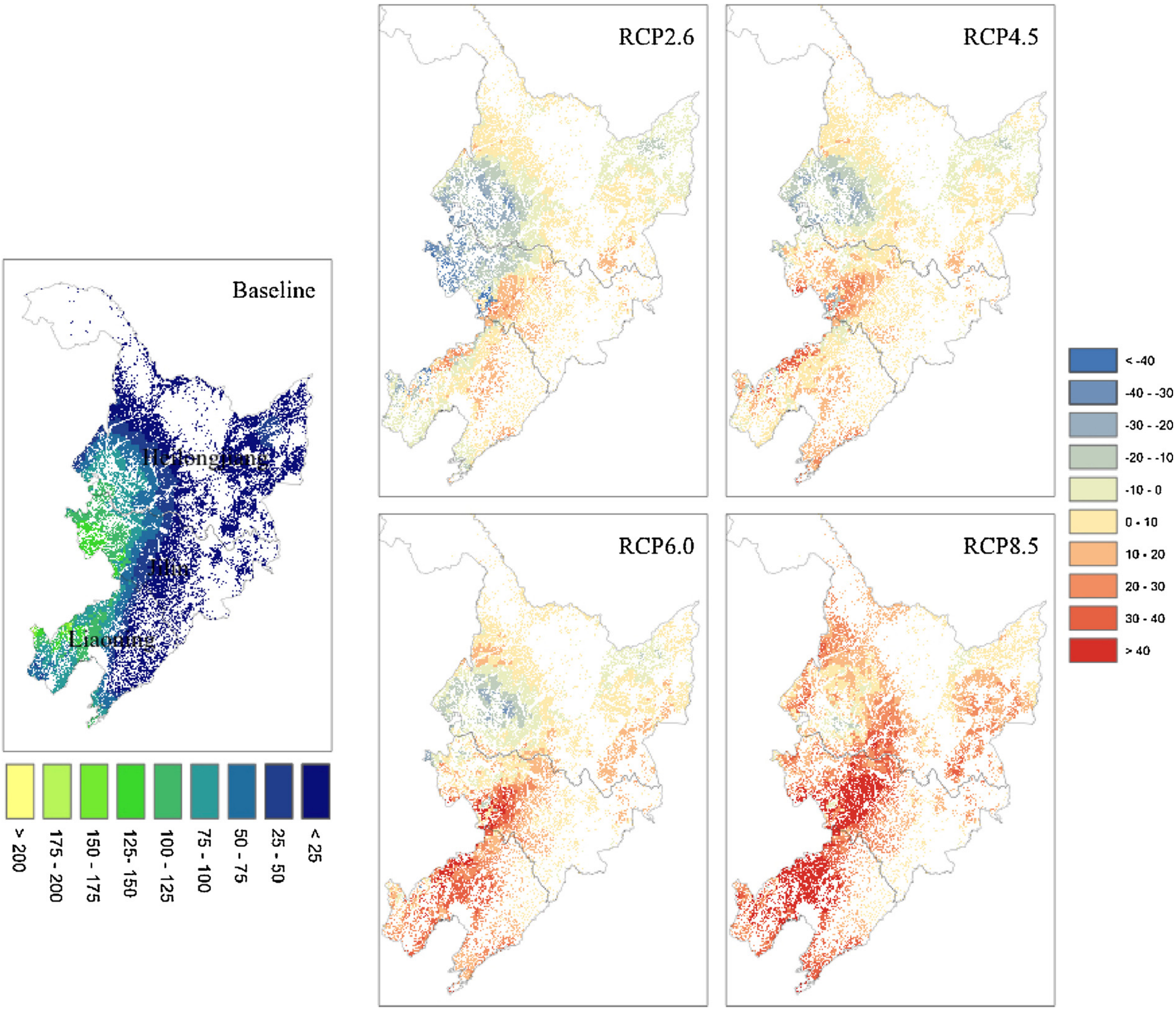

Fig. 3. Averaged total crop irrigation water requirement of rainfed maize in the historical period (1981–2010) in the NFR and the changes between the baseline and the 2050s driven by five climate models under four RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5).

development and the composition of evapotranspiration is dominated by crop transpiration. Therefore, such water shortfall during G3 would have significant negative consequences to maize production in the region by the 2050s. In the later stage (G4), the extent of change in the IWR becomes very moderate, similar to the case in G1 (Fig. 4-d).

3.6. Shift in the probability of extreme IWR under climate change during the growth season and different growing stages

Fig. 5 depicts a clear shift in the probabilities of extreme IWR for the whole growing period both in terms of the mean value and the shape of the distribution. The median values in Fig. 5 indicate that there is 50% chance that the extreme IWR will become 1–1.8 times of the climatological probability of 10% by the 2050s. The results show the probability distribution functions from pooling all grid boxes from the periods 1981–2010 and 2041–2070. In all cases the distribution between the two periods are shown to be statistically significantly different from each other of exceeding a particular critical value x_c during the whole growing season. Because we are focusing on extreme years, x_c is chosen to be the 10% value based on all years. In regard to the IWR, the results from the AEZ model indicate that much of the NFR has experienced an increase in the probability of extreme water shortfall under climate change during whole growing season. While the asymmetry appears to have increased between the two periods, results indicate that the distribution in the future has become worse.

Compared to the IWR for the whole growing season, results in different growing stages are more homogenous, with an increase in the probability of extreme IWR under climate change compared with the baseline. The pdf characterizing the IWR in the NFR shows lower in the peak, so that the changes in the pdf occur primarily in the peak and tails. While it is true that extreme IWR become more likely with future warming due to the asymmetric effect of even small shifts to rare events, it has also been implied that the IWR is becoming more variable in the sense of each year drawing from a broadening probability distribution (Fig. 6).

4. Conclusions and discussions

In this study, we combined outputs from a wide range of GCM-RCP combinations to produce detailed projections suitable for assessing the impact of climate change on irrigation water requirement (IWR) in different growth stages of maize in the Northeast Farming Region (NFR) of China, a region which produces about one-third of the national maize output. We employ an updated AEZ model to analyze the impact of irrigation water shortfall on maize yield and production under current and future climate conditions in the NFR. Main findings of this study are as follows:

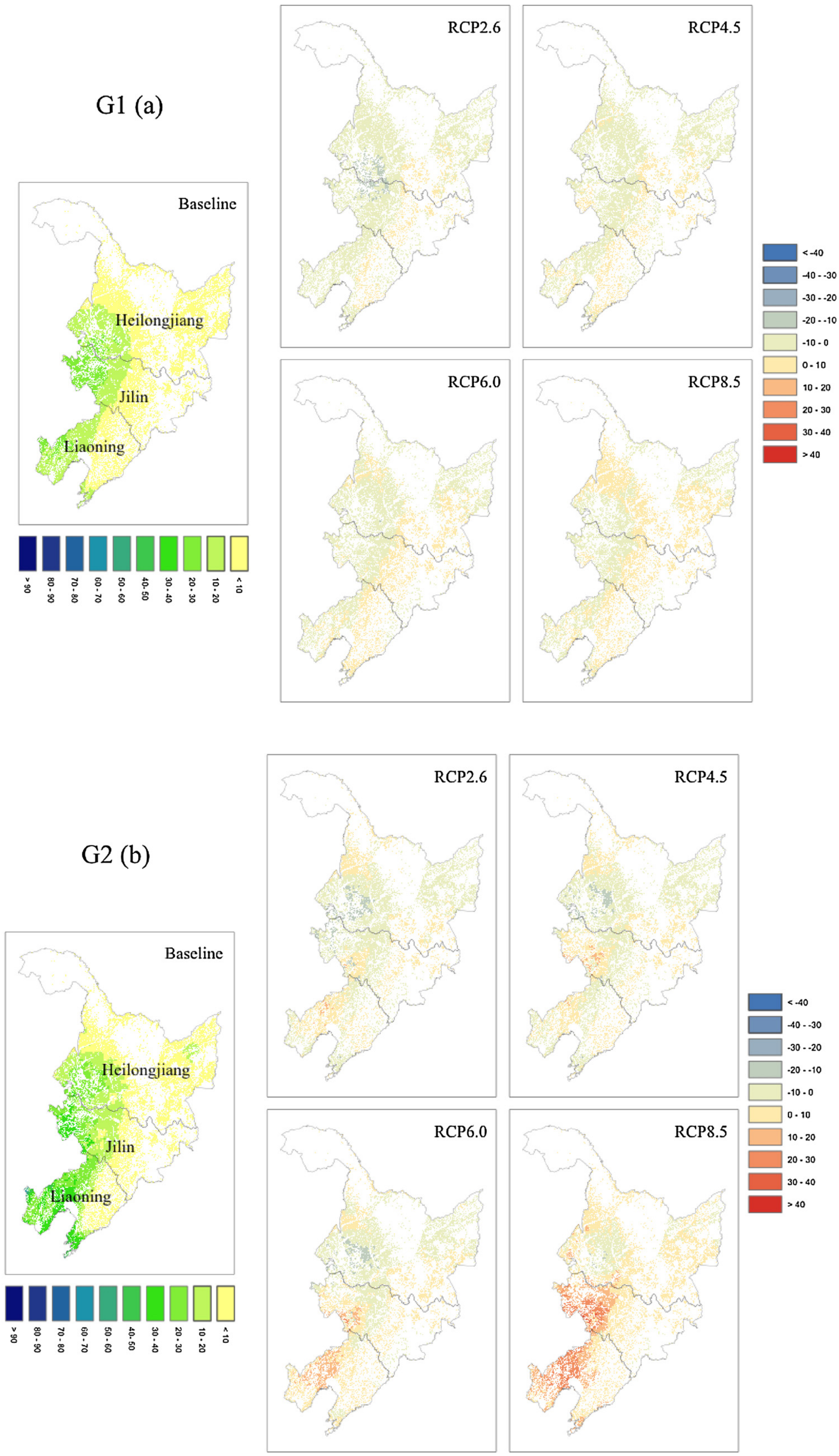

Fig. 4. Comparison of the simulated irrigation water requirement of rainfed maize at different growing stages (G1-G4) between the historical (1981–2010) and future period 2041–2070 (2050s) driven by five GCMs under four RCP scenarios (RCP2.6, RCP4.5, RCP6.0 and RCP8.5).

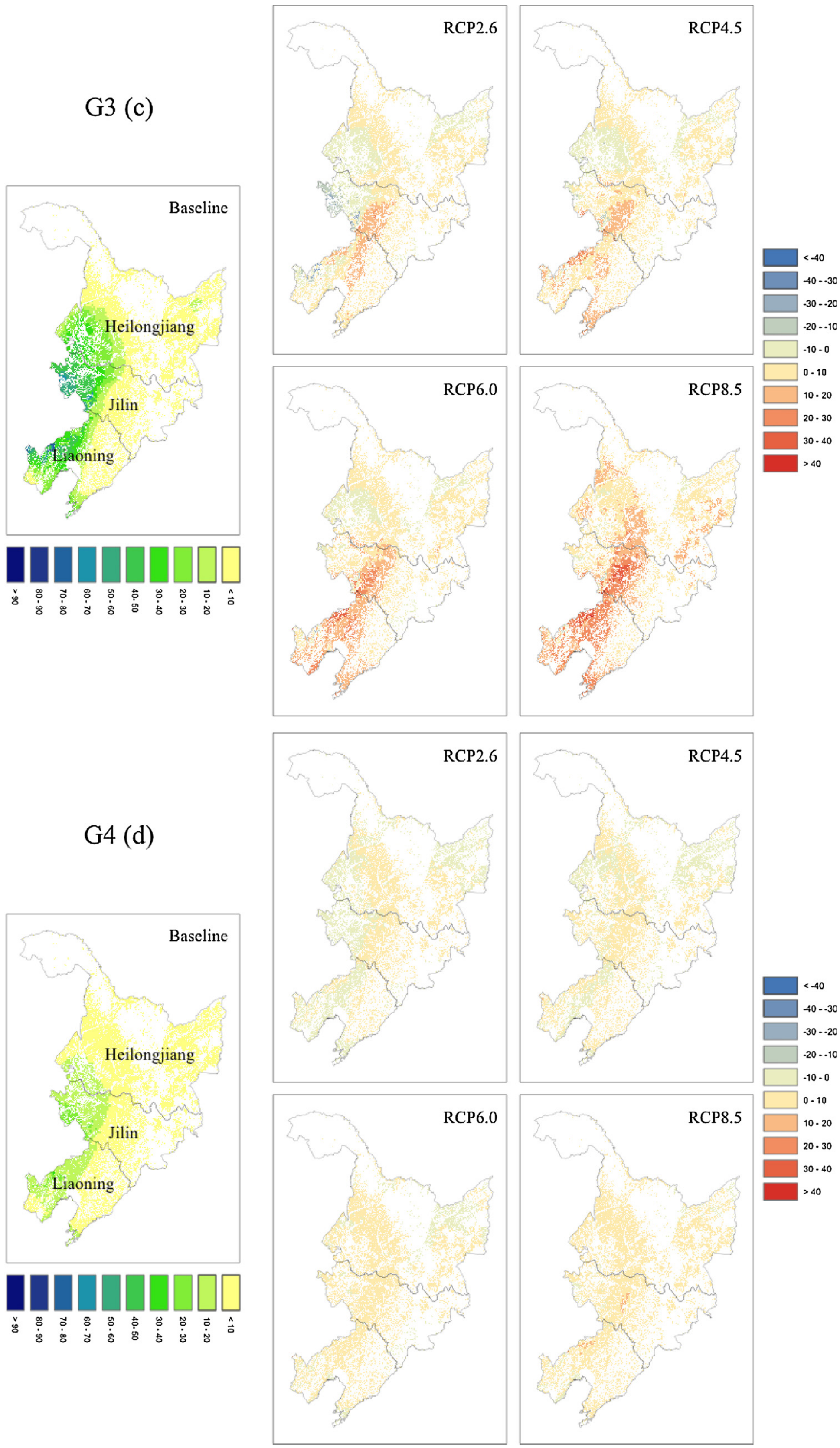

Fig. 4. (*continued*)

(1) Significant increase in the IWR is expected in the mid-season stage (G3), the critical development stage of maize growth, under future climate change scenarios. The increase is highest in the RCP8.5 scenario, followed by the RCP6.0, RCP4.5 and RPC2.6 scenarios.

(2) Current results indicate that significantly higher mean temperature and moderate change in rainfall during G3 would have a significant negative impact on maize yield in the future. Therefore, earlier planning of irrigation infrastructure and development of more

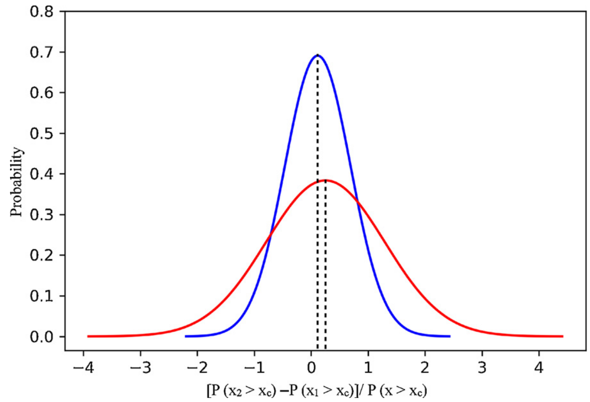

Fig. 5. Probability density plot showing the shift of the probability of extreme IWR in the future period (2041–2070, red line) compared to the historical period (1981–2010, blue line) defined as [P ($x_2 > x_c$)–P ($x_1 > x_c$)]/ P ($x > x_c$) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

efficient irrigation technologies is of great importance to secure maize production level of the region.

(3) The NFR will exhibit a substantial increase in the probability of extremely high level of the IWR under future climate. There is 50% chance that the extreme IWR will become 1–1.8 times of the climatological probability of 10% by the 2050s. For different growing stages, the increase in IWR is most significant in the mid-season stage (G3), in which maize growth is most sensitive to water shortfall. The increase in the probability of extremely high level of the IWR in G3 largely results from broaden probability distribution and shift in the mean.

Anticipatory water management planning at regional and national level, coping with future climate change should include suitable measures related to future IWR to deal with climate change uncertainties. In particular, the spatial and temporal variations in the irrigation water requirement of maize for the upcoming periods should be taken into account in agricultural water resources management.

Despite the above important findings, some limitations are worth mentioning. First, improvements can be achieved with respect to the climate model selection. This paper uses the GCM-RCPs scenario data proposed in the IPCC AR5, which shows improvements compared to CMIP3 in mode resolution and experimental design. However, large uncertainties still remain in the model simulations and further analysis of the uncertainty is still needed. Second, because the hydrogeology observations of groundwater resources in a large part of NFR are not available (MacDonald et al. 2012), irrigation from the groundwater is not considered in this study, which might have an impact on the current estimation of maize production. Third, compounding weather extremes (i.e., drought and high temperatures, rainstorms, freezing and fog) may have adverse effects on maize production, but these factors are not fully considered in our study. Fourth, it is worth highlighting that the adoption of crop cultivar variety is often determined by farmers' economic calculations and such calculation may not be consistent with the suitability consideration of agronomists. Future work is needed to quantify the uncertainty caused by the changing inter-annual variability and will benefit from an extended analysis based on multiple crop models.

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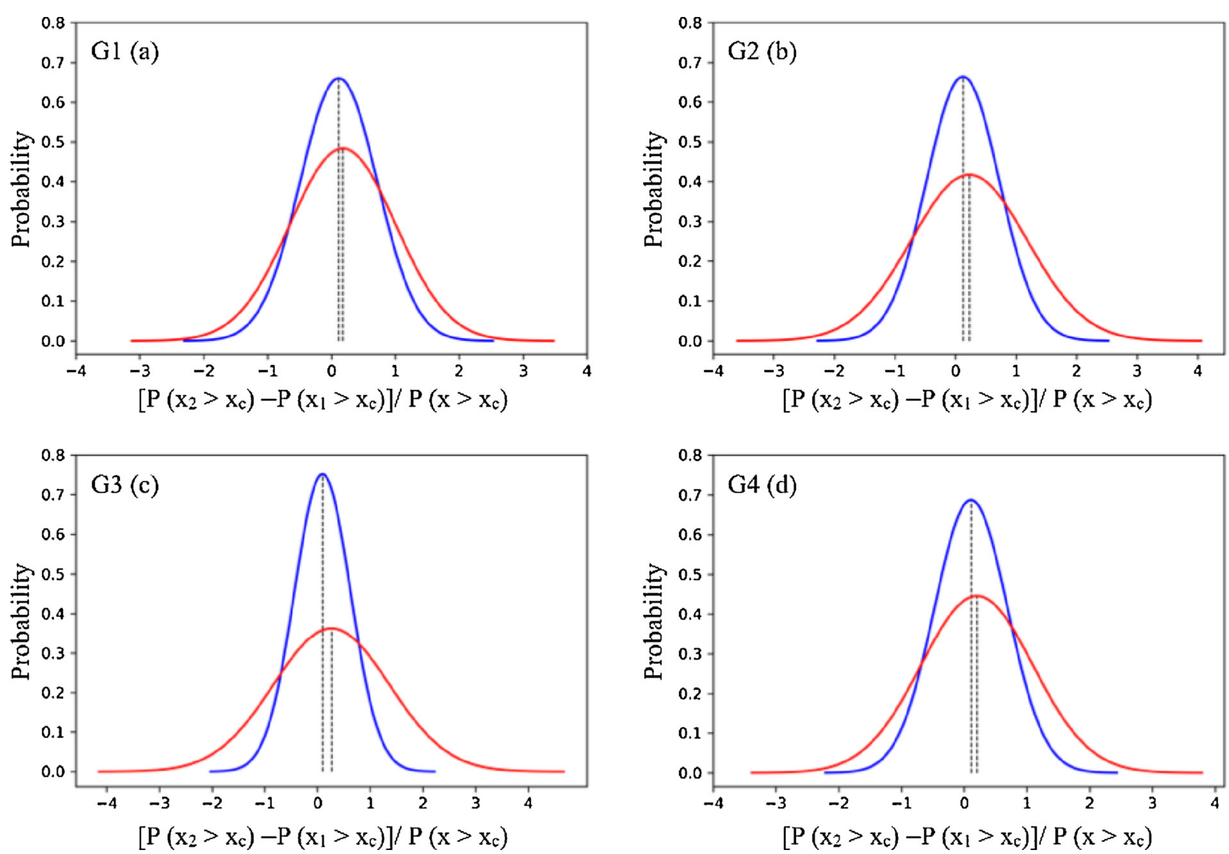

Fig. 6. Same as Fig. 5, but for different crop growth stages.

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