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Using a cross-scale simulation tool to assess future maize production under multiple climate change scenarios: An application to the Northeast Farming Region of China

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ABSTRACT

The Northeast Farming Region (NFR) is a major maize cropping region in China, which accounts for about 30% of national maize production. Although the regional maize production has an increasing trend in the last decades, it has greater inter-annual fluctuation. The fluctuation is caused by the increased variations of the local temperature and precipitation given the dominance of rainfed maize in the region. To secure high and stable level of maize production in the NFR under the warmer and drier future climate conditions, we employed a cross-scale model-coupling approach to identify the suitable maize cultivars and planting adaptation measures. Our simulation results show that, with proper adaptations of maize cultivars and adjustments of planting/harvest dates, both maize planting area and yield per unit of land will increase in most regions of NFR. This finding indicates that proactive adaptation can help local farmers to reap the benefits of increasing heat resource brought in by global warming, thus avoiding maize production losses as reported in other studies. This research can potentially contribute to the development of agricultural climate services to support climate-smart decisions for agricultural adaptations at the plot, farm and regional scales, in terms of planning the planting structure of multiple crops, breeding suitable maize varieties, and optimizing planting and field management schedules.

Practical implications

There have been a large body of studies investigating the impacts of climate change on crop production in China and around the world. However, the literature does not pay much attention on applying this knowledge to develop agricultural climate services. This study attempts to analyze the influence of climate change on maize production and outlines an agricultural climate services tool based on coupling two crop models at different spatial scales, with an application focus on Northeast Farming Region of China. The tool aims to support climate-smart decisions for agricultural adaptations at the plot, farm and regional scales, in terms of, for instance, planning the planting structure of multiple crops, breeding suitable maize varieties, and optimizing planting and field management schedules.

In more detail, we first employ a process-based crop growth dynamic model – DSSAT – and agro-meteorological observations to calibrate the phenological and physiological parameters of the DSSAT maize module at 14 representative farm-sites of the region. We then convert these parameters into the eco-physiological parameters set of the Agro-Ecological Zone (AEZ) model to enrich and update its cultivar set. The AEZ model, which runs across 10 km × 10 km grid-cells in the region, becomes well suited for crop suitability, zoning, and productivity assessments in the region with the help of such enriched parameters. In our application of the updated AEZ model for analyzing the impact of future

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climate change on the planting structure of crops, potential yield, cultivar adaptation and suitable planting area, we work with the ensemble outputs of the combinations of multiple climate models and representative concentration pathways (RCPs), which enable us to conduct a probabilistic assessment. This approach can bridge the gap between the climate information being developed by scientists and service providers and the practical needs of end-users, such as national and regional climate institutions (decision makers), breeders and farmers.

For National and regional climate institutions (decision makers): Agriculture is highly exposed to climate change, as decision-makers can take measures to mitigate the climate risk. In this paper, we discuss the relative driving mechanism of climate factor, potential maize yield and the changes in the planting structure of crops. The approach can help policy-making departments to make efficient use of agricultural climate resources, adjust agricultural planting structure across national and regional scales.

Crop breeder: Future climate change represents a challenge for breeders. We need to speed up the development of new crop varieties since current cultivars may be poorly suited for the future warming climate. The AEZ model can indicate the impact of climate change in a spatially explicit way and be used to predict long-term breeding objectives. Based on this, breeder can give appropriate weighting to different influences, thereby skewing gene frequency in favor of adaptation to the predicted conditions in the target region to mitigate the effect of climate change. Given these predictions, it is sensible for plant breeders to assume what crop varieties will be beneficial in the future production environment.

Farmers: Farmers across the Northeast Farming Region (NFR) rely on increasingly unpredictable rainfall to grow maize. Climate information services generated by the AEZ model at a large farmland scale are a powerful tool to provide the information about locations which are suitable for particular maize varieties. This information can help farmers to reduce production risks by adopting suitable maize varieties during the planting season. The results of this study can provide farmers in the NFR with a variety of strategies to improve capabilities in managing agricultural risks and uncertainties. Such strategies include choosing suitable locations to a specific crop, varying planting dates, matching varieties to the corresponding length of the growing season brought in by future warming climate.

Our current work provides an annual assessment of the adaptive capacity of the agricultural sector for maize production in the NFR. While this approach demonstrated above is based on long-term climate data, e.g. the climate projections of The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) driven by the four RCPs, it can be also based on seasonal climate forecasting data to facilitate the efforts of local governments and climate service institutions to provide innovative seasonal and short-term agro-meteorological advisory services and to support climate-smart decisions. In addition, once high-resolution long-term regional climate prediction data become available, they can be directly incorporated into our service tool for government and communities to improve simulation accuracy and better manage climate risk.

The results show that, under the 20 climate change scenarios, the suitable areas for the maize cultivars with a length of growth cycle at 150 and 160 days exhibit a robust northward expansion in the NFR. Although the impact of climate change on maize yield is spatially uneven and there are some differences between the different GCM-RCP combinations, the spatial patterns of yield change are overall consistent across these different climate projections and the aggregate results show a beneficial future for maize production in the region. These findings illustrate that the updated AEZ model can serve as a bridge to connect climate services to the broader agricultural development effort.

1. Introduction

Maize has become number one crop in China in recent years and its production stability is critical for the country's food and feed security (Gustafson et al., 2014). The Northeast Farming Region of China (NFR) accounts for 30% of the nation's total maize production and 36% of the total maize growing areas (Liu et al., 2013). This region has experienced a climate warming of 0.38 °C per decade in the last 50 years (Liu et al., 2012b). It has been acknowledged in the literature that without effective adaptation, the warmer climate would accelerate maize growth, shorten maize growing length and thus reduce maize yield of traditional varieties (Porter, 2005; Olesen, 2008; Tubiello et al., 2000; Challinor et al., 2014). On the other hand, literature on maize in the NFR region indicates that local farmers has adopted new maize cultivars with longer growing cycle, which allows earlier sowing and later harvest compared with traditional local maize cultivar, and longer maize growing length has mitigated the maize yield loss (Meng et al., 2016; Zhao and Yang, 2018). Field experiments show that such adaptation measures can increase maize yield by 13–38% (Liu et al., 2012b; Chen et al., 2012; Yuan et al., 2012).

From a regional perspective, another benefit from the warmer climate to the regional maize production is the northward extension of maize planting areas (Liu et al., 2013). The adoption of cultivars with longer growing period and the extension of maize growing limits are the major contributor to the maize yield and total maize production increase in the NFR. However, such increase was very unstable due to the increased variations of temperature and precipitation in the NFR (Liu et al., 2012a).

Many researchers have conducted numerous studies to assess the impact of observed and future climate change on crop production in China and around the world (Moss et al., 2010; Blanc and Sultan, 2015). However, without considering agricultural adaptations, studies will produce misleading conclusions such as maize yield reductions and agricultural economic losses under warmer climate in the NFR (Zhang et al., 2017). A typical weakness in the existing studies is that crop cultivars are kept fixed under different climate scenarios (Yu et al., 2013; Song et al., 2013). To overcome this weakness, this research applies a cross-scale model-coupling approach to identify simple but effective agricultural adaptation strategies at the regional scale under various future climate projections. Our model-coupling method aims to capture different key agricultural processes and mechanisms which influence maize growth and development at different scales, and to improve the spatial performance of the evaluation simulations across alternative adaptation measures. At the site level, the Decision Support System for Agro-Technology Transfer (DSSAT) model is employed to obtain the information of new maize cultivars (Jones et al., 2003). Across all grid-cells of the region, we adopt the Agro-Ecological Zone (AEZ) model (Fischer et al., 2012) to search for maize cropping strategy which best fit the projected climate conditions in the grid-cell. The AEZ model has been widely applied in many studies (Fischer and Sun 2001; Fischer et al., 2002; Fischer et al., 2005; Fischer et al., 2012; Tian et al., 2012, 2014, 2018).

To overcome the uncertainty from the choice of carbon emission scenarios, climate models, and crop models (Trnka et al., 2014), few studies has carried out ensemble analysis using climate projections from the combinations of multiple climate model and CO_2 emission scenarios (e.g., among others, Yang et al., 2017; Hansen et al., 2006; Tebaldi and Lobell 2008). We employed the same ensemble approach to control for uncertainty and provide robust results.

Climate services are becoming more demanded by agriculture and other economic sectors given the challenges we have faced in the efforts to deal with the increasing climate variability and foreseen climate change. The research of this paper focusses on how to provide robust and useful information to connect climate services with agriculture and to solve the fundamental issue on cross-scale interactions of the agro-climatological dynamics and crop growth process. Making use of crop

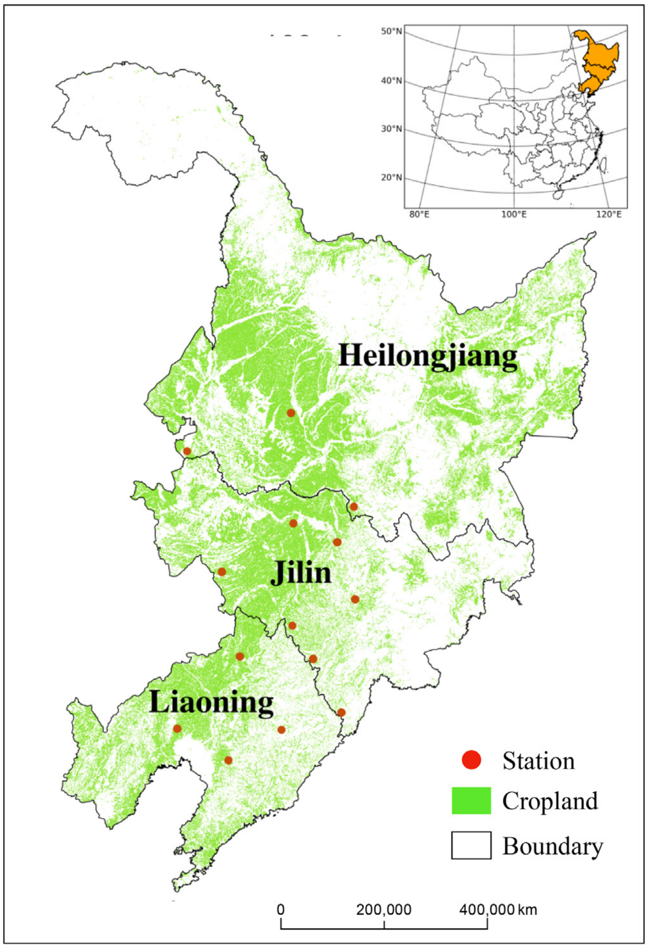

Fig. 1. Cropland and field observation stations in the NFR.

Table 1
Climate models and scenarios.

Code	Name	Emissions scenario			
		RCP2.6	RCP4.5	RCP6.0	RCP8.5
A	GFDL-ESM2M	√	√	√	√
B	HadGEM2-ES	√	√	√	√
C	IPSL-CM5A-LR	√	√	√	√
D	MIROC-ESM-CHEM	√	√	√	√
E	NorESM1-M	√	√	√	√

models and climate forecasting in the way as we proposed would contribute to the development of agricultural climate services which support climate-smart decisions for best management practices.

The rest of the paper is structured as follows. Sections 2.1 provides a description of the study region and data used in this study. Section 2.2 presents the approach to couple DSSAT and AEZ models, to conduct model validation and to develop prototype climate services for maize production in the NFR. Section 3 reports the results on the update of the cultivar parameters in the AEZ model, the changes in planting extent for maize production, and changes in maize yield and total output under future multiple climate change scenarios. Finally, Section 4 concludes.

2. Materials and methods

2.1. Study region and data

The Northeast Farming Region (NFR) (118°50′–135°05′ E, 38°43′–53°24′ N) is located in the Northeast Plain of China, it consists of Heilongjiang, Jilin and Liaoning provinces (Fig. 1). The NFR has played an important role in China's grain production and has made important contribution to China's national food security. The NFR covers an area of 787,300 km^2 with a population of 112 million in 2010. In 1981–2010, the number of continuous days with daily average temperature ≥10 °C are between 120 and 160, the effective accumulated temperature (≥10 °C) is between 2000 and 3600 °C, and the annual sunshine hours are between 2200 and 3000.

Detailed observation records of maize growth and management measures at 14 agro-meteorological observation stations from 1981 to 2010 are provided by National Meteorological Networks of China Meteorological Administration (CMA). These 14 stations spread across the whole maize growth areas of the region as shown in Fig. 1. The records include: basic site information, detailed dates of maize growth and development (sowing date, emergence date, blossom date, and harvest date), yield component (grain number per tiller, grain weight, tiller number per plant and plant density) and crop management data. These records can be used to update the cultivar parameters of both DSSAT and AEZ models.

The meteorological data (1981–2010) are obtained from the Data Center of China Meteorological Administration, including the daily observations of sunshine hours, precipitation, maximum and minimum temperature, wind speed and relative humidity. This set of historical observation data were employed in the DSSAT calibration only. We calculated solar radiation required by the DSSAT model from the daily sunshine hours based on the global radiation model (Pohlert, 2004). Other daily weather observations can be used directly in the DSSAT model. The climate baseline and projections used in the AEZ simulation of this study are taken from the ISI-MIP ensemble of five Global Circulation Models (GCMs) under four Representative Concentration Pathways (RCPs). The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP) is a community-driven modeling effort with the goal of providing cross-sectoral global impact assessments based on the newly developed climate scenarios. The selection of the five climate models was done by the ISI–MIP based on consensus across the participants of the project (Warszawski et al., 2014; Yin et al., 2015; Rosenzweig et al., 2014). The climate data input processing method of the AEZ model are from Tian et al. (2014). Detailed future climate change data from the global climate models are listed in the table below (Warszawski et al., 2014) (Table 1).

The Harmonized World Soil Database (HWSD), which was developed by the Land Use Change and Agriculture Program of International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization of the United Nations (FAO) (FAO/IIASA/ISRIC/ISSCAS/JRC 2009) is used directly as the soil base for the AEZ model. By contrast, the HWSD can only partially meet the minimum requirement for soil properties in the DSSAT model. We calculated the missing soil properties using the method described by Tian et al. (2014). The detailed method of soil data processing in the AEZ model is from Tian et al. (2014).

The spatial distribution of cultivated land data is derived from the 2015 land-use database developed by the Chinese Academy of Sciences (Fig. 1). There are six major land-use groups in this dataset, including cropland, woodland, grassland, water body, built-up area and unused land. In our study, we treat all cropland in the NFR as potential cropping area for maize. The resolution of soil map and cropland map is 1 km × 1 km. Climate data in the historical period are at a 10 km × 10 km spatial resolution. The climate projections of 2041–2070 and 2071–2100 are at a 0.5° spatial resolution. All the above input data for the AEZ are bilinear interpolated into the same spatial resolution of 10 km × 10 km using ArcGIS. Consequently, the spatial resolution of crop simulations is also 10 km × 10 km.

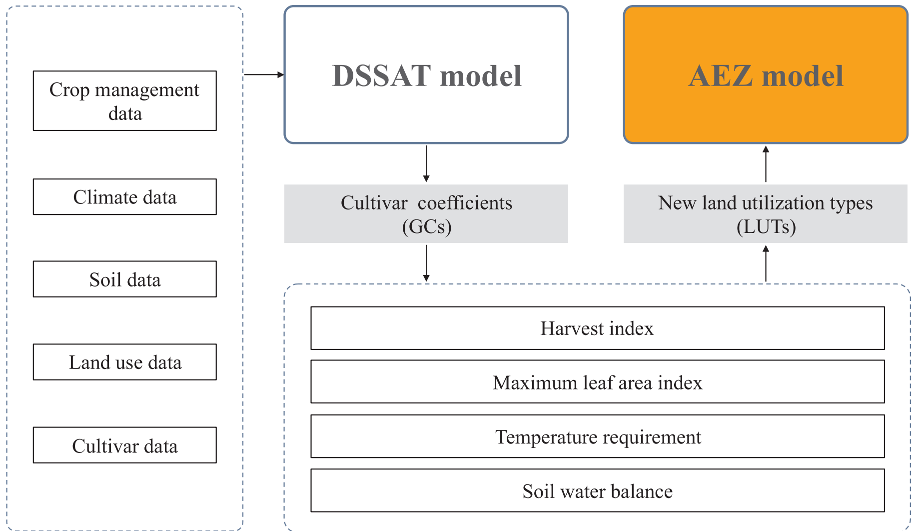

Fig. 2. Flowchart of the DSSAT-AEZ coupling.

Table 2
Change in daily mean precipitation and temperature between the baseline and 2050s at the 14 representative stations.

Site	Precipitation (mm) and standard deviation of the change (in parentheses)			
	RCP2.6	RCP4.5	RCP6.0	RCP8.5
Jiamusi	0.00 (0.08)	0.06 (0.09)	−0.07 (0.06)	0.06 (0.08)
Dunhua	0.10 (0.26)	0.11 (0.08)	−0.11 (0.21)	0.08 (0.26)
Haerbing	0.03 (0.10)	0.09 (0.11)	−0.09 (0.13)	0.09 (0.20)
Shuangcheng	−0.55 (0.16)	−0.48 (0.12)	−0.65 (0.23)	−0.57 (0.22)
Haicheng	0.40 (0.30)	0.37 (0.33)	0.08 (0.31)	0.36 (0.34)
Zhuanghe	0.21 (0.32)	0.15 (0.44)	−0.09 (0.38)	0.13 (0.34)
Dengta	0.35 (0.17)	0.35 (0.15)	0.18 (0.16)	0.38 (0.16)
Changtu	0.25 (0.09)	0.27 (0.07)	0.11 (0.13)	0.29 (0.20)
Benxi	0.23 (0.19)	0.24 (0.18)	0.06 (0.19)	0.27 (0.17)
Meihekou	0.33 (0.09)	0.36 (0.09)	0.20 (0.13)	0.37 (0.16)
Liaoyuan	0.37 (0.09)	0.39 (0.08)	0.23 (0.13)	0.41 (0.17)
Changling	0.19 (0.08)	0.19 (0.03)	0.09 (0.09)	0.19 (0.14)
Wuchang	0.05 (0.07)	0.07 (0.05)	−0.06 (0.06)	0.07 (0.10)
Tailai	0.10 (0.06)	0.13 (0.05)	0.05 (0.09)	0.09 (0.10)
	Temperature (°C) and standard deviation of the change (in parentheses)			
Jiamusi	0.10 (0.70)	0.66 (0.73)	0.53 (0.70)	1.57 (1.02)
Dunhua	0.98 (0.66)	1.49 (0.69)	1.34 (0.70)	2.35 (0.90)
Haerbing	1.30 (0.73)	1.91 (0.73)	1.77 (0.69)	2.93 (1.26)
Shuangcheng	0.96 (0.66)	1.61 (0.66)	1.52 (0.66)	2.66 (1.21)
Haicheng	−0.22 (0.48)	0.30 (0.50)	0.06 (0.52)	1.22 (0.71)
Zhuanghe	2.02 (0.47)	2.56 (0.47)	2.21 (0.53)	3.39 (0.68)
Dengta	0.26 (0.32)	0.77 (0.44)	0.42 (0.58)	1.68 (0.79)
Changtu	2.00 (0.23)	2.57 (0.42)	2.24 (0.56)	3.49 (0.78)
Benxi	1.40 (0.32)	1.91 (0.44)	1.55 (0.58)	2.82 (0.78)
Meihekou	1.89 (0.34)	2.44 (0.48)	2.12 (0.62)	3.37 (0.83)
Liaoyuan	1.79 (0.30)	2.36 (0.46)	2.03 (0.60)	3.28 (0.81)
Changling	2.19 (0.24)	2.81 (0.44)	2.50 (0.58)	3.76 (0.83)
Wuchang	1.51 (0.39)	2.11 (0.53)	1.78 (0.66)	3.09 (0.90)
Tailai	1.21 (0.39)	1.86 (0.55)	1.53 (0.65)	2.83 (0.97)

2.2. *Methods*

2.2.1. *The DSSAT model*

The DSSAT model is a popularly-employed model for simulating the dynamic process of crop growth. Many researches based on the DSSAT do pay a great attention to the impact of climate change on maize growth (Challinor et al., 2014; Bassu et al., 2014; Corbeels et al., 2016). The crop cultivar parameters, which are called genetic coefficients in DSSAT, quantitatively describe how a particular genotype of a cultivar responds to environmental factors (Hunt, 1993), thus enabling the integration of genetic information on physiological traits into crop growth models. Each crop in the model has a specific set of parameters that represent the genetic information of different cultivars. In the DSSAT-maize model, 5 parameters are used to describe the genetic information of different maize cultivars (Jones et al., 2003).

Ideally, the genetic coefficients of DSSAT can be calibrated using well-designed field experiments. Unfortunately, such experiment has been scarce in Northeast China. In our research, we collected the observed phenology records and yield data from 14 agrometeorological stations for 30 years. These records are based on typical farm-field conditions, which includes the stresses caused by poor weather conditions, pests and diseases. Fortunately, the literature on climate change impact assessment has developed an effective way to run DSSAT calibration based on the best attainable yields and climate conditions of those years with good harvests at a farm site (Yang et al., 2009; Tian et al., 2012, 2014, 2018). The best attainable yields is calculated using the optimum yield components of observations at the same site, which include the maximum grain number per tiller and the correspondent grain weight, maximum tiller number per plant and the optimum plant density. In this research, we employed the DSSAT model and its GLUE (the Generalized Likelihood Uncertainty Estimation) module to calibrate cultivar genotype parameters based on a time series of phenology records and yield data in good harvest years under the ordinary farm-field conditions (He et al., 2010; Wang et al., 2015). We further validate the DSSAT calibration using flowering and maturity dates (Tian et al., 2014, 2018).

2.2.2. *The AEZ model*

The AEZ model is designed to simulate the impact of climate and other agronomic resources on crop production potentials at the grid-cell level across a large area (Fischer et al., 2012). The AEZ model was jointly developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization (FAO) of the UN (IIASA/FAO, 2012). It uses the prevailing climate resources, soil profile and topography conditions, and detailed agronomic-based knowledge to simulate crop productivity and soil water balance with standardized soil-plant-atmosphere interaction algorithms. Such standardized methodologies make the AEZ well suited for crop productivity assessment at the regional level where detailed and spatially explicit input data are relatively limited (Tubiello and Fischer, 2007; Gohari et al., 2013).

The crop cultivar parameters, which are organized into Land

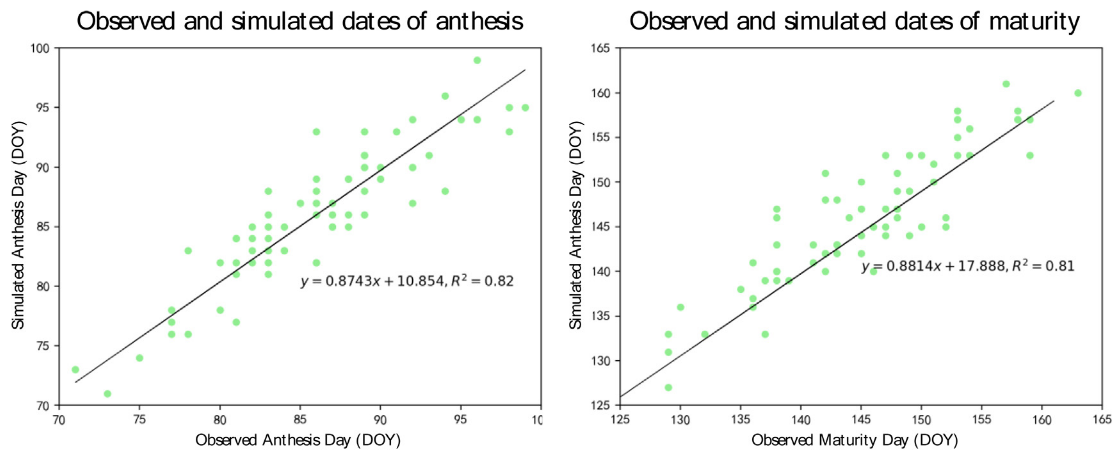

Fig. 3. Observed and simulated dates of anthesis (left) and maturity (right) days at the 14 observation stations (unit: day of year or DOY).

Table 3
Comparison of the original and new cultivars coefficients.

Cultivar	Original Parameters							New Parameters						
	LGC	HI	MLAI	TMN	TREF	TS1n	TS1x	LGC	HI	MLAI	TMN	TREF	TS1n	TS1x
1	90	0.45	3	10	22.5	1800	2700	90	0.43	0.43	12	22.5	1800	2925
2	105	0.45	3	10	22.5	1950	3150	105	0.43	0.43	12	22	1950	3255
3	120	0.45	3.5	10	21	2100	3600	120	0.44	0.44	11.5	21.5	2100	3600
4	135	0.45	4	10	20	2250	4050	130	0.45	0.45	11.5	21	2210	3785
								140	0.46	0.46	11.5	20.5	2310	3960
5	150	0.45	4.5	10	20	2400	4500	150	0.47	0.47	11	20	2400	4125
6	165	0.45	5	10	17.5	2550	4950	160	0.48	0.48	11	19	2500	4160
								170	0.49	0.49	11	18	2600	4200
7	180	0.45	5.5	10	15	2700	5400	180	0.5	0.5	11	17	2700	4230

Note: Cyl: Length of Crop Growth; HI: Harvested Index; MLAI: Maximum Leaf Area Index; TMN: Minimum Temperature during LGC; TREF: Temperature Requirement during LGC; TS1n: Minimum Optimum Accumulated Temperature; TS1x: Maximum Optimum Accumulated Temperature.

Table 4
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	10,147	9005	9782	10,416	4.539
Haicheng	12,285	11,708	12,667	13,839	5.655
Zhuanghe	8692	7402	8084	8943	7.193

Utilization Types (LUTs) in the AEZ, quantitatively describe how a particular genotype of a cultivar responds to environmental factors. In this research, we enrich and update LUTs based on the observation data we collected and the outputs of our DSSAT calibration.

2.2.3. Cross-scale model coupling framework

In order to improve the overall performance of crop simulations in every grid-cells across the maize growing areas in the NFR, we coupled two well-known crop models, which are the process-based and specific DSSAT model and the cropping zone centered AEZ model, as we introduced in Sections 2.2.1 and 2.2.2 above. The procedure to couple these two models is as follows (Fig. 2). First, the detailed observation records of maize growth, development and management are employed to calibrate the phenological and physiological parameters of DSSAT model at the 14 agro-meteorological observation stations in the NFR. Second, we convert these parameters to the eco-physiological parameters of the AEZ model to enrich and update the cultivar parameters set of the AEZ model. Finally, we apply the AEZ model with the new parameters set to investigate the impact of climate change on the extent of maize growing areas and the best attainable yields in this region.

3. Results

3.1. Changes in precipitation and temperature at the 14 stations

Table 2 reports the changes in daily mean precipitation and temperature in the growth period of maize between the baseline (1981–2010) and the 2050s (2040–2069) at the 14 agro-meteorological observation stations. As shown in the table, there is no statistically significant changes in daily mean precipitation in majority cases. Nevertheless, Shuangcheng station is going to become drier by a small margin (0.48–0.65 mm) and by contrast, Meihekou and Liaoyuan will become wetter by a small margin (0.20–0.41 mm) under all 4 RCP scenarios. In addition, Changling station is going to become a little bit wetter under RCP2.6 and RCP4.5, Tailai will become a little bit wetter under RCP4.5.

In sharp contrast to the case of precipitation, the statistically significant increases in daily mean temperature are present in vast majority cases and the extent of increase is large: between 1.21 °C (Tailai, RCP2.6) and 3.76 °C (Changling, RCP8.5). Statistically insignificant warming is associated with Jiamusi under all 4 RCPs, with Haicheng under RCP4.5, 6.0, and 8.5, with Dengta under RCP2.6, 4.5, and 6.0, and with Dunhua, Haerbing, and Shuangcheng under RCP2.6 only. Statistically insignificant cooling is associated with Haicheng under RCP 2.6 only.

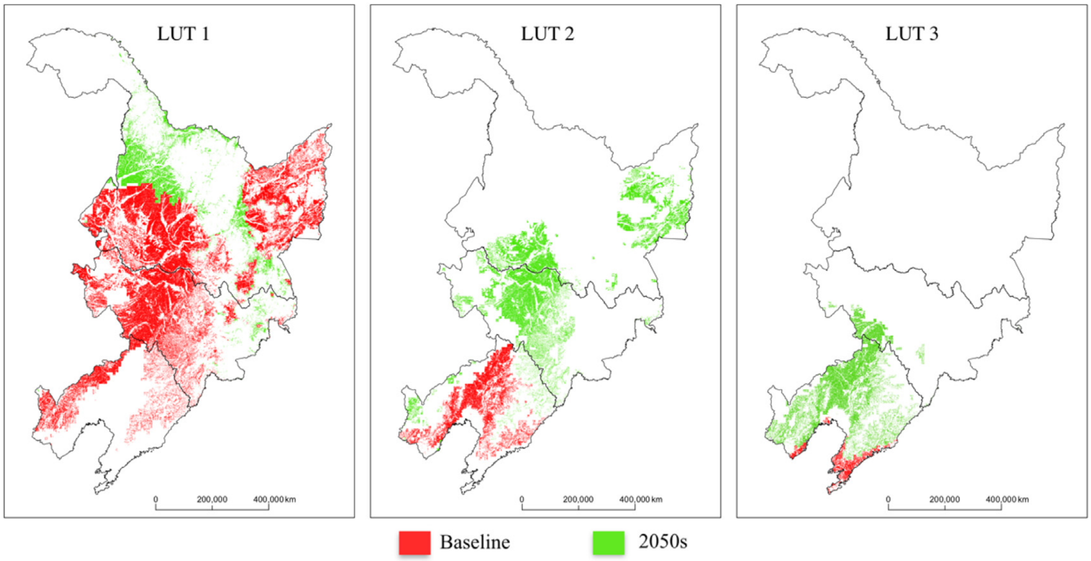

Fig. 4. AEZ simulation results on the northward shift of maize planting boundary from that under the baseline (1981–2010) to that under the 2050s climate for LUT1, LUT2 and LUT3.

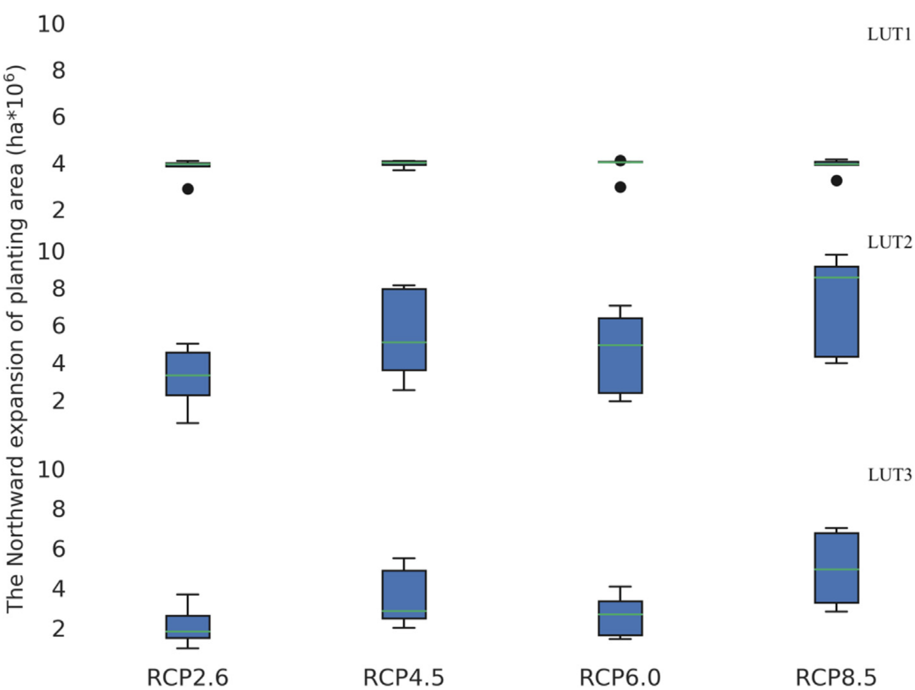

Fig. 5. Box plots showing the expansion of suitable planting areas for LUT1, LUT2 and LUT3 under four RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) from the baseline period (1981–2010) to the 2050s (2041–2070). The colored rectangle represents the 25th and 75th percentile. The horizontal line in the rectangle denotes the ensemble median ($ha \cdot 10^6$) of the five GCMs times 30 years.

3.2. Model calibration and validation

3.2.1. The calibration and validation of the DSSAT model

The observed phenology records and yield data from the 14 agro-meteorological stations for 30 years are used for the DSSAT model calibration and validation. Fig. 3 shows the performance of the calibrated DSSAT model in the 14 observation stations. Results show that our simulations of anthesis and maturity dates match the observations very well, with the R-squared values of 0.82 and 0.81, (P-value < 0.01).

3.2.2. Enriching the LUT parameters set of AEZ model

Eco-physiological parameters are stored in Land Utilization Types (LUTs) in the AEZ model. A subset of LUT parameters such as Maximum Leaf Area Index (MaxLAI), Harvest Index (HI), and Length of Growing Cycle (LGC) can be directly taken from the calibrated DSSAT outputs.

Temperature plays an important role in crop growth and development. The AEZ model calculates the effect of the thermal profile on crops based on conditions at each grid cell, using the temperature demand distribution equation. Based on the outputs of the DSSAT model, as well as the detailed observations and historical climate data, we revised the temperature demand equation by reducing the proportion of the low temperature stage of the maize growth period and assigning specific temperature distribution requirements to newly added maize varieties. For example, the LUT parameters set of the AEZ model has been enriched by adding the cultivars with a length of growth cycle (LGC) at 135 and 165 days, and updated by adopting the cultivar parameters of the recently prevalent varieties as recommended by the DSSAT-GLUE calibration and the observed data.

Parameter changes are summarized in Table 3. The annual average value of MaxLAI and HI from the DSSAT simulations are used to update LUTs with the same LGC. The MaxLAI value of maize in the NFR decreased for all cultivars, while the HI value decreased in LUTs with

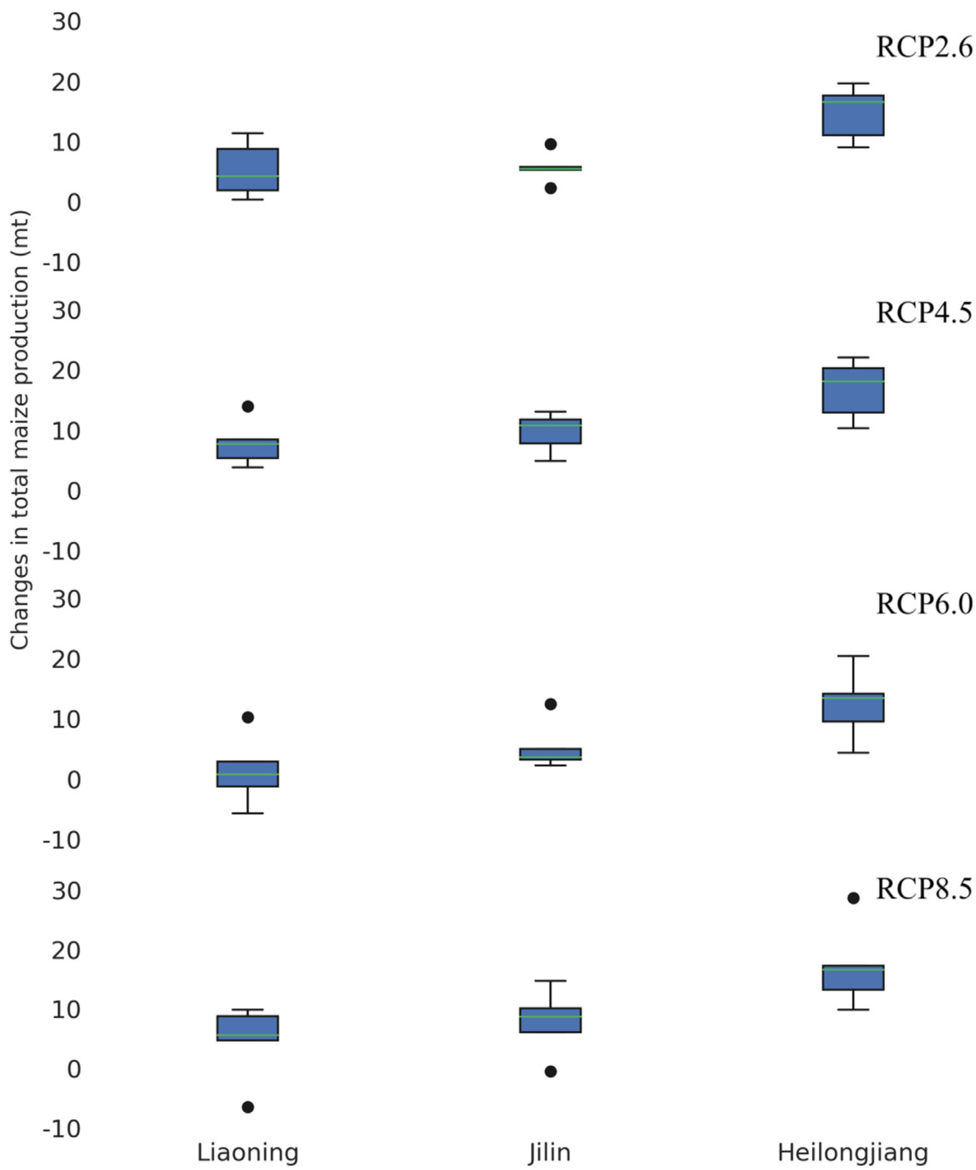

Fig. 6. Box plots showing the changes of total maize production under four RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) in Liaoning, Jilin and Heilongjiang province from the baseline period (1981–2010) to the 2050 s (2041–2070). The colored rectangle represents the 25th and 75th percentile. The horizontal green line in the colored rectangle denote the ensemble median (mt) of the five GCMs times 30 years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

shorter LGCs and increased in LUTs with longer LGCs. The minimum temperature (TMN, °C) is calculated from the temperature requirements (temperature sum) during the LGC. According to the temperature curve calibration based on historical data and the expected climate warming, we improve the minimum temperature limit in the model by eliminating the extremely low temperature days. This improvement makes the simulation results more in line with the observed practices in very recent years. Finally, to be consistent with the correction of the temperature distribution, we reduced the maximum threshold (TS1x) of the optimum accumulated temperature during the growth period for LUTs with longer LUTs, so that the demand for high temperature during the growth period is reduced.

3.2.3. The validation of the AEZ model

The validation of the AEZ model was carried out at six sites (Table 4). Table 4 reports the attainable yield from observations and model simulations (including the minimum, mean, and maximum), and the average Relative Absolute Error (RAE) at the six stations (1981–2010). Table 2 shows that the performance of the AEZ model in simulating the maize potential yield are quite well, with an average RAEs between 4.54% and 7.63%.

3.3. Maize cropping area expansion under multiple climate change scenarios

The AEZ simulation is able to automatically select the cultivar with the highest yield among all maize LUTs suitable to the local agro-climatic conditions. This means that under the warming condition in the NFR, the AEZ simulation will select the cultivar with the longest LGC among all suitable cultivars at each grid-cell, because a cultivar with longer LGC has higher yield. In this way, the AEZ simulation takes into account the farmers' natural adaptation behavior in cultivar choice and avoid the limitation of assessing the impact of warming on fixed genotypes and pre-set planting date, as typically done in the existing literature.

The AEZ simulation selected LUTs with the LGCs of 130, 150, and 160 as the most popular cultivars in the 2050s. Therefore, we opt to put an emphasis on these three LUTs to reduce the presentation burden.

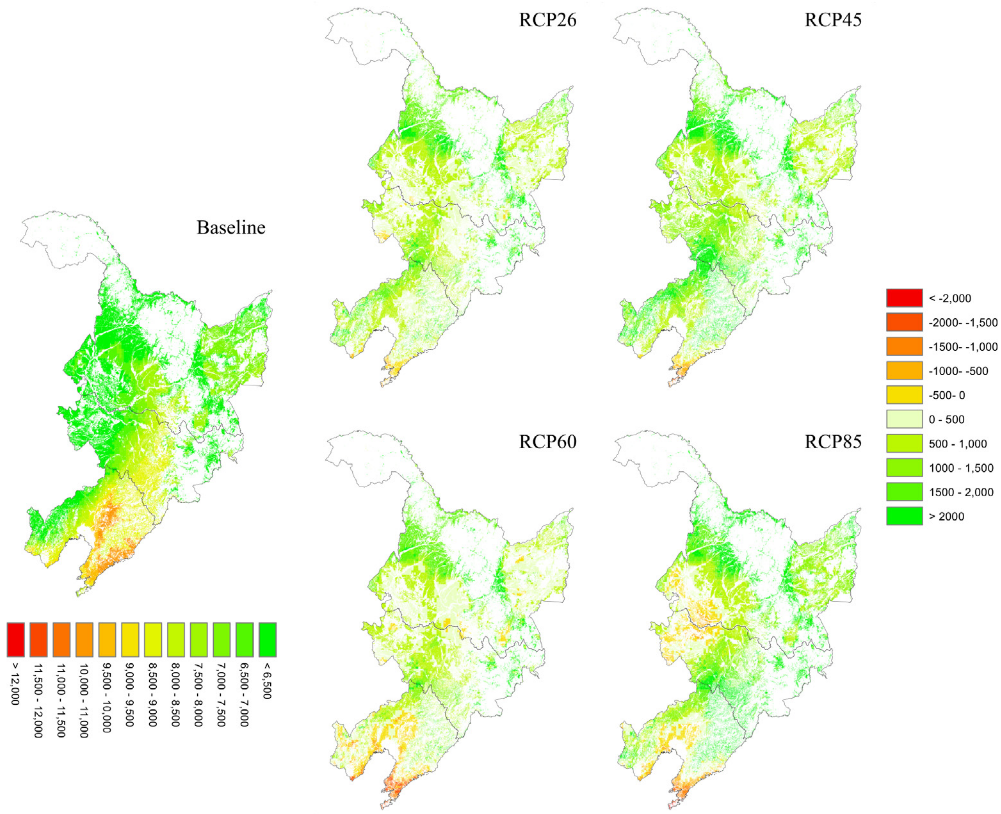

Fig. 7. Spatial patterns of changes in average maize yield between the baseline and the 2050s.

Fig. 4 visualizes the AEZ simulation results on the expansion of the suitable planting areas for cultivars with longer LGC under the rainfed condition from the baseline period (1981–2010) to the 2050s. In Fig. 4, the LUT1, LUT2 and LUT3 represent maize cultivars with an LGC of 130, 150 and 160 days, respectively. The boxplots of Fig. 5 show the uncertainty of increase in the maize cropping areas under the 20 climate change scenarios. For example, the average extent of expansion of the suitable areas for the LUTs with LGCs of 150 and 160 days under the RCP2.6 scenario will increase by 3.16×10^6 ha and 2.11×10^6 ha, respectively. The corresponding figures of increase under the RCP8.5 scenario will be 7.14×10^6 ha and 4.96×10^6 ha, respectively.

3.4. Changes in total production under future multiple climate scenarios

Fig. 6 presents the box plots of the simulated maize production in Liaoning, Jilin and Heilongjiang province under 20 climate projections in 2050s compared with baseline (1981–2010). Fig. 6 shows that the increase in total production will take place in Heilongjiang, thanks to the northeastward expansion of LUT2 area to the province and northwestward expansion of LUT1 area in the province (Fig. 4). In contrast, although Liaoning is the largest maize producing province now, the median values of change indicate a moderate increase of less than 8 million tons. Moreover, under RCP6.0 and RCP8.5, Liaoning will become the most vulnerable province among the three and have the risk of reduction in the total maize production up to 10 million tons. Although thermal conditions in the Liaoning province are the best among the three provinces, uncertainty in precipitation might be the most critical constraint for stabling high level of maize production in the province.

Fig. 7 shows the spatial distribution of the changes in average maize yield at the grid-cell level (1 km × 1 km) between the baseline and the 2050s. The figure indicate that yield increase will be dominant across the NFR, with higher and more widespread increase in the Heilongjiang province. However, yield reduction is highly likely to become dominant in the Liaoning peninsula (the south-most part of Liaoning Province) under all four RCPs and become dominance in middle and south parts of Liaoning Province under RCP6.0 and RCP8.5.

4. Conclusions and discussions

In this research, we employed a cross-scale model coupling framework to grasp the interaction of agro-ecological processes across different scales and investigate the potential of such quantification for agriculture climate services. In the coupling process, we first calibrated the site-focused DSSAT model using observation data from 14 agro-meteorological observation stations. We then converted these calibrated parameters from the DSSAT model into eco-physiological parameters of the cropping-zone centered AEZ model. By doing so, we enriched and updated the maize varieties in the AEZ model and enhanced the performance of the AEZ model in regional scale simulations. The AEZ model can be quickly run across all grid-cells in a large region and can easily take climate forecasting/projection information into its agro-climate resource assessment module. This means that our approach can bridge the gap between the climate information being developed by scientists and service providers and the practical needs of end-users, such as national and regional climate institutions (decision makers), breeders and farmers.

Our findings suggest that, by adapting new maize cultivars which are more suitable to a warming climate, maize production farmers in most parts of the Northeast Farming Region of China will be able to benefit from future climate change. We applied the AEZ model with an updated parameter set to investigate the impact of climate change on maize production, driven by five General Circulation Models (GCMs) and four Representative Concentration Pathways (RCPs). Using an ensemble approach ensures that we can account for uncertainties associated with the climate projections. We also considered the potential increase in agro-climatic resources in the region caused by future warming and conducted scenario analyses over the temporal and spatial variation of agro-climate resources and its implications for future maize production in the NFR. This work can provide science-informed data for future planning of maize production and agricultural development in the region. The tool demonstrated in this research can help government agencies and farming communities to evaluate the performance of alternative crop varieties in a timely manner via computer simulation.

Some limitations of this study are worth mentioning. Firstly, about 15% of the maize growing areas in the NFR are irrigated and the irrigation is heavily dependent on groundwater. Because of insufficient data on groundwater resources in the NFR (MacDonald et al., 2012), we have to focus on rain-fed maize production only in this research. This limitation can be overcome by coupling hydrological models and available groundwater observations in the future. Secondly, drought risk should be further quantified across space once climate projection outputs from regional climate model with much finer resolution become available. It is because our results have shown that changing drought risk under future climate change may cause yield decreases over the southern and western part of the NFR. The drought risk assessment should pay more attention to different maize growth stages. Thirdly, further research is also needed to quantify the uncertainty caused by changes in inter-annual climate variability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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