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Modelling China's potential maize production at regional scale under climate change

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Abstract With the continuing warming due to greenhouse gases concentration, it is important to examine the potential impacts on regional crop production spatially and temporally. We assessed China's potential maize production at 50×50 km grid scale under climate change scenarios using modelling approach. Two climate changes scenarios (A2 and B2) and three time slices (2011–2040, 2041–2070, 2071–2100) produced by the PRECIS Regional Climate Model were used. Rain-fed and irrigated maize yields were simulated with the CERES-Maize model, with present optimum management practices. The model was run for 30 years of baseline climate and three time slices for the two climate change scenarios, without and with simulation of direct CO_2 fertilization effects. Crop simulation results under climate change scenarios varied considerably between regions and years. Without the CO_2 fertilization effect, China's maize production was predicted to suffer a negative effect under both A2 and B2 scenarios for all time slices, with greatest production decreases in today's major maize planting areas. When the CO_2 fertilization effect is taken into account, production was predicted to increase for rain-fed maize but decrease for irrigated maize, under both A2 and B2 scenarios for most time periods.

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1 Introduction

The concentration of atmospheric CO_2 has increased from about 280 parts per million (ppm) in 1,800–367 ppm in 1999, increasing rapidly from 315 to 375 ppm during the past 40 years along with other ‘greenhouse’ trace gases (Decker 1994; Houghton et al. 1992). This trend is expected to continue and to result in an approximate doubling of the current CO_2 level by the end of this century [Intergovernmental Panel on Climate Change (IPCC), 2001a,b; Morison and Lawlor 1999]. Increased CO_2 concentrations can affect plant growth directly through stimulation of photosynthesis, reduced stomatal conductance and hence transpiration, greater leaf area index, greater numbers of panicles per hill (in the case of rice), and improved water use efficiency (WUE) (Rosenberg et al. 1990; Grant et al. 1999; Norby et al. 2001; Tubiello and Ewert 2002; De Costa et al. 2003; Widodo et al. 2003; Triggs et al. 2004; Ewert 2004). These physiological responses known as the CO_2 fertilization effect, can increase crop yields significantly (Allen et al. 1997; Kimball et al. 2002). Changes in temperature and precipitation may either benefit or damage agricultural systems in various ways in different parts of the world (Peiris et al. 1996; Rosenzweig and Hillel 1998). However, there remains significant uncertainty in future crop yields due to altered water and fertilizer application regimes, increased concentration of other greenhouse gases (e.g. tropospheric ozone), increased climatic extremes, and changing pest and disease prevalence (Cannon 1998; Ewert et al. 2002; Engvild 2003; Fuhrer 2003) etc. It is therefore difficult to predict overall effects of an increase in CO_2, temperature and other variables, as the result depends on the relative effects of variables in the particular combination occurring for a given region. However, simulation models offer a way in which this can be attempted.

There is an emerging need to support policy formulation and decision-making in agriculture at very large geographic scales (Satya and Ryosuke 2001), particularly in the field of climate change impact assessment. According to a recent report by the Intergovernmental Panel on Climate Change (IPCC), future work on the impacts of climate change on agriculture should be focused on the use of regional models, while paying careful attention to local features (Tan and Shibasaki 2003). Thus, it is important to take into account spatial variation in the main parameters across the region in question. Most previous work on climate change impacts on agriculture has used crop simulation models which predict crop responses to environmental conditions at a specific point. Such crop simulation models usually require site-specific data as inputs, such as information on weather, physical and chemical soil properties, genotype characteristics, and crop management (Whistler et al. 1986; Penning de Vries et al. 1989; Chipanshi et al. 2003). However, the applicability of these models can be extended to much broader spatial scales by combining them with appropriate datasets within a Geographic Information System (GIS) (e.g. Curry et al. 1990; Thorton 1991; Priya and Shibasaki 2001; Yun 2003; Hartkamp et al. 2004). In such an approach, the overall study area can be subdivided into smaller geographic areas for which unique sets of homogeneous driving variables (e.g., climate, soil properties, management and landuse) are derived and then supplied to the models (Eatherall 1997; Paustian et al. 1997; Matthews et al. 2000; Thomson et al. 2005). With adequate computing power and spatially representative data, especially the higher resolution weather data provided by Regional Climate Models (RCM), it is practicable to predict plant growth and yield and nutrient dynamics under different agricultural practices at national to sub-continental scale.

Maize (*Zea mays L.*) is one of the most important staple crops in China, comprising 22 million ha of harvested area and 106 million metric tons of production in 2000 (FAOSTAT database; The Editorial Board of Chinese Agricultural Yearbook 2001). Maize is planted over most of China owing to its adaptation to a wide range of temperatures and precipitation regimes. Climate change may affect overall maize production by altering the production area, yields (Mati 2000; Southworth et al. 2000) or both. The production area extent will be influenced by changes in the maize-growing environment, either by allowing maize to be grown where or when it is not grown currently, or, where it is currently grown, by reducing yields to below an economic threshold. Yields are influenced by the direct effect of climate change on the physiological mechanisms of maize growth. There are many impact studies focused on maize, including statistical regression techniques (Chang 2002; Decker and Achutuni 1990; Newman 1982; Blasing and Solomon 1982; Bach 1979), physiologically based plant-process models and climate change scenarios derived from General Circulation Models (GCMs) (e.g. Jones and Thornton 2003; Dhakhwa et al. 1990; Cooter 1990). Some of the studies incorporated the possible direct effect of CO_2 fertilization into the simulation (e.g. Tubiello et al. 2000; Dhakhwa et al. 1997; Phillips et al. 1996; McKenney et al. 1992). Recently, the focus has changed to regional and national assessment of potential effects of climate change on agriculture using the combination of GIS, crop models and Regional Climate Models (RCM; Brignall et al. 1991; Quinn et al. 2004; Tsvetsinskaya et al. 2003). The integrated assessment of potential impacts at national scale which consider climate, social economy, and adaptation options etc. has been increasingly emphasized by some researches (Edmonds and Rosenberg 2005; Rosenberg et al. 2003; Magalhaes 1992; Parry 1990; Adams et al. 1990). However, the majority of these regional assessments are focused on developed counties. The purpose of this study was to evaluate and analyze the impacts of climate change on China's maize production spatially and temporally, by using a high resolution Regional Climate Model (RCM), and to provide insights for future agricultural decision making.

2 Materials and methods

The study area chosen is mainland China, which lies between the latitudes of 18° and 53° N and the longitudes of 74° and 134° E. It is bounded by the Pacific Ocean on the EAST, and in the southwest by the Himalayan mountain range. For consistency with the projected daily weather data resolution (~50 km), the simulation resolution was set to 50 × 50 km. Ultimately there were 2,622 grids classified as arable land, based on the land use map of China (Liu et al. 2002). The simulation and data processing methodology is illustrated in Fig. 1.

2.1 Greenhouse gases emissions and climate change scenarios

The use of climate change scenarios, built from the results of GCM simulations, has been at the core of climate change assessments on agricultural and water resources for the past 20 years (Rosenberg 1992). A climate change scenario is defined as a physically consistent set of changes in meteorological variables, based on generally accepted projections of the atmospheric concentrations of CO_2 and other trace gases (Fischer et al. 1994). In order to cover the possibility of future greenhouse gases emissions and the corresponding socio-economic development, a range of future greenhouse emission scenarios have been defined by IPCC in their Special Report on Emission Scenarios (SRES). These are the A1FI, A2, B1 and B2 scenarios, with changes in carbon emissions from energy/industrial sources by 2100 (compared to estimated year 2000 emissions) ranging from a decrease of 4% (B2 scenario) to an increase of about 320% (A2 scenario). These estimated future emissions rates assume no climate policy implementation (Nakicenovic and Swart 2001). For more information on the details of the SRES scenarios used here, see Arnell et al. (2003).

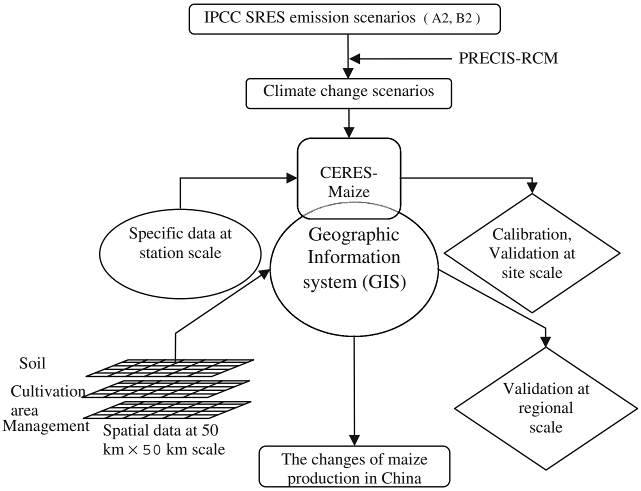

Fig. 1 The illustration of method

After downscaling the socio-economic projections from SRES using the approach of Gaffin et al. (2004), the B2 scenario, which reflects a heterogeneous world where there is diverse technological change, low population growth and emphasis on local solutions to economic, social and environmental sustainability problem, was considered by the authors to be the 'mostly likely' scenario for China's long term national plan, and was used in this study. The contrasting A2 scenario, which describes a very heterogeneous world of high population growth, slow economic development and strong regional cultural identities (Cholaw 2003; Cholaw et al. 2003), was also selected to estimate what the impacts would be under a pessimistic development pathway. Using the emission scenarios as drivers, regional climate scenarios were developed following the nested climate model methodology described by United Kingdom Climate Impact Program (United Kingdom Climate Impacts Programme (UKCIP); UKCIP (2002); Mitchell 2000, 2003), in which a coupled ocean-atmosphere global climate model (HadCM3H; ~300 km grid interval) was used to drive a high resolution (~50 km grid interval) atmospheric regional model [PRECIS – Providing REgional Climates for Impacts Studies (Jones and Wilson 2002; Jones et al. 2004)] for China. The detailed regional climate experiment and its validation can be obtained from Xu et al. (2006). Summary details of the resulting climate scenarios are given in Table 1.

2.2 Crop model and its validation

The CERES-Maize model (Ritchie et al. 1998), embedded in DSSAT v 3.5 was used to simulate the growth of maize in each 50×50 km grid. The model operates on a daily timestep, and requires inputs of daily weather (including daily solar radiation, maximum and minimum temperatures, and precipitation), soil parameters, and agronomic practices. Phenological stages simulated include sowing, germination, emergence, juvenile period, floral initiation, silking, grain filling, and physiological maturity. The rate of progression through these stages is dependent on the temperature and genotype, and additionally on photoperiod during floral induction from the end of the juvenile period to the start of floral initiation. Daily biomass production is calculated as a function of leaf area index (LAI), incident solar radiation, atmospheric CO_2 concentration, and a radiation use efficiency

Table 1 Climate scenarios, emission scenarios, and CO_2 concentration (Hulme and Sheard 1999; Lin 2004)

Periods	A2			B2		
	Temperature increase (°C)	Rainfall increase (%)	CO_2 (ppm)	Temperature increase (°C)	Rainfall increase (%)	CO_2 (ppm)
Baseline (1961–1990)	–	–	376	–	–	376
2020 (2011–2040)	1.4	3.3	440	0.9	3.7	429
2050 (2041–2070)	2.6	7.0	559	1.5	7.0	492
2080 (2071–2100)	3.9	12.9	721	2.0	10.2	561

parameter (RUE), but can be reduced by high temperatures, drought stress, or nitrogen deficiency. LAI is a function of leaf numbers and leaf size, both of which are dependent on the rates of leaf appearance and expansion. These rates can also be reduced by water and nitrogen deficiencies. Allocation of the biomass produced each day to the various plant components depends on the phenological stage of the plant, and can be altered by water and nutrient deficiencies. The water balance sub-model simulates the daily evaporation, run-off, percolation, and crop water uptake. Potential evapotranspiration is calculated using a modified version of the Priestley and Taylor (1972) method. The model also simulates soil nitrogen transformations associated with mineralisation/immobilisation, urea hydrolysis, nitrification, denitrification, ammonia volatilisation, losses of N associated with runoff and percolation, and uptake and utilisation of N by the crop.

Modification in CERES accounts for changes in CO_2 concentration through the direct effect on photosynthesis and evapotranspiration (ET) rates. Elevated CO_2 increases photosynthesis for maize, simulated by a multiplicative coefficient that increases the daily potential dry matter production at optimum temperature and water availability, summarized from observational studies (Cure and Acock 1986; Kimball 1983). Elevated CO_2 also reduces ET due to significant reductions in stomatal conductance and, consequently, transpiration, which cause higher water use efficiency (WUE). A ratio applied to the calculation of transpiration rates that accounts for stomatal closure under higher CO_2 concentration (Hoogenboom et al. 1995). The model assumes that increases in stomatal resistance under elevated CO_2 are independent of water, nutrient, and temperature stress. (Fig. 2)

Model calibration and validation was based on the field experiments collected from local agricultural meteorological experimental stations, which are maintained by the Chinese Meteorological Agency (Tao et al. 2006). In this study, we selected four stations to calibrate and validate the CERES-Maize model, they are Changjizhou (44°N, 87.43°E, Xinjiang province, cultivar: SC-704), Zhengzhou (34.72°N, 113.65°E, Henan province, cultivar: Yedan 13), Guangyuan (32.43°N, 105.85°E, Sichuang province, cultivar: jiaodanjiao 3), and Harbin (45.75°N, 126.77°E, cultivar: Yedan 19). The experimental data from 1990–1997 were used for the calibration of the model and the data from 1998–2000 were used for validation. The validation showed simulated maize growth duration and grain yields were in good agreement with the observed data (Fig. 3), resulting in an r^2 of 0.99 ($P<0.01$) and 0.96 ($P<0.01$), respectively.

2.3 Spatial data and simulation runs

Spatial datasets required by the CERES-Maize model include soil characteristics, climate variables, crop cultivar parameters, and crop management information.

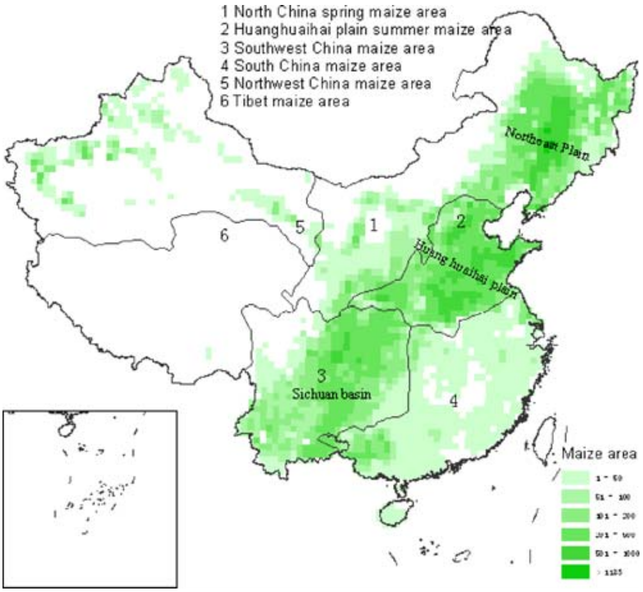

Fig. 2 Agroecological zones and the cultivation area (×10,000 ha) for maize in China. (maize cultivation area is originally from Qiu et al. 2003)

A digital map of the China border was used as a background within ARC/INFO 8.0. According to the resolution of PRECIS, another layer with the regional model grid (50× 50 km) was created as the simulation resolution; ultimately, there were 2,622 grids classified as arable land in China based on the land use map of China. Soil data was obtained by overlaying the regional model grid coverage with the digital soil map of China (1:1,000,000 scale; Wu et al. 2003). A spatial data processing method described in detail by Knox et al. (2000) was used to transfer soil properties of agricultural soils from the mapping unit into the 50×50 km grid unit, and to aggregate the soil properties into median values for topsoil (0–30 cm) and subsoil (30–100 cm) from the original values distributed across each profile layer.

Climate data was developed by PRECIS. The baseline scenario used the PRECIS simulated daily weather data for the period 1961–1990, with the CO_2 concentration set to 330 ppm. Two climate change scenarios (A2 and B2) for periods 2011–2040 (2020), 2040–

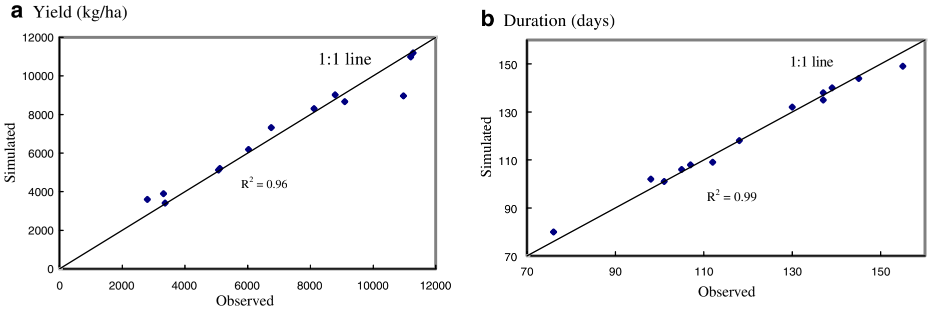

Fig. 3 Comparison of **a** yields and **b** growth durations between measured and simulated in four field experiment stations from 1998–2000

2070 (2050), and 2070–2100 (2080) were generated. The design of this climate change experiment and extraction of the weather data can be obtained from Xu et al. (2006), UKCIP (2002), and Jones et al. (2004). (Table 2)

Five representative maize cultivars (Table 3) and their present average sowing date (Table 2) were assigned to each grid based on Agro-Ecological Zones (AEZ; Fig. 2; The National Mapping Office 1989). Nutrients were assumed to be unlimited in all seasons. The area of maize in each grid was derived from maps of cropland distribution for the 1990's in China (Qiu et al. 2003), and was assumed to be unchanged in the future. The change of maize production was calculated as function (1).

$$yc_{m,n,r,i} = \left(\sum_{j=1}^{2622} \left(M_{m,n,i,j,r} \times A_j \right) \middle/ \sum_{j=1}^{2622} \left(M_{baseline,i,j} \times A_j \right) \right) \times 100\% \tag{1}$$

where m denotes the climate scenarios (A2 and B2), n is the period (2020, 2050, and 2080), r means if the CO_2 fertilization is considered (with or without), i means the rainfed or irrigated maize, j is the number of grid. M denotes the mean yield of 30 years (baseline: 1961–1990, 2011–2400, 2400–2070, and 2071–2100), and A stands for the cultivation area for maize.

3 Results and discussion

Table 4 indicates the changes of maize production in China by scenarios and periods. This table does not reflect how yields would change if farmers implemented adaptation measures such as changing planting dates or switching varieties, etc.

3.1 The performance of CERES-Maize model for regional simulation

Researchers frequently use crop simulation models to estimate the impacts of climate change on agricultural production. While most models used for this purpose have been validated at the plot level, few studies have evaluated them for multiple years, at the regional level and with inputs commonly used in climate impact studies (Carbone et al. 2003). Here, we examined how well CERES-Maize performs across space and time at a grid level using representative cultivars, daily weather data from the nearest observed weather station, and grid-averaged soil characteristic. Closeness between observed and simulated yields is important when making long-term decisions. This exercise was done for Jilin province (in northeast China) where historical statistical county-level crop yield data are available. Because the simulated yields assumed a constant level of technology

Table 2 Description of the maize planting management corresponding to each agro-ecological zones (AEZ), sowing date is the day of the year, duration is the days from sowing until crop maturity

AEZ	Variety name	Sowing date	Duration	Comments
1	Dongnong-248	116	137	Spring maize
2	Yedan 13	160	101	Summer maize
3	Jiao3dianjiao	106	121	Spring maize
4	Sc-704	109	143	Spring maize
5	Yedan 19	158	103	Summer maize
6	No data			

Table 3 Genotype parameters of the varieties used in the simulation

Variety name	P1	P2	P5	G2	G3	PHINT
Dongnong-248	240	0.19	650	314	10	38.9
Yedan 13	280	0.3	870	670	7.5	38.9
Sidan 19	280	0.3	790	720	8.5	38.9
Sc-704	270	0.3	800	700	8.0	38.9
Jiao3danjiao	320	0.3	900	700	9.2	38.9

PHINT Phyllochron interval; the interval in thermal time between successive leaf tip appearances.

P1: Thermal time from seedling emergence to the end of the juvenile phase (expressed in degrees Celsius above a base temperature of 8°C) during which the plant is not responsive to changes in photoperiod. P2: extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h). P5: thermal time from silking to physiological maturity (expressed in degrees Celsius above a base temperature of 8°C). G2: maximum possible number of kernels per plant. G3: kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day^{-1})

throughout the test period, historical county maize yields from 1981–2000 were detrended to a 2000 technology level by using a linear trend analysis technique (Hollinger et al. 2001), and then county yields were aggregated to 50 km×50 km grid level yields by using area-weighting approach (Jagtap and Jones 2002). Yields were simulated for each year (from 1981 to 2000) and each grid by using the CERES-Maize, grid-level soil, homogeneous management data (cultivar: Dongnong-248; Irrigation: non-irrigated condition; planting date: 25th Apr.; planting density: 9 plants m^{-2}, nitrogen is assumed to be applied as ammonium nitrate before planting (60 kg ha^{-1}), with the remainder (120 kg ha^{-1}) applied after 60 days of planting), and observed daily weather data from nearest weather stations.

The model was evaluated with respect to its ability to replicate the mean and standard deviation (SD) of observed yield. Simulated mean yields were significantly larger than statistical mean yields (one-tailed *t* test, $P<0.05$), shown by a value of RMSD [Root Mean Square Difference (Ghaffari et al. 2002]=1,898 kg·ha^{-1}. The likely causes of this overestimation were (a) that the crop model is not sensitive to many environmental stresses such as cold temperatures, drought, flooding, pest, harvest lost, etc., which have been mentioned by many people (e.g. Chipanshi et al. 1999; Jagtap and Jones 2002); (b) limited weather stations, there were only 34 weather stations for this region; (c) a combination of errors in the spatial database, which included homogeneous geographic parameters for grids, uniform model parameters for whole region, etc. and (d) errors in census yields and in aggregating the census yields to grid level. Nevertheless, simulated mean yields and

Table 4 Changes of mean maize production (%) across China sorted by climate change scenarios and time period

Scenarios	With or without CO_2 fertilization	Rain-fed maize			Irrigated maize		
		2020	2050	2080	2020	2050	2080
A2	Without	−11.4	−12.5	−15.8	−6.6	−8.6	−10.1
	With	2.1	1.1	−0.1	1.0	−2.8	−6.6
B2	Without	−9.5	−8.9	−11.4	−4.6	−5.8	−7.6
	With	1.8	0.7	−0.7	−2.0	−1.9	−4.8

observed yields were correlated ($R^2=0.243$) across all grids ($P<0.05$ Pearson correlation analyses), and simulated annual yields from 1981–2000 correlated to observed annual yields in 77 of the 112 grids at the 95% level of confidence. These girds are located in the major maize producing central part of the province (Fig. 4b). The distribution of relative bias of simulated mean yields to observed yields, and simulated Standard Deviation (SD) to observed SD are shown in Fig. 4a,b, respectively. It is obvious that the model tended to overpredict reported census yields in most grids, especially those grids showing low yield levels (Northwest and eastern areas of the province), while gave a good estimation or slight underprediction in high yield level grids. In terms of SD, the model overestimated in low yield level grids and underestimated in high yield level grids.

This comparison was not done using the simulated daily weather data from baseline scenario, because the baseline climate scenario had a different time period to the census yield data. But the performance of the model within a regional simulation proved that the model could give a reasonable results with inputs commonly used in climate impact studies, especially for the major maize planting areas.

3.2 Climate change impacts on maize production in China

In 2000, the total maize production and cultivation area of China were 106 million metric tonne and 22 million ha, respectively (The Editorial Board of Chinese Agricultural Yearbook 2001). Assuming the same maize cultivation area, same cultivars as present, without nutrient stress, simulated potential mean maize productions of baseline (1961–1990) for China were 179 and 264 million metric tonne, for rain-fed and irrigated maize respectively. First, the relative maize production changes derived from climate change without incorporating CO_2 fertilizer effect are presented (Table 5).

For all time periods, rainfed maize production was predicted to decrease under both A2 and B2 scenarios, causing a 11.4–15.8% and 9.5–11.4% lower yields compared to the baseline for A2 and B2 respectively. The decrease was highest under A2 in 2080, giving a 15.8% decline. Production decreased more under A2 than B2, with the highest decrease occurring in the 2080s and the lowest in the 2020s. Those decreases were mainly due to an acceleration in maturation (Wolf and Van Diepen 1995; Maytín et al. 1995) caused by the temperature increase. Preliminary results (Table 4) indicated that the projected productions

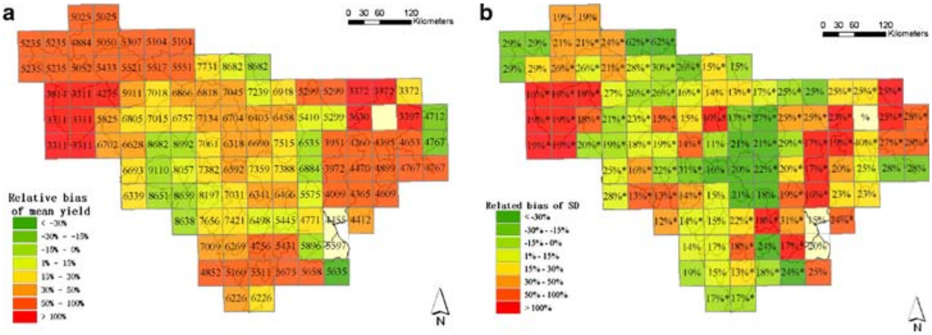

Fig. 4 Spatial distribution of: **a** relative bias of simulated mean yields to observed mean yields, *label* is the observed mean yields; **b** relative bias of simulated SD to observed SD, *label* is the observed SD, *Asterisk* indicates simulated yields and observed yields were correlated ($p<0.05$) over the 20-year period of analysis

under both the A2 and B2 scenarios were similar. The relevant changes of maize production predicted by CERES-Maize are summarized in Table 4 for alternative climate and time periods.

For irrigated maize, the magnitude of the production decline showed a significant decrease under both A2 and B2 for all time periods, compared to rainfed maize. Irrigation might counteract the declining trend in rainfed maize production (assuming sufficient water is available), but it was impossible to stop the decline trend completely. The range of yield offsetting by irrigation was between 7 and 12%, adjusting the production changes figures to −10.1 to −4.6%. However, it should be remembered that these results were based on the assumption that farmers continue to plant the same varieties in the same way and in the same places – it is likely that research and plant breeding will mitigate many of the detrimental effects (Jones and Thornton 2003).

3.3 Carbon dioxide fertilization effect on maize production

In addition to the effect of any changes in climate on maize production, changes in the atmospheric concentration of CO_2 would also affect maize growth directly. A CO_2 'fertilization effect' has been observed in some controlled environments (Rogers et al. 1996) and free-air carbon dioxide enrichment (FACE) experiments (Kimball et al. 1995).

For rainfed maize, with the CO_2 fertilization effect included in the simulation, production was predicted to increase slightly under both the A2 and B2 scenarios for 2020 and 2050, but decrease slightly in the 2080s (Table 4). The CO_2 fertilization effect

Table 5 Changes of maize production (million tonnes) for selected provinces in 2080 under climate change scenarios (with the CO_2 fertilization effect)

Province (code, alias)	Actual Production in 2000 (million tonnes)	2080 under A2 scenario		2080 under B2 scenario	
		Rainfed	Irrigated	Rainfed	Irrigated
Shandong (37, SD)	15.83	0.25	−0.21	0.02	−0.2
Liaoning (22, LN)	10.44	−0.03	−0.22	0.11	−0.14
Henan (41, HN)	9.68	0.12	−0.22	0.03	−0.18
Heilongjiang (23, HLJ)	8.41	0.17	−0.1	0.14	−0.1
Sichuan (51, SC)	6.12	−0.07	−0.15	0.06	−0.07
Neimeng (15, NM)	5.9	0.15	−0.09	0.27	−0.05
Jilin (21, JL)	5.61	−0.08	−0.25	−0.01	−0.18
Yunnan (53, YN)	4.37	0.14	−0.02	0.18	−0.02
Guizhou (52, GZ)	3.72	0.05	−0.13	0.16	−0.09
Shanxi (14, SX)	3.63	0.54	0.22	0.42	0.24
Anhui (34, AH)	2.47	0.04	−0.21	0.05	−0.19
Jiangsu (32, JS)	2.35	0.05	−0.13	0.12	−0.12
Chongqing (50, CQ)	2.22	0.22	−0.23	0.15	−0.12
Gansu (62, GS)	2.2	0.26	0.07	0.31	0.12
Hubei (42, HB)	1.99	0.06	−0.15	0.04	−0.08
Guangxi (45, GX)	1.81	−0.08	−0.16	0.13	−0.03
Hunan (43, HN)	1.34	0.01	−0.22	0	−0.08
Ningxia (64, NX)	0.83	0.01	−0.07	−0.03	−0.04
Fujian (35, FJ)	0.11	0.35	−0.1	0.32	−0.15
Jiangxi (36, JX)	0.08	0.1	−0.21	0.2	−0.12

posed a 9–15% production increase compared to those without the CO_2 effect, which could be interpreted as increased photosynthsis and evapotranspiration under elevated CO_2 concentration. In China, maize is not irrigated in some of the northern areas, which are the primary maize production areas, either because of equipment or water limitations, or as a deliberate policy to maximise profit. Maize production in those areas is variable and highly dependent on the climate (e.g. due to vulnerability to drought), which resulted in low mean yields for the baseline, a small range of yields increases due to elevated CO_2 could lead to a big percentage yield change.

In addition, maize has presented a dramatic increase in water use efficiency (WUE) when grown in carbon dioxide enrichment environments. This effect has been incorporated into the CERES model to adjust the stomatal resistance, transpiration, and WUE (Dhakhwa et al. 1997; Phillips et al. 1996; Southworth et al. 2000). According to the simulation results, a higher CO_2 concentration would cause a stable production level for most years and improve the capacity of maize to confront drought disaster, ultimately, it results in relatively high mean yields, and causes a production rise under the climate change scenarios. There were few differences in climate change impacts between the A2 and B2 scenarios for rain-fed maize.

For irrigated maize, production was estimated to decrease under both A2 and B2 scenarios for all periods, with −6.6%, −4.8% changes under A2 and B2 in 2080 respectively (see Table 4). It is obvious that the CO_2 fertilization effect is more beneficial to rainfed maize than to irrigated maize. Water is the key determinant for maize production in China (Mo et al. 2005), where farmers in irrigated areas (e.g. NX; Fig. 5) have achieved very similar yields as trial experiments. Sufficient irrigation would bring stable and high yields, and gives high yields level under the baseline scenario. A very limited photosynthesis increase (as a C4 plant and without increases for WUE under irrigated condition) caused by elevated CO_2, might not offset the adverse impacts in crop production caused by warming temperature. The A2 scenario showed more negative impacts on irrigated maize than B2.

With the CO_2 effect incorporated in the simulation, production is predicted to increase for rainfed maize but decrease for irrigated maize. Elevated CO_2 enrichment alone would not benefit maize production significantly, especially for irrigated maize, which agrees with the results of Alexandrov and Hoogenboom (2000) although different climate models were used. Higher CO_2 will benefit rainfed maize more then irrigated maize, possibly due to the increase of drought tolerance which has been observed in some FACE experiments (e.g. Wechsung et al. 2000).

3.4 The spatial variability in yield changes under climate change

China's large size has created considerable variations in natural and socio-economic conditions. These variations have brought about significant disparities in regional grain production. Referring to maize production, the spatial distribution is uneven and production is highly concentrated in the northern and northeastern regions due partly to the favourable natural conditions and specialised production (Yang 1994). The production is particularly large in Liaoning (LN), Jilin (JL), Heilongjiang (HLJ), Shandong (SD), Hebei (HB), Henan (HN), and Sichan (SC) provinces (Fig. 2), which together account for over 70% of the country's total maize production. Uneven spatial yields changes between regions could contribute to differing total maize production in the climate change scenarios and time slices. The distribution of yields changes of rainfed and irrigated maize under the A2 and B2 scenarios in 2080 (with the direct CO_2 fertilization effect included) are shown in Fig. 5,

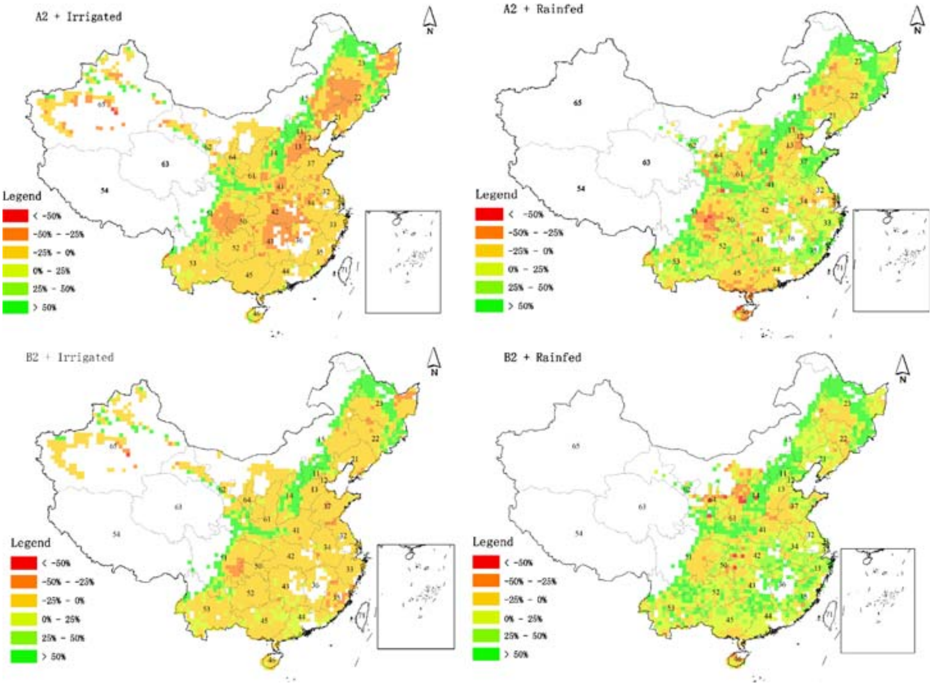

Fig. 5 The spatial pattern of yields change for rainfed and irrigated maize under A2 and B2 scenarios in 2080 (with the CO_2 fertilization effect). *11*. Beijing (BJ), *12*. TianJin (TJ), *13*. Hebei (HB), *14*. Shanxi (SX), *15*. Neimengu (NM), *21*. Jilin (JL), *22*. Liaoning (LN), *23*. Heilongjiang (HLJ), *31*. Shanghai (SH), *32*. Jiangsu (JS), *33*. Zhejiang (ZJ), *34*. Anhui (AH), *35*. Fujian (FJ), *36*. Jiangxi (JX), *37*. Shangdong (SD), *41*. Henan (HN), *42*. Hubei (HB), *43*. Hunan (HUN), *44*. Guangdong (GD), *45*. Guangxi (GX), *46*. Hainan (HAN), *50*. Chongqing (CQ), *51*. Sichuan (SC), *52*. Guizhou (GZ), *53*. Yunan (YN), *54*. Xizhang (2XZ), *61*. Shananxi (SAX), *62*. Gansu (GS), *63*. Qinghai (QH), *64*. Ningxia (NX), *65*. Xingjiang (XJ), *71*. Taiwai (TW)

with the results for some selected provinces listed in Table 5. Three types of maize yield responses to climate change were found:

1. Regions where maize yields were predicted to decrease for rainfed and irrigated conditions under both the A2 and B2 scenarios. One is the northeast Plain, including JN, LJ and south part of HLJ, in which yields were predicted to change by up to −35% in 2080 under A2, and −30% under B2; second is HB, SAX, and NX, currently the main rainfed (HB) and irrigated (SAX, NX) maize planting areas, especially HB province; the third is Sichuan Basin (SC), which is a traditional maize planting area with high yields due to its favourable climate. Simulations suggested that yields would decrease in some key provinces for the state maize production (Table 5).
2. Regions in which yields were predicted to benefit from climate change for rainfed and irrigated conditions under both A2 and B2 scenarios. Two regions were identified in Fig. 5, one was the north part of HJL, where substantial localized yields increases were estimated, sometimes up to 120%. Another is along the strip from northeast to southwest China, in the semi-arid farming pasture zone, including BJ, SX and south SAX and west SC. These regions are usually identified as marginal maize producing areas for their low temperature (north HJL), or soil and water constraints (south SAX or west SC).
3. Regions in which yields were predicted to decrease under the irrigated condition, whilst increase under rainfed condition, for both A2 and B2 scenarios. One was Huang Huai

Hai plain, including SD, HN. Others were provinces along Yangtze river, south east and south China, including HB, JX, ZJ, HUN, AH, FJ, GD, and GX. Huang Huai Hai plain is a traditional key maize producing area for its higher efficiency of resource utilisation (Yang 1994), as water scarcity is the main problem for this area. The other areas mostly are dominated by rice production, so that the total maize production of all these provinces accounts less than 8% of the state total.

The overall integration of climate change impacts on the distribution of maize yield change is clearly extremely complex, but our analysis suggested that yields would decrease for some of the major maize production areas, e.g. northeast China, Sichuan basin, but increase in margin areas. Maize development is sensitive to the rise in temperature; its growth is affected greatly by temperature elevation and precipitation variation (Shang 2000). Present agronomic management for those key maize production areas has adapted to the current climate, so that for some of these areas (e.g. JL, NL, etc.) the yields would not increase under climate change if the same agronomic management as present was maintained, even allowing for the positive effects of CO_2 elevation. However, for some margin areas (e.g. north of HLJ), stress factors (e.g. drought, low temperature, soil, etc.) restrict the maize production at present, so that the future higher temperature, changed patterns of precipitation, and particularly the elevated CO_2 would likely increase stress tolerance. Expanding the intensive maize production to those areas might be a good adaptation option to future climate change. To summarize, climate change is unlikely to benefit China's maize production as the potential maize yields may decrease in key maize planting areas, if the present agronomic practices are not adapted to the changing climate.

4 Limitations

This study was to evaluate the possible changes in maize production in China under changes in mean climate, by applying a RCM and crop model at the regional scale. The results were based on the prediction of climate change by the Hadley Regional Climate Model – PRECIS using the IPCC SRES emission scenarios, and CERES-Maize crop model. Such potential changes provided insight into possible large societal changes needed to control and reduce CO_2 in the atmosphere and to help select appropriate strategies to prepare for change (Adams et al. 1990). 30 years of consecutive weather data was considered long enough to encompass a representative range of current climatic conditions including extreme weather events (Parry et al. 1993), and represented a reference against which scenarios of future climate and its impacts on agriculture may be evaluated (Ghaffari et al. 2001).

The IPCC SRES gave a general framework for world development in the twenty-first century and projected CO_2 emissions under different social economic pathways. It has increasingly become a reference document for modelling the human dimension component of impacts assessment (Gewin 2002). The Hadley Regional Climate model predicted a medium temperature increase scenario compared to other climate models (Houghton et al. 2001), projected a 0.9–3.9°C temperature increase for China. For any change in temperature there are a range of potential regional patterns of climate change with concomitant changes in precipitation and other meteorological variables (Hitz and Smith 2004). As a result the reported simulation results are highly dependent on the projections of PRECIS, so that its conclusions will differ from studies which have used different RCMs or GCMs.

Like most studies on climate change effects on agriculture using crop models, there were several sources of uncertainties and limitations in this study. For instance, only one

Regional Climate Model was used, irrigation water was assumed to be unlimited for irrigated maize, pests (insects, diseases, weeds) were assumed to pose no limitation on crop growth and yields under both current and future climate scenarios, land use did not change in future, technological progress on agriculture was not taken into account in the analysis, etc. The agronomic adaptations strategies, e.g. fertilization rates, adjustments in sowing dates, irrigation applications, and new cultivars, etc. are significant factors in determining future crop growth, yet they were not modelled here. The effects of increased CO_2 levels in the crop model were derived from a limited number of experiments, often in controlled environments, and were, therefore, not fully tested, particularly for warmer, more variable conditions under climate change conditions.

Other limitations related to the simplified field management and maize cultivars represented by the representative farms in each Agro-ecological Zone, and the spatial geo-database. The weighted averaged soil data and homogenous field practices will underestimate spatial variability in yield. The temporal and spatial resolutions of the simulations and the observed data and how they are integrated were other sources of errors and uncertainties. As a country with a large territory, China has a great number of crop genotypes, varieties, and agronomic managements. Even in one 50×50 km grid, there are also diverse varieties, planting dates, irrigation and fertilizers practices, etc. For this simulation, it was impossible to collect all this information and incorporate it into the simulation for the whole country. Averaging these information according to their geographical distribution not only benefited the data collection and shortened the time for data preparation.

5 Conclusion

The CERES-Maize crop model, combined with a spatial database and climate change scenarios (A2 and B2) generated by RCM-PRECIS, has been used to predict mean maize production change across China for the 2020s, 2050s, and 2080s at a 50×50 km grid scale. The model was calibrated and validated using farm experiments, and the regional simulation was validated for Jilin province. Adaptation was not taken into account in the analysis although it will play a great role in future maize production.

Results suggested that predicted future climate change would likely affect overall maize production in China, either positively or negatively, depending on the climate change scenarios, the CO_2 fertilization effect, irrigation and time periods. If the direct CO_2 fertilization effect was not taken into account in the simulation, production was predicted to decrease for rainfed maize under both A2 and B2 scenarios and for all time slices (2020, 2050, and 2050), but irrigation could offset these decreases significantly. With CO_2 fertilization, rainfed maize yield was predicted to increase slightly under both A2 and B2 scenarios for the 2020s and 2050s and decrease for 2080, but irrigated maize yield was estimated to decrease under both A2 and B2 for all time periods. The simulations predict that there will be a significant change in the distribution of future maize production. Key current maize producing areas, e.g. northeast plain, Sichuan basin, and some of north China, would suffer yield declines caused by the shortened growth duration, while some margin areas, e.g. north of the northeast China, would benefit from the longer growing season and elevated CO_2 concentration. These distributions of yield changes will result in a negative or same as present maize production under climate change, even with the CO_2 fertilization effect. Adaptation options, such as intensifying the maize production in marginal areas, adopting new agronomic practices for key maize producing areas, have to be carried out to adapt the climate change. To reduce the uncertainties of this prediction, more RCM and emission scenarios should be involved, and some important factors such as land use change, technology progress, and policy etc. should be incorporated.

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