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Climate change impacts on agriculture and soil carbon sequestration potential in the Huang-Hai Plain of China

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Abstract

For thousands of years, the Huang-Hai Plain in northeast China has been one of the most productive agricultural regions of the country. The future of this region will be determined in large part by how global climatic changes impact regional conditions and by actions taken to mitigate or adapt to climate change impacts. One potential mitigation strategy is to promote management practices that have the potential to sequester carbon in the soils. The IPCC estimates that 40 Pg of C could be sequestered in cropland soils worldwide over the next several decades; however, changes in global climate may impact this potential. Here, we assess the potential for soil C sequestration with conversion of a conventional till (CT) continuous wheat system to a wheat–corn double cropping system and by implementing no till (NT) management for both continuous wheat and wheat–corn systems. To assess the influence of these management practices under a changing climate, we use two climate change scenarios (A2 and B2) at two time periods in the EPIC agro-ecosystem simulation model. The applied climate change scenarios are from the HadCM3 global climate model for the periods 2015–2045 and 2070–2099 which projects consistent increases in temperature and precipitation of greater than 5 °C and up to 300 mm by 2099. An increase in the variability of temperature is also projected and is, accordingly, applied in the simulations. The EPIC model indicates that winter wheat yields would increase on average by 0.2 Mg ha^{-1} in the earlier period and by 0.8 Mg ha^{-1} in the later period due to warmer nighttime temperatures and higher precipitation. Simulated yields were not significantly affected by imposed changes in crop management. Simulated soil organic C content was higher under both NT management and double cropping than under CT continuous wheat. The simulated changes in management were a more important factor in SOC changes than the scenario of climate change. Soil C sequestration rates for continuous wheat systems were increased by an average of 0.4 Mg ha^{-1} $year^{-1}$ by NT in the earlier period and by 0.2 Mg ha^{-1} $year^{-1}$ in the later period. With wheat–corn double cropping, NT increased sequestration rates by 0.8 and 0.4 Mg ha^{-1} $year^{-1}$ for the earlier and later periods, respectively. The total C offset due to a shift from CT to NT under continuous wheat over 16 million hectares in the Huang-Hai Plain is projected to reach 240 Tg C in the earlier period and 180 Tg C in the later period. Corresponding C offsets for wheat–corn cropping are 675–495 Tg C.

Keywords: Soil organic carbon; China; Climate change mitigation; Agriculture; Simulation modeling

1. Introduction

Human activities during the past two centuries have elevated to unprecedented levels the atmospheric concentrations of CO_2, CH_4, N_2O, and other greenhouse gases; this is expected to lead to large-scale alterations in the global climate (Houghton et al., 2001). Soil carbon (C) sequestration (SCS) has been emerging as a plausible strategy with near-term potential for mitigating increasing atmospheric concentrations of greenhouse gases. The IPCC Second Assessment Report estimated that it may be possible, over the course of the next 50–100 years, to restore about two-thirds of the estimated 55 Pg C lost to the atmosphere through cultivation of agricultural soils (Cole et al., 1996). Management for SCS includes practices that conform to principles of sustainable agriculture such as reduced tillage, erosion control, diversified cropping systems and improved soil fertility (Lal et al., 1998a,b; Paul et al., 1997). Soil C sequestration in climate change mitigation was found to be a

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substantial contributor to offsetting industrial CO_2 emissions in an analysis with the global energy model MiniCAM (Edmonds et al., 1996a,b, 1999). While the potential for SCS is finite, large-scale implementation of the already available technologies can be used to offset C emissions while other mitigation options and clean energy technologies needed to stabilize atmospheric concentrations are developed.

The People's Republic of China accounted for 13% of the world's C emissions in 2002 and that share is projected to rise to 18% by 2025 (US DOE, 2004). Most of these emissions result from energy production and transportation; however, agricultural land also contributes to C emissions. All these reasons make SCS a viable option for near-term climate change mitigation. Most regions of China have been cultivated for thousands of years, primarily with rice (*Oryza sativa* L.) and grain crops such as wheat (*Triticum aestivum* L.). Historically, agriculture has been of low intensity and relied on organic fertilizers and the return of crop residues to the soil-practices that helped prevent erosion and maintain soil fertility. Since 1940, agricultural production has intensified in China and the area of cultivation expanded in response to policy changes and rapid population growth (Tong et al., 2003). This has resulted in declines in soil organic matter (SOM) as tillage is intensified and crop residues are removed or burned (Crook and Colby, 1996; Li et al., 2003). The decline in SOM results in lower levels of soil nutrients such as nitrogen (N), thereby increasing fertilizer needs (Li, 2000). While grain yield per unit area has steadily increased, yield per unit of fertilizer added has declined (Gale et al., 2002; Li, 2000). Cultivation-induced C losses of China's soils have been estimated on average at 15 Mg C ha^{-1}, representing a total loss of 2 Pg C (Song et al., 2005).

The Huang-Hai Plain of China is the country's most productive wheat growing region and has been cultivated for many centuries. Land productivity has been maintained in recent years with increasing introduction of the double cropping of summer crops, such as corn (*Zea mays* L.), with winter wheat. Currently, rainfed grain agriculture is possible but studies indicate that this region will be vulnerable to climate change. While the HadCM3 GCM used in this study projects increased precipitation, other global climate models project a decline in precipitation. In one climate change analysis, Tao et al. (2003) found agriculture to be negatively impacted due to soil moisture deficits from higher temperatures and declining precipitation. Erda (1996) found that a combination of agronomic characteristics and socio-economic circumstances contribute to the vulnerability of the Huang-Hai Plain under GCM projections of sharply reduced precipitation. A companion study by Jinghua and Erda (1996) modeled corn production and found declining yields, leading to the conclusion that yields will become more vulnerable to climatic variability if the projected climate changes occur.

Alternative management in the Huang-Hai Plain could reduce the vulnerability of the region to what are still uncertain changes in climate and, at the same time, contribute to climate change mitigation by sequestering C in soils. The greatest soil C stocks in China are found in the northeast and the lowest values in the west and south (Zhou et al., 2003). More regionally focused accountings of soil C stocks have begun (Wang et al., 2002a,b) and modeling studies have examined the impacts of management practices on soils. Modeling corn production systems with the RothC model, Yang et al. (2003) compared the performance of different fertilizer treatments on soil organic C (SOC) and found that the most beneficial practice was returning crop residues to the soil. Without supplemental fertilization, they found, SOC levels decline. In a comparison with US croplands, Li et al. (2003) found a much higher rate of annual SOC loss for the year 1990 in China (1.6%) than in the US (0.1%). This difference is attributed to lower crop residue return in China (25%) compared to the US (90%).

Here, we report on the modeling of alternative management practices designed to improve soil quality by reducing tillage and increasing the return of crop residue to the soil. We examine these management strategies under scenarios of possible future changes in climate to determine a range of potential future crop production and SOC stocks and to determine whether a changing climate would impact SOC response to management change. In essence, we assess the technical potential of soils in the Huang-Hai Plain to act as sinks of atmospheric CO_2 under changing climate and the extent to which alternate management practices could influence this potential.

2. Methods

2.1. Study region

The Huang-Hai Plain of China is an important agricultural, economic, and cultural region that extends between latitudes 34°39′ and 42°62′N and longitudes 113°46′ to 122°7′E. It includes the provinces of Beijing, Tianjin, Hebei and Shandong (Fig. 1). It is a large alluvial plain developed by the intermittent flooding of the Huang, Huai and Hai rivers (Zhu et al., 1983) with a semi-arid to sub-humid warm temperate climate. A monsoonal precipitation distribution results in droughts and floods frequently impacting agricultural production.

Dominant soils are classified as Fluvisols (FAO taxonomy) or Fluvi-aquic (Chinese Soil Taxonomy; Wu et al., 2003). Soil properties for 18 study sites were selected by Sun et al. (2001) from the most comprehensive dataset available, the Second National Soil Census of China (Chinese National Soil Survey Office, 1997, 1998). The soil properties from this database are used to initialize the model runs in each of the 18 representative farms (Table 1). The soil database was combined with weather records in a GIS to create 18 modeling regions for the Huang-Hai Plain (Fig. 1). The agricultural land area of each of these regions was calculated based on the percentage of land in agriculture

in each province in China (Fischer et al., 1998; Table 1). While the soil database is comprehensive and widely applied (e.g. Song et al., 2005), independent datasets of soil properties and SOC change over time have not been readily available. Thus, confidence in the SOC model projections is inferred from previous validations (Izaurralde et al., 2005).

2.2. Climate change scenarios

The climate change projections were obtained from runs of the HadCM3 model (Gordon et al., 2000; Pope et al., 2000), archived by the IPCC Data Distribution Center, for the A2 and B2 scenarios developed for the Third Assessment Report (Cubasch et al., 2002; Nakicenovic and Swart, 2000). The monthly values for maximum temperature, minimum temperature and precipitation were obtained from the IPCC database for a baseline period (1961–1990) and two future 30 years periods—2015–2045 and 2070–2099. These are referred to hereafter by the middle year—2030 and 2085, respectively (Table 3). The changes from the HadCM3 baseline period for 2030 and 2085 were calculated and applied to the historical baseline climate record for each study site. In addition, the record of daily maximum and minimum temperature and precipitation for the baseline

Table 1
Initial soil properties for each representative farm as taken from the National Soil Survey Office of China

ID	Site	Agricultural land area (million hectares)	Layer depth (cm)	Bulk density	Organic C (Mg m^{-3})	Sand (%)	Silt (%)	Clay
5200	Shijiazhuan	0.93	0–50	1.24	0.74	34	48	19
	Hebei		50–95	1.30	0.38	63	23	14
5201	Xintai	0.70	0–14	1.24	1.32	34	48	19
	Hebei		14–30	1.30	0.78	63	23	14
5202	Zhangjiakou	1.42	0–17	1.13	2.73	49	30	21
	Hebei		17–39	1.57	1.38	48	29	23
5203	Chengde	1.30	0–10	1.36	0.69	50	22	27
	Hebei		10–21	1.42	0.64	35	35	30
5204	Beijing	0.41	0–30	1.58	2.88	49	30	21
	Beijing		30–60	1.58	1.73	48	29	23
5205	Tianjin	0.50	0–15	1.33	3.10	72	13	16
	Tianjing		15–33	1.45	1.80	65	16	19
5206	Tangshan	1.17	0–14	1.42	3.48	70	21	9
	Hebei		14–31	1.43	1.33	65	24	11
5207	Baoding	0.79	0–5	1.33	0.31	73	13	14
	Hebei		5–15	1.43	0.31	74	13	13
			15–25	1.57	0.18	84	6	11
5208	Changzhou	0.78	0–15	1.42	3.10	72	13	16
	Hebei		15–33	1.43	1.80	65	16	19
5209	Dezhou	1.33	0–20	1.42	1.75	39	38	24
	Shandong		20–28	1.43	0.99	35	38	27
5210	Yantai	0.47	0–20	1.37	4.10	77	13	10
	Shandong		20–47	1.50	2.80	71	20	10
5211	Jinan	1.16	0–20	1.42	1.75	43	36	21
	Shandong		20–28	1.43	0.99	17	44	39
5212	Taian	1.44	0–25	1.13	0.93	45	32	24
	Shandong		25–46	1.57	0.69	46	31	23
5213	Weifang	0.87	0–24	1.13	1.74	55	23	22
	Shandong		24–39	1.57	0.98	47	30	23
5214	Laiyang	0.55	0–14	1.42	0.71	39	41	20
	Shandong		14–25	1.37	0.72	38	41	21
5215	Qingdao	0.65	0–20	1.41	0.71	41	22	37
	Shandong		20–35	1.37	0.63	18	30	52
5216	Hezhe	0.74	0–17	1.33	0.80	62	8	31
	Shandong		17–41	1.57	0.59	32	33	35
5217	Linxi	0.80	0–20	1.41	0.71	53	30	17
	Shandong		20–45	1.37	0.56	50	31	19

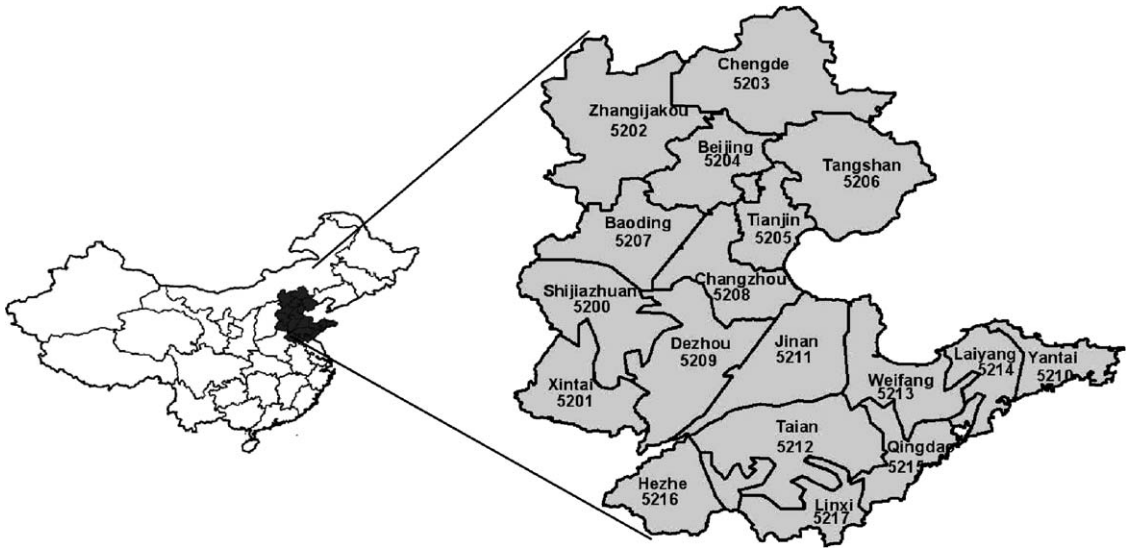

Fig. 1. Name and number of the 18 representative farms and the location of the study area in China.

period was used to generate monthly climatic statistics needed to drive the EPIC model.

The A2 scenario describes a very heterogeneous world of high population growth, slow economic development and strong regional cultural identities. In contrast, the B2 scenario reflects a heterogeneous world where there is diverse technological change, low population growth and emphasis on local solutions to economic, social and environmental sustainability problems. Scenario A2 has a higher rate of atmospheric CO_2 accumulation and therefore a greater associated climate change. In the baseline period, CO_2 concentration is 370 ppmv; at the 2030 period, it is 450 ppmv for the A2 and 430 ppmv for the B2 scenario. A greater change is seen in the 2085 period where CO_2 in the A2 scenario reaches 735 ppmv, compared to 535 ppmv for the B2 scenario.

One limitation of this type of study has been that while GCMs project changes in average monthly temperature and precipitation, they do not provide data on changes in variability. Increases in the range of climate variability, an anticipated effect of climate change, could be particularly important to the agricultural sector. Here, we assume that while variability of climate may change, the relationship between daily variability and monthly variability remains constant. Using the daily and monthly data for the baseline period, we defined the relationship between the monthly (Std_{mo}) and daily (Std_{do}) standard deviations in both maximum and minimum temperature. Then, using the standard deviations from the monthly climate change data (Std_{mc}), we calculated the daily standard deviations under climate change as $Std_{dc} = Std_{mc} \times Std_{do}/Std_{mo}$.

2.3. Agricultural management

The matrix of simulations (Table 2) includes four crop management options: continuous winter wheat, double cropped wheat–corn, conventional tillage (CT) and no tillage (NT). Under both CT and NT management, the continuous wheat system is fertilized twice with N (46-0-0) and once with N and P (10-46-0). Conventional tillage is simulated with passes of moldboard plow, offset disk, and spike harrow before planting with a grain drill. All tillage operations are eliminated to simulate NT management. The double cropped system is winter wheat with a summer corn crop. The corn crop is fertilized at the same rate as the wheat and a no till planter is used with an additional disking operation at planting for the CT management. All simulations were run without irrigation. Planting dates were adjusted automatically by the EPIC model to adapt to changing temperatures using data on growing season length and weather.

Simulations included wind and water erosion processes and soil properties were treated dynamically by the model to allow for an explicit accounting of the long term-effects of changes in climate and management on soil C stocks. The final soil profile for each farm from the baseline period (year

Table 2
Matrix of EPIC model runs at each of the 18 representative farms for both the A2 and B2 scenarios

Time period	Tillage[a]	Cropping system[b]
2030	CT	W
		W–C
	NT	W
		W–C
2085	CT	W
		W–C
	NT	W
		W–C

[a] CT = conventional till; NT = no till.
[b] W = continuous winter wheat; W–C = wheat–corn double cropping.

1990) was used to initialize the soil for the 2030 simulation and the soil profile from the 2030 period (year 2045) was used to initialize the 2085 run.

2.4. EPIC model description

Environmental Policy Integrated Climate (EPIC) Version 3060 is a biophysical process model which can simulate detailed farm management and the associated impact on crop production and soils (Williams, 1995). The concept of radiation-use efficiency is used to simulate crop growth by calculating the potential daily photosynthetic production of biomass. The daily potential growth is decreased by stresses caused by shortages of water and nutrients; by temperature extremes; and by inadequate soil aeration. Daily potential photosynthesis is proportionally decreased according to the most severe stress of the day. Stockle et al. (1992a,b) adapted EPIC to simulate the CO_2-fertilization effect on radiation-use efficiency (RUE) and evapotranspiration (ET). Elevated atmospheric CO_2 concentration (CO_2) increases photosynthesis in C_3 plants and reduces evapotranspiration in both C_3 and C_4 plants due to reduced stomatal conductance, thereby improving water use efficiency. A non-linear equation was developed in EPIC to express the RUE response to increasing CO_2 following experimental evidence summarized by Kimball (1983). That analysis showed crop yield increases of 33% with a doubling of atmospheric CO_2, and assigned a 99% confidence in this response ranging from 24 to 43%. Stockle et al. (1992a,b) modeled this response as a function of crop type and while those parameters have not been specifically tested against observations, they are consistent with results arising from free air CO_2 (FACE) experiments (Amthor, 2001).

Izaurralde et al. (2005) introduced algorithms in EPIC, based on the approach used in the Century model (Parton et al., 1987), to simulate soil C dynamics in response to land use change, soil management, and climate change. The C routines interact directly with soil moisture, temperature, erosion, tillage, soil density, leaching, and translocation functions in EPIC. Additionally, the algorithms describe the effect of soil texture on C stabilization and model lignin concentration as a sigmoidal function of plant age. The model has been tested against data from long term agricultural experiments and found to be reasonably accurate in reproducing loss and accumulation of soil C at five sites in the US Great Plains and one site in Canada (Izaurralde et al., 2005).

2.5. EPIC model validation

The EPIC model has been validated extensively in the US and other regions of the world. EPIC has undergone improvements and validation under a variety of climates, soils, and management environments including water erosion and snowmelt runoff (Chung et al., 1999; Puurveen et al., 1997), wind erosion (Potter et al., 1998), crop yield (Roloff et al., 1998), climatic variability (Izaurralde et al., 1999; Legler et al., 1999), climate change (Brown and Rosenberg, 1999; Easterling et al., 1996; Izaurralde et al., 2003; Thomson et al., 2002), nutrient cycling (Cavero et al., 1998), and soil C sequestration (Izaurralde et al., 2001, 2005).

Here, we use government crop yield statistics to compare against EPIC simulations of wheat and corn yields. Provincial wheat and corn yields were extracted from the Agricultural Economy Database (http://www.naturalresources.csdb.cn/ny/cdroom/tx2new.asp) prepared by the Institute of Geographical Sciences and Natural Resources Research at the Chinese Academy of Sciences. The annual average yield for each province, based on total provincial production and land area under cultivation, steadily increases from 3.1 to 4.3 Mg ha^{-1} during 1960–1990. It is clear that increases in yields have occurred in the past 50 years with the use of higher yielding crop varieties and agricultural reforms (Hsu and Gale, 2001; Sinclair and Bai, 1997). However, the state reported crop yield and other agricultural statistics are likely biased upwards due to underestimation of crop land area (Crook and Colby, 1996; Frolking et al., 1999; Gale et al., 2002). Most studies of agriculture in China use these state-reported statistics as the primary countrywide data set (Jinghua and Erda, 1996; Tong et al., 2003; Wang et al., 2002a,b, 2003; Wu et al., 2003; Zhou et al., 2003). EPIC simulations by Sun et al. (2001) recreated the historically increasing trend of the average provincial yields by increasing the planting density, fertilizer applications and irrigation each year. We compared the baseline simulations of this study to the provincial yield records. The average winter wheat yields reported for 1960–1990 range from 1.7 to 2.5 Mg ha^{-1}, while EPIC simulated average yields range from 0.2 to 2.0 Mg ha^{-1}. The simulated yields consistently under predict the reported values by 0.3–1.5 Mg ha^{-1}. The annual simulated yields over-predict yield in the first half of the baseline period (1960–1975) by as much as 4.0 Mg ha^{-1}. After 1975, the simulations under-predict yields by as much as 3.0 Mg ha^{-1}.

An alternative to official government statistics is to validate simulation models with field data from agricultural experiment stations. However, the lack of a central source of data complicates this type of model validation. In some instances, field data have been used to parameterize simulation models for specific sites in China (Kang et al., 2003; Li et al., 2003; Liu et al., 1998; Yang et al., 2003). Zhang et al. (1999) report winter wheat yields from four experiment stations within our study region. Dryland wheat yields at Luaocheng and Gaocheng experiment stations are 2.58 and 2.61 Mg ha^{-1}, respectively, and the average EPIC wheat yield for the baseline period in that region is 2.5 Mg ha^{-1} (representative farm 5200). Dryland wheat yield at the Nanpi experiment station was 3.2 Mg ha^{-1} while at the Linxi experiment station it was 2.8 Mg ha^{-1}. The corresponding EPIC yields for the representative farms in those regions are on average too low (1.5 Mg ha^{-1} at farm

5208 and 1.4 Mg ha^{-1} at farm 5209, respectively), although the maximum yields during the EPIC 30 years simulation are 3.2 and 2.7 Mg ha^{-1}, respectively, showing that the model is capable of simulating the potential production at these sites.

For larger regional and country-wide studies, remote sensing provides some information for model testing (Frolking et al., 1999; Gao and Xhang, 1997). Other studies of agriculture in China have been similarly limited by data availability, particularly with regards to soil data from agricultural experiments. Wang et al. (2002) in a prior study using EPIC to simulate erosion in China, acknowledge the limitation due to lack of data for validation. Other studies with proven agricultural simulation models have likewise been hampered by difficulties in verifying model output of specific locations in China (Erda, 1996; Matthews et al., 1997; Terjung et al., 1983) and authors discuss the limitations on studies due to the difficulty of obtaining site data and the unreliability of state-reported crop yields (Verburg et al., 2000; Wang et al., 2002a,b).

2.6. Statistical analysis of simulation results

The EPIC simulation results were analyzed with the GLM procedure in SAS (SAS Inst. Inc., Cary, NC) in a factorial design of 4 climate scenarios by four management treatments with 18 replications (farms). Mean separations were obtained using Fisher's least significant difference at the 0.05 level of probability ($L.S.D._{0.05}$). Assumptions of normal distribution of the data were tested and confirmed using the UNIVARIATE procedure in SAS (options 'normal' and 'plot') on residual values calculated with the GLM procedure.

The rate of change of C in soils is calculated for the top 30 cm of the soil profile. The difference in soil C mass from the initial soil and the final soil is taken and divided by the simulation length. Soil C offsets due to no till are calculated as $[(NT_{final} - NT_{initial}) - (CT_{final} - CT_{initial})]$ and offsets from conversion to a wheat–corn system from a continuous wheat system are calculated as $[(WC_{final} - WC_{initial}) - (WF_{final} - WF_{initial})]$. Naturally, a soil may lose C under both CT and NT treatments; but, if the loss is smaller under NT, then a potential emission of C has been offset by the management practice.

3. Results and discussion

3.1. Climate change projections

3.1.1. 2030 (2015–2045) period

Temperature increases during the period centered around 2030 are moderate, ranging from 0.5 to 2 °C for both maximum and minimum temperature (Table 3). Increases in maximum temperature are greater than increases in minimum temperature, an effect that increases heat stress on crops. There is little difference in temperature change between the A2 and B2 scenarios during this period. Precipitation is projected to increase during the 2030 period, with the exception of some drying (~30 mm) that might occur over the southern part of the study area in the A2 scenario. The pattern of change is varied with large increases over the central region (200 mm) and small increases in the north (50–100 mm). Under the B2 scenario, increases in precipitation across the study region range from 25 to 75 mm.

3.1.2. 2085 (2070–2099) period

Changes in climate increase in magnitude during the period centered around 2085. Temperature increases for A2 and B2 range from 2.5 to over 5 °C. Under A2, the maximum temperature increases by an average of 5 °C; the average minimum temperature increases by 3.6 °C. Temperature increases are greater in the northern part of the study region. The pattern of change in the B2 scenario is similar, but the magnitude is smaller with a maximum temperature increase of 3.2 °C and a minimum temperature increase of 2 °C. Precipitation is projected to increase uniformly over the study region under both A2 and B2 scenarios. The increase ranges from 200 to 300 mm under A2 and from 100 to 240 mm under B2. In a region where baseline precipitation is between 400 and 900 mm annually, such changes would be capable of impacting crop production.

Many GCM's project increases in nighttime (minimum) temperatures greater than the increases in daytime (maximum) temperatures. In this region, the HadCM3 model projects an opposite relationship. Minimum temperatures control the break in dormancy and spring crop growth. Also, higher maximum temperatures could increase respiration losses as well as induce heat stress on crop growth and development.

3.1.3. Variability

The standard deviation (Std) of maximum and minimum temperatures increase under the scenarios studied. During the 2030 period, only those of the A2 scenario increase by an average of 0.27 °C. In the 2085 period, the Std increases for both the A2 and B2 scenarios. Under the A2 scenario, the Std increases by 0.79 °C and under the B2 scenario, by an average of 0.54 °C. In general, there is little difference in the change in Std between maximum and minimum temperatures. The Std of air temperatures is projected to increase towards the later part of the century with larger increases under the A2 scenario.

3.2. Crop production

Average winter wheat yields for the 1960–1990 baseline period range from 0.5 to 2.5 Mg ha^{-1} across the 18 representative farms (Table 4). Yields are positively influenced by the increasing precipitation projected under the climate change scenarios, with the highest average yields in the 2085 time period when the precipitation increase is

Table 3
Air temperature and precipitation at 18 representative farms in the Huang-Hai Plain under baseline climate and the changes projected

Farm ID	Baseline			Deviations from baseline											
				A2 2030			A2 2085			B2 2030			B2 2085		
	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)	T_{max} (Δ°C)	T_{min} (Δ°C)	Precipitation (Δmm)	T_{max} (Δ°C)	T_{min} (Δ°C)	Precipitation (Δmm)	T_{max} (Δ°C)	T_{min} (Δ°C)	Precipitation (Δmm)	T_{max} (Δ°C)	T_{min} (Δ°C)	Precipitation (Δmm)
5200	19.1	7.8	509	0.9	1.6	96	3.4	4.8	235	0.8	1.6	75	1.6	2.9	207
5201	19.5	8.0	505	0.9	1.6	96	3.4	4.8	235	0.8	1.6	75	1.6	2.9	207
5202	14.8	2.7	385	1.8	1.7	59	4.1	5.1	191	1.2	1.8	54	2.5	3.4	135
5203	15.7	3.3	506	1.7	1.7	56	4.1	5.1	191	1.2	1.8	54	2.5	3.4	135
5204	17.7	6.5	562	1.7	1.7	56	4.1	5.1	191	1.2	1.8	54	2.5	3.4	135
5205	17.8	8.2	557	1.7	1.7	56	4.1	5.1	191	1.2	1.8	54	2.5	3.4	135
5206	17.0	6.1	631	1.4	1.3	8	4.8	5.3	193	1.5	1.8	40	3.0	3.3	102
5207	18.5	7.3	526	1.7	1.7	56	4.1	5.1	191	1.2	1.8	54	2.5	3.4	135
5208	18.4	7.9	600	0.9	1.6	96	3.4	4.8	235	0.8	1.6	75	1.6	2.9	207
5209	18.8	8.2	559	0.9	1.6	96	3.4	4.8	235	0.8	1.6	75	1.6	2.9	207
5210	16.2	9.5	658	0.8	0.8	68	3.7	3.9	283	0.8	0.9	69	2.1	2.3	237
5211	19.4	10.1	655	0.9	1.6	96	3.4	4.8	235	0.8	1.6	75	1.6	2.9	207
5212	18.8	7.5	692	1.2	1.4	−33	3.8	4.5	300	1.0	1.3	53	2.3	2.9	188
5213	18.5	7.5	603	0.8	0.8	68	3.7	3.9	283	0.8	0.9	69	2.1	2.3	237
5214	17.6	6.0	691	0.8	0.8	68	3.7	3.9	283	0.8	0.9	69	2.1	2.3	237
5215	15.8	9.6	706	0.9	0.9	−10	3.7	3.9	273	0.9	1.0	29	2.3	2.4	136
5216	19.5	9.1	623	1.2	1.4	−33	3.8	4.5	300	1.0	1.3	53	2.3	2.9	188
5217	18.8	8.9	831	0.9	0.9	−10	3.7	3.9	273	0.9	1.0	29	2.3	2.4	136

Table 4
Average baseline winter wheat grain yield and the change in average winter wheat yields over the 30 years simulation periods for each of the study sites

ID	Baseline (Mg ha^{-1})	A2 2030 (Mg ha^{-1})				B2 2030 (Mg ha^{-1})				A2 2085 (Mg ha^{-1})				B2 2085 (Mg ha^{-1})			
		Continuous wheat		Wheat–corn		Continuous wheat		Wheat–corn		Continuous wheat		Wheat–corn		Continuous wheat		Wheat–corn	
		CT	NT	CT	NT	CT	NT	CT	NT	CT	NT	CT	NT	CT	NT	CT	NT
5200	2.5	1.0	0.7	−0.1	−0.2	0.6	0.5	−0.5	−0.6	1.7	1.5	0.7	0.6	1.5	1.2	0.6	0.5
5201	0.9	0.4	0.3	0.1	0.0	0.2	0.1	−0.1	−0.1	1.0	0.9	1.1	1.0	1.0	0.9	1.0	0.9
5202	0.7	0.1	0.0	−0.3	−0.3	0.1	0.0	−0.4	−0.4	0.5	0.5	0.1	0.0	0.5	0.4	0.0	−0.1
5203	1.1	−0.1	−0.2	−0.5	−0.6	−0.4	−0.4	−0.6	−0.5	0.5	0.4	0.2	0.1	−0.1	−0.2	−0.3	0.0
5204	1.2	−0.2	−0.3	−0.4	−0.5	−0.2	−0.3	−0.5	−0.5	0.2	0.1	0.1	0.0	0.1	0.0	−0.1	−0.1
5205	1.4	0.0	−0.1	−0.6	−0.6	−0.2	−0.3	−0.6	−0.6	0.5	0.4	0.0	−0.1	0.2	0.2	−0.1	−0.3
5206	1.7	−0.2	−0.3	−0.7	−0.7	−0.2	−0.3	−0.7	−0.7	0.4	0.3	0.1	0.1	0.0	−0.1	−0.2	−0.3
5207	0.5	−0.1	−0.1	−0.2	−0.3	−0.1	−0.1	−0.2	−0.3	0.3	0.3	0.2	0.1	0.2	0.2	0.1	0.0
5208	1.5	0.6	0.5	0.0	−0.1	0.2	0.1	−0.3	−0.3	1.1	0.9	0.6	0.5	1.0	0.9	0.6	0.5
5209	1.4	0.6	0.4	0.3	0.2	0.3	0.2	0.0	0.0	1.6	1.4	1.3	1.3	1.4	1.2	1.2	1.1
5210	1.5	0.4	0.3	−0.1	−0.1	0.0	0.0	−0.3	−0.3	1.2	1.1	0.6	0.6	0.9	0.7	0.4	0.3
5211	1.2	0.6	0.5	0.3	0.3	0.3	0.2	−0.1	−0.1	1.1	1.0	1.2	1.2	1.0	1.0	1.0	0.9
5212	1.8	−0.3	−0.4	−0.8	−0.8	0.1	0.0	0.0	−0.1	1.1	0.9	1.8	1.5	0.8	0.7	1.1	1.0
5213	1.6	0.4	0.2	0.1	0.1	0.0	−0.1	−0.2	−0.1	1.2	1.0	1.5	1.3	0.8	0.7	1.2	1.0
5214	1.8	0.1	−0.1	0.2	−0.1	0.1	−0.1	0.0	−0.1	0.9	0.8	1.6	1.0	0.7	0.5	1.3	0.6
5215	2.3	0.0	−0.2	−0.2	−0.3	0.7	0.3	0.7	0.4	1.5	1.3	2.7	1.6	1.4	1.1	2.3	1.2
5216	1.3	−0.2	−0.2	−0.3	−0.4	0.2	0.2	0.1	0.1	1.3	1.1	1.5	1.3	0.9	0.9	1.0	0.9
5217	1.7	−0.1	−0.2	−0.2	−0.3	0.4	0.2	0.3	0.2	1.0	0.8	0.8	1.0	0.8	0.7	0.9	0.7

Table 5
Crop yields, water erosion, SOC change, eroded C, residue C and respired C annual means grouped by climate change scenario and cropping system

Scenario	Period	Crop yield (Mg ha^{-1})	Water erosion (Mg ha^{-1})	ΔSOC (Mg ha^{-1})	Eroded C (Mg ha^{-1})	Residue C (Mg ha^{-1})	Respired C (Mg ha^{-1})
A2	2030	1.39	0.33	2.36	0.46	5.51	5.95
	2085	2.30	0.38	2.53	0.54	7.26	7.50
B2	2030	1.39	0.39	3.01	0.46	5.70	6.12
	2085	2.07	0.39	3.50	0.52	7.04	7.26
L.S.D.$_{0.05}$[a]		0.26	0.09	5.84	0.02	0.48	0.51
Crop	**Tillage**						
Wheat	CT	1.94	0.89	−8.03	0.46	5.25	5.86
	NT	1.83	0.16	5.59	0.43	4.86	5.10
Wheat	CT	1.75	0.31	−10.76	0.55	7.77	8.42
Corn	NT	1.64	0.15	24.60	0.54	7.62	7.45
L.S.D.$_{0.05}$[a]		0.26	0.09	5.84	0.02	0.48	0.51

[a] Fisher's least significant difference treatment differences within a group that are larger than the L.S.D.$_{0.05}$ are significantly different at $p < 0.005$.

greatest. The ANOVA analysis shows that yields of winter wheat are significantly different during the 2085 period (Table 5) and that the crop management system does not significantly affect yield. Crop yields are influenced more by the time period than by the GCM scenario due to the pronounced increase in precipitation for both the A2 and B2 scenarios in 2085 and the substantial increase in atmospheric CO_2. The variability of wheat yields was not significantly affected by the changes in climate or in management practice.

Increases in dryland winter wheat yields are similar to those found by Sun et al. (2001) in a study with the HadCM2 model projections of climate change. The Huang-Hai Plain was identified by Erda (1996) as one of the most vulnerable agricultural regions of China primarily as a result of precipitation declines projected by a different GCM. The HadCM3 projects increased precipitation for the region, which is beneficial to dryland crop yields and would also reduce irrigation demand. The future of agricultural production in the region is vulnerable to changes in precipitation, and further studies with global and regional climate change projection models are necessary to assess the full range of potential climate change impacts and adaptation strategies.

3.3. Agro-ecosystem carbon balance

3.3.1. Impact of climate and management on soil C stocks

The pattern of crop residue C responses to treatment variables was similar to those of crop yields. Residue C was impacted primarily by the crop mix, with the highest residue C values occurring in 2085 time period, when crop production is greatest, under the wheat–corn double cropping system. These projections of residue C input and therefore soil C may be biased downward due to under prediction of grain crop yields. In contrast, eroded C is significantly influenced by tillage practice and by cropping system (Table 5). Soil C stocks in the top 30 cm change significantly as a result of management changes (Tables 5 and 6). Climate change did not influence soil C stocks, but conversion from CT to NT induced differences. Some increase in soil C occurs due to the conversion to a wheat–corn double cropping system under NT, but not under CT.

The magnitude of the simulated soil C change was a function of initial soil C (Fig. 2). Regardless of the climate scenario or the management option, the simulated data suggests that soils low in C content would tend to accrue more C than soils high in C content. In the EPIC model, soil C change is regulated by two major mechanisms: C inputs and variations in decomposition rates of C material (Izaurralde et al., 2005). Soils relatively rich in soil C content may not accrue C because they may already be near their saturation level (Hassink, 1996; Six et al., 2002) or the simulated C inputs are not large enough to offset the losses dictated by the decomposition rates. Conversely, soils relatively poor in soil C content respond more readily to changes in management showing significant increases, especially under NT and double cropping. To facilitate the visualization of the trends portrayed in Fig. 2 we fitted third order polynomials between initial soil C and soil C change. These curvilinear relationships, however, lack predictive value. Thus, the small soil C increases predicted at the high end of soil C content are artifacts of the curvilinear fit rather than a prediction of soil C accrual.

3.3.2. Soil C offset rates

The soil C mass in the top 30 cm of the soil was calculated for each simulation and the total change and rate of change over the 30 years period are given in Tables 6–8. The IPCC estimated that changes in agricultural management practices could result in C sequestration in soils at a rate of 0.36 Mg C ha^{-1} year^{-1}

in non-Annex I countries, including China (Watson et al., 2000). In this simulation study, the study region loses soil C under CT by an average of 0.27 Mg C ha^{-1} $year^{-1}$ while NT continuous wheat and wheat–corn result in soil C accumulation of 0.10 and 0.32 Mg C ha^{-1} $year^{-1}$, respectively (Table 6). For the NT simulations, the rates of change are generally greater during the first period, 2030, and smaller during the second, 2085. The reduction in rate is greatest for the NT wheat–corn management which sequesters the greatest amount of soil C during the first period and approaches a saturation point in the second period. The soils under CT management continue with an equal or greater rate of soil C increase in the 2085 time period. The soil C rate change is not consistently different as a result of the scenario selected (A2 or B2).

Soil C offsets under NT are given in Table 7, expressed as the rate of change in soil C in Mg C ha^{-1} $year^{-1}$ over the 30 year simulation period. With a few exceptions, the NT always results in a positive soil C offset averaging 0.23–0.37 Mg C ha^{-1} $year^{-1}$ for continuous wheat and 0.34–0.86 Mg C ha^{-1} $year^{-1}$ for wheat–corn. A higher rate for wheat in a rotation was also calculated by West and Post (2002) in a global analysis of soil C sequestration rates. They found a rate of 0.25 (±0.26) Mg C ha^{-1} $year^{-1}$ for continuous wheat and 0.74 (±0.52) Mg C ha^{-1} $year^{-1}$ for wheat in rotation in the years following the conversion from CT to NT. They also found an average sequestration rate of 0.16 (±0.14) Mg C ha^{-1} $year^{-1}$ for increasing rotation complexity under CT and 0.26 (±0.56) Mg C ha^{-1} $year^{-1}$ for increasing rotation complexity under NT. The rate for increasing the rotation complexity of a wheat system was found to be 0.51 (±0.47) Mg C ha^{-1} $year^{-1}$. The increase in rotation complexity simulated by the wheat–corn system in this study resulted in soil C offsets that were slightly negative or neutral under CT and positive under NT (Table 8).

These results suggest that a change to NT wheat–corn double cropping is the management practice that would result in the greatest soil C sequestration or offset. This management causes the least disturbance to the soil and returns the greatest amount of organic inputs from crop residues under both the A2 and B2 scenarios of climate change. Although in most cases the soils continue to sequester or offset C the rate of change slows in the second time period (2085), indicating a potential C saturation point in the future.

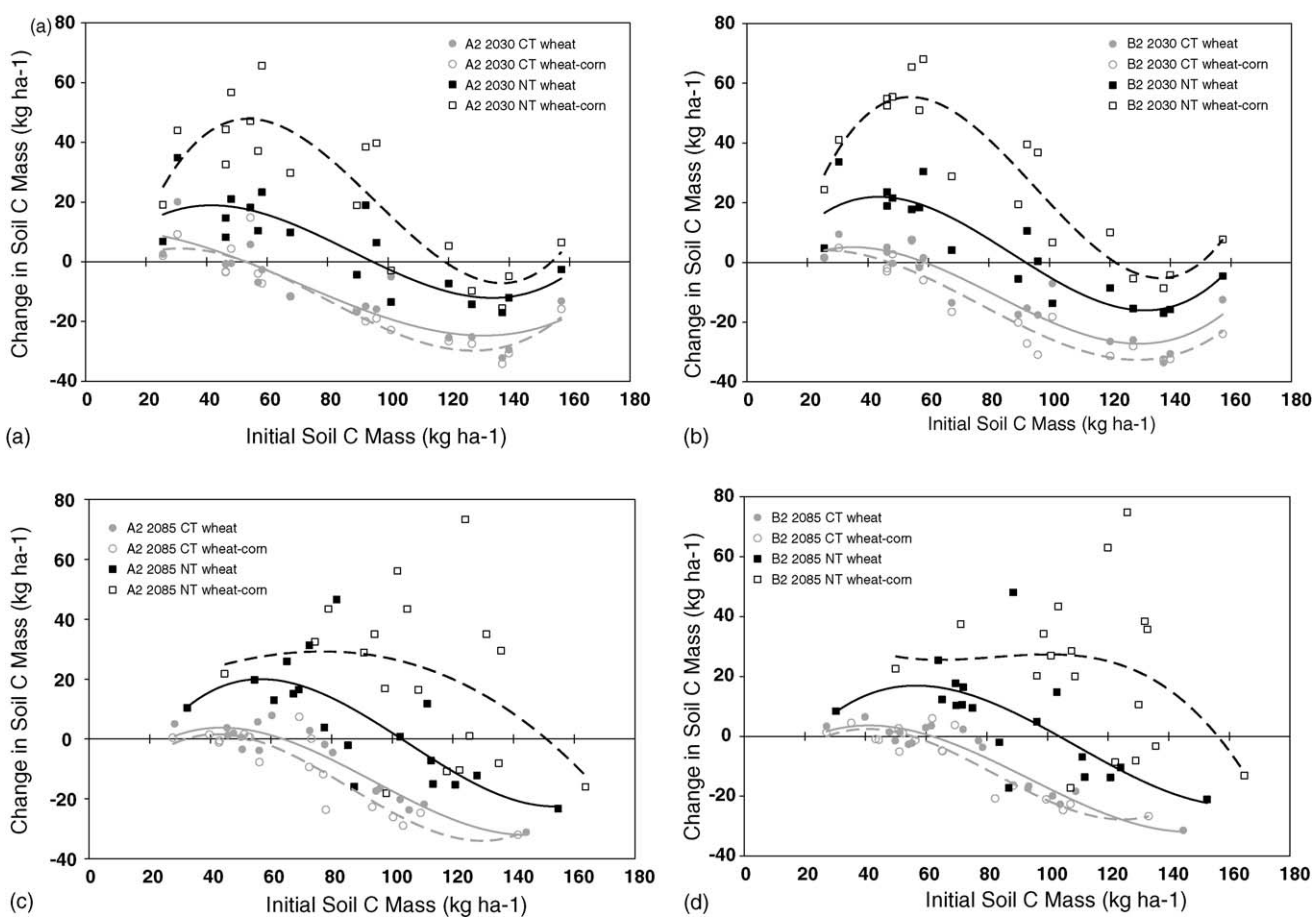

Fig. 2. Relationship between initial soil C and the change in soil C over the 30 years simulation period described using the third order polynomial. The polynomials were fitted to facilitate the visualization of the trends and not for predictive purposes.

Table 6
Rate of change in soil C mass in the top 30 cm over 30 years (Mg C ha^{-1} $year^{-1}$)

ID	Conventional tillage–continuous wheat				No tillage–continuous wheat				Conventional tillage–wheat–corn				No tillage–wheat–corn			
	A2		B2		A2		B2		A2		B2		A2		B2	
	2030	2085	2030	2085	2030	2085	2030	2085	2030	2085	2030	2085	2030	2085	2030	2085
5200	0.04	0.10	0.01	0.10	0.63	0.55	0.60	0.54	0.01	0.00	−0.10	0.07	0.84	0.45	0.77	0.56
5201	−0.18	−0.06	−0.22	−0.03	0.24	0.18	0.15	0.25	−0.20	−0.13	−0.29	−0.07	0.52	0.03	0.51	0.41
5202	−0.51	−0.27	−0.55	−0.28	−0.54	−0.16	−0.58	−0.19	−0.84	−0.39	−0.78	−0.34	−0.38	−0.23	−0.22	−0.20
5203	−0.04	0.08	−0.09	0.02	0.17	0.39	0.15	0.20	0.04	0.07	−0.04	0.06	0.54	0.62	0.83	0.72
5204	−0.62	−0.44	−0.71	−0.42	−0.32	−0.21	−0.35	−0.18	−0.75	−0.52	−0.78	−0.44	−0.15	−0.11	−0.06	−0.06
5205	−0.56	−0.40	−0.60	−0.39	−0.20	−0.17	−0.26	−0.15	−0.62	−0.51	−0.69	−0.41	−0.16	−0.09	−0.06	−0.06
5206	−0.51	−0.32	−0.54	−0.31	−0.10	−0.07	−0.11	−0.07	−0.54	−0.40	−0.64	−0.28	0.09	0.05	0.16	−0.21
5207	−0.01	0.04	−0.03	0.02	0.09	0.15	0.05	0.13	−0.03	−0.01	−0.03	0.00	0.25	0.27	0.31	0.30
5208	−0.51	−0.36	−0.53	−0.31	−0.11	−0.13	−0.18	−0.09	−0.56	−0.42	−0.68	−0.35	0.02	−0.45	0.02	−0.39
5209	−0.26	−0.06	−0.29	−0.05	0.36	0.25	0.26	0.30	−0.35	−0.19	−0.48	−0.11	0.64	0.18	0.66	0.29
5210	−0.79	−0.53	−0.79	−0.54	−0.48	−0.31	−0.51	−0.33	−0.82	−0.55	−0.95	−0.45	−0.24	−0.61	−0.22	−0.57
5211	−0.29	−0.13	−0.30	−0.10	0.14	0.04	0.06	0.10	−0.35	−0.25	−0.55	−0.11	0.64	0.09	0.60	0.18
5212	−0.26	0.08	−0.11	0.00	0.19	0.40	0.35	0.29	−0.19	0.09	−0.10	0.04	0.69	0.52	1.04	0.41
5213	−0.34	−0.11	−0.36	−0.12	0.03	0.07	0.01	0.06	−0.30	−0.19	−0.39	−0.10	0.47	0.03	0.48	0.10
5214	−0.01	0.10	−0.02	0.08	0.49	0.41	0.49	0.43	0.13	0.09	0.88	0.14	0.95	0.88	0.91	0.88
5215	−0.05	0.17	0.07	0.10	0.58	0.26	0.71	0.26	−0.06	0.12	−0.02	0.10	1.15	1.09	1.19	1.13
5216	−0.18	0.07	−0.07	0.01	0.09	0.42	0.29	0.31	−0.20	0.05	−0.16	0.04	0.53	0.53	0.85	0.34
5217	−0.11	0.12	0.01	0.06	0.26	0.32	0.42	0.28	−0.13	0.03	−0.11	0.04	0.81	0.25	1.03	0.23

Table 7
Soil C offset as a result of implementing no till (Mg C ha^{-1} $year^{-1}$)

ID	Continuous wheat				Wheat–corn			
	A2		B2		A2		B2	
	2030	2085	2030	2085	2030	2085	2030	2085
5200	0.58	0.46	0.59	0.44	0.83	0.45	0.86	0.49
5201	0.42	0.24	0.37	0.28	0.73	0.16	0.80	0.48
5202	−0.03	0.11	−0.03	0.10	0.45	0.17	0.56	0.13
5203	0.22	0.31	0.24	0.18	0.50	0.55	0.86	0.66
5204	0.30	0.24	0.36	0.23	0.59	0.41	0.71	0.38
5205	0.36	0.23	0.34	0.24	0.46	0.42	0.63	0.35
5206	0.41	0.25	0.43	0.24	0.63	0.45	0.80	0.07
5207	0.10	0.11	0.09	0.10	0.28	0.29	0.34	0.30
5208	0.40	0.23	0.36	0.22	0.58	−0.03	0.71	−0.04
5209	0.63	0.32	0.55	0.35	0.99	0.37	1.15	0.40
5210	0.32	0.22	0.27	0.20	0.58	−0.06	0.73	−0.11
5211	0.43	0.17	0.36	0.20	0.99	0.34	1.15	0.29
5212	0.45	0.32	0.46	0.29	0.88	0.43	1.14	0.36
5213	0.36	0.18	0.36	0.19	0.77	0.22	0.87	0.21
5214	0.50	0.31	0.50	0.34	0.82	0.78	0.84	0.74
5215	0.62	0.09	0.64	0.16	1.21	0.97	1.22	1.02
5216	0.27	0.35	0.36	0.30	0.73	0.47	1.02	0.30
5217	0.37	0.21	0.42	0.22	0.93	0.22	1.14	0.19

Table 8
Soil C offset as a result of implementing double cropping of corn with wheat (Mg C ha^{-1} $year^{-1}$)

ID	Conventional tillage				No tillage			
	A2		B2		A2		B2	
	2030	2085	2030	2085	2030	2085	2030	2085
5200	−0.03	−0.10	−0.10	−0.03	0.21	−0.10	0.17	0.02
5201	−0.02	−0.07	−0.07	−0.04	0.28	−0.15	0.36	0.16
5202	−0.33	−0.12	−0.23	−0.05	0.16	−0.07	0.36	−0.02
5203	0.08	−0.01	0.05	0.04	0.37	0.23	0.67	0.52
5204	−0.12	−0.08	−0.07	−0.02	0.17	0.10	0.28	0.12
5205	−0.05	−0.11	−0.09	−0.02	0.04	0.08	0.20	0.09
5206	−0.03	−0.09	−0.10	0.03	0.19	0.12	0.27	−0.14
5207	−0.02	−0.06	0.00	−0.02	0.16	0.12	0.26	0.17
5208	−0.05	−0.06	−0.15	−0.04	0.13	−0.33	0.20	−0.30
5209	−0.09	−0.12	−0.19	−0.06	0.28	−0.07	0.40	−0.01
5210	−0.03	−0.03	−0.16	0.09	0.24	−0.30	0.29	−0.23
5211	−0.06	−0.12	−0.25	−0.02	0.50	0.05	0.54	0.08
5212	0.07	0.01	0.01	0.04	0.50	0.12	0.69	0.11
5213	0.04	−0.08	−0.04	0.02	0.45	−0.04	0.47	0.04
5214	0.15	0.00	0.09	0.06	0.46	0.47	0.42	0.45
5215	−0.02	−0.05	−0.09	0.00	0.57	0.83	0.48	0.86
5216	−0.02	−0.02	−0.09	0.03	0.44	0.10	0.57	0.03
5217	−0.02	−0.08	−0.12	−0.03	0.54	−0.07	0.61	−0.06

Table 9
Total C change and offset in each simulation period for the study region (Pg C)

Scenario		Continuous wheat		Wheat–corn		Carbon offset with no till		Carbon offset with double cropping	
		Conventional till	No till	Conventional till	No till	Continuous wheat	Wheat–corn	Conventional till	No till
Baseline		−0.20							
A2	2030	−0.13	0.04	−0.15	0.20	0.18	0.35	−0.02	0.16
	2085	−0.04	0.08	−0.07	0.10	0.12	0.18	−0.03	0.02
B2	2030	−0.13	0.05	−0.17	0.25	0.17	0.43	−0.05	0.21
	2085	−0.05	0.07	−0.05	0.11	0.11	0.16	0.00	0.05

3.3.3. Total soil C stock

The rates of change in soil C vary by representative farm. Thus, in order to examine the total impact of management changes on the soil C stock of the Huang-Hai Plain region, we multiplied the rate of change by the land area under cultivation (Table 1). The potential change in soil C stock over the simulation time periods is calculated assuming that the management practices are applied uniformly over the representative farm region.

Total soil C stocks in the Huang-Hai Plain region decline under all climate scenarios with CT but increase under NT management (Table 9), indicating that management changes are more significant than climate scenarios in determining future SOC. The increases in soil C under NT are greater with the wheat–corn double cropping system because of greater C inputs to soil. This results in soil C sequestration and, consequently, greenhouse gas emission offsets. The offsets due to implementation of a wheat–corn double cropping system are slightly negative under CT due to the increased disturbance of the soil, but positive when NT is adopted.

4. Conclusions

The total soil C sequestration potential of the Huang-Hai Plain if NT were to be fully adopted would range from 0.11 to 0.18 Pg C for CT and from 0.16 to 0.43 Pg of C for wheat–corn double cropping (Table 9). The soil C sequestration potential of the region is greatest in the near-term and will decline over time as management practices that sequester soil C or offset soil C losses are adopted. These changes in soil C can be achieved through alteration in management practices without significant positive or negative impact on crop yields. The specific development scenario (A2 or B2) did not significantly alter the C sequestration potential of the region, but future precipitation increases simulated would prove beneficial to both crop yields and soil organic C. This study was conducted with the projections of the HadCM3 GCM. Other climate change projections and models could, of course, result in different outcomes for the agricultural simulations.

The estimated potential SCS under adoption of no till management represents a small fraction of the IPCC's estimate of 40 Pg of C that might potentially be sequestered in agricultural soils worldwide. However, our simulations show that a switch to double cropping and NT could contribute to climate change mitigation efforts in China. This analysis considers only one agricultural region of China, and further analyses considering other regions and cropping systems, particularly paddy rice, might identify other management practices appropriate for climate change mitigation efforts. Assessments of climate change impacts and adaptation and mitigation strategies in China would be greatly enhanced by wider availability of field data and field experimental results.

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