Global Famine after a Regional Nuclear War

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Abstract

A regional nuclear war between India and Pakistan could decrease global surface temperature by 1 to 2°C for 5 to 10 years, and have major impacts on precipitation and solar radiation reaching Earth's surface. Using a crop simulation model forced by three global climate model simulations, we investigate the impacts on agricultural production in China, the largest grain producer in the world. In the first year after the regional nuclear war, a cooler, drier, and darker environment would reduce annual rice production by 30 Mt (29%), maize production by 36 Mt (20%), and wheat production by 23 Mt (53%). With different agriculture managements – no irrigation, auto irrigation, 200 kg/ha nitrogen fertilizer and 10 days delayed planting date, simulated national crop productions reduce 16-26% for rice, 9-20% for maize and 32-43% for wheat during five years after the nuclear war event. This reduction of food availability would continue, with gradually decreasing amplitude, for more than a decade. Assuming these impacts are indicative of those in other major grain producers, a nuclear war using much less than 1% of the current global arsenal could produce a global food crisis and put a billion people at risk of famine.

Key Points

1. Agriculture responses to climate changes of a regional nuclear war were simulated with a crop model.
2. Chinese production of rice, maize and wheat fell significantly.
3. These agriculture responses could cause Chinese, as well as global, food insecurity.

Keywords: regional nuclear war, nuclear winter, agriculture impacts, China, DSSAT, agricultural modeling, famine

1. Introduction

The potential for nuclear war to cause global famine has been known for three decades, since the nuclear winter research of the 1980s [*Turco et al.*, 1983; *Harwell and Cropper*, 1989]. Smoke from fires ignited by nuclear weapons dropped on cities and industrial areas would block out the Sun, making it cold, dark, and dry at Earth's surface. This danger from a full-scale nuclear war between the United States and Russia remains with us to this day [*Toon et al.*, 2008].

Even a small-scale regional nuclear war, using much less than 1% of the global nuclear arsenal could produce climate change unprecedented in recorded human history [*Robock et al.*, 2007a], reducing food production in the Midwest United States [*Özdoğan et al.*, 2013] and China [*Xia and Robock*, 2013]. Those results were based on only one climate model simulation [*Robock et al.*, 2007a] of 5 Tg of soot injected into the upper troposphere over India and Pakistan [*Toon et al.*, 2007], and applying the resulting changes in surface air temperature, precipitation, and insolation to crop models simulating soybean and maize production in the U.S. and rice production in China. Now two more climate model simulations of the same scenario are available [*Stenke et al.*, 2013; *Mills et al.*, 2013]. The results from the new models bracket the original results, making the climate response in this scenario much more robust, and also providing a measure of the range of possible responses. For China, the results are more variable than for global averages, as expected. Because China is the world's largest producer of grain, we have applied the climate change scenarios from of all three models to rice, maize, and wheat production in China, and found much larger reductions in food production, especially for wheat. Because China is the world's largest producer of rice and wheat, and second (after the U.S.) in maize, and the food reduction lasts for a decade, these results suggest a food crisis not just for those living marginal existences, but for the entire world.

2. Agricultural simulations for China

We used the Decision Support System for Agrotechnology Transfer (DSSAT) crop model version 4.5 [*Jones et al.*, 2003] to simulate crop responses to climate changes of a regional nuclear war at 51 locations in China for ten years. The model was previously evaluated for rice and maize in China [*Xia and Robock*, 2013; *Xia et al.*, 2013]. The evaluation for wheat is shown in Figures 1 and 2. While the model does not do as well for winter wheat as it does for spring wheat, rice, and maize, its performance is quite good. We used a 30-year control run with weather observations of 1978-2007 to get control yields of rice, maize and wheat. To create nuclear war weather input for DSSAT, monthly simulated climate anomalies from the National Aeronautics and Space Administration Goddard Institute for Space Studies (GISS) ModelE [*Robock et al.*, 2007a], the Solar Climate Ozone Links (SOCOL) [*Stenke et al.*, 2013], and the Community Earth System Model - Whole Atmosphere Community Climate Model (CESM1(WACCM)) [*Mills et al.*, 2014] models were downscaled to daily anomalies to perturb 30 years of daily observations [*Xia et al.*, 2013]. We used the average of climate anomalies of three ensemble members for each climate model, since that method showed no significant difference in crop production compared with averaging crop production forced by individual ensemble members of nuclear war simulations (Supplemental Material, Figures 1 and 2), with the exception of maize, for which the productivity reduction is slightly larger when using individual ensemble forcing. To exclude other influences, all default simulations used fixed fertilizer (150 kg/ha), fixed planting dates for each cultivar, constant CO_2 concentration (380 ppm), and no irrigation. The dependence of the results on different agriculture management practices was also investigated.

Figure 3 shows monthly climate anomalies from the three climate models averaged over 51 locations (Table 1) in China compared with climate model control run conditions. The different atmospheric dynamics in the three climate models produce different lifetimes of black carbon in the atmosphere and hence cause slightly different climate responses after the injection of 5 Tg black carbon. However, a regional nuclear war between India and Pakistan results in cooler, drier, and darker conditions in China in all three climate models, but of different magnitudes than the global averages [*Robock et al.*, 2007a; *Stenke et al.*, 2013; *Mills et al.*, 2013]. Compared with the control, temperature drops immediately after the injection of black carbon on 1 May of year 0 in the GISS and SOCOL simulations and on 1 January of Year 0 in WACCM (Figure 3a). The first winter after the nuclear conflict, GISS ModelE, WACCM and SOCOL showed temperature drops of 2.6 K, 4.0 K and 3.4 K, respectively, and this cooling effect continues in GISS ModelE and WACCM through the end of year 9, while in SOCOL, the temperature is back to the control run values by year 6. Temperature reduction is much stronger in winter than summer (Figure 3a) because of a stronger Arctic Oscillation (AO) due to the larger stratospheric temperature gradient between the tropics and polar regions [*Robock*, 2000, *Deser*, 2000], which would enhance the Siberian High and the winter monsoon in East Asia [*Going et al.*, 2012]. Surface downwelling solar radiation under all sky conditions decreases immediately after the injection. In GISS ModelE and WACCM, ten years are not long enough for solar radiation to recover back to the control level, but at year 5, SOCOL shows positive solar radiation anomalies already because of a shorter black carbon lifetime and local cloud responses (Figure 3c). A cooler continental surface reduces the temperature gradient between land and ocean and therefore reduces summer monsoon precipitation in Asia [*Robock et al.*, 2007a]. The three models produce different precipitation changes in China, although overall they agree on precipitation reduction during the first several years after a regional nuclear war (Figure 3b). GISS ModelE shows summer precipitation reductions of 0.9 mm/day and 0.6 mm/day in years 0 and 1, respectively. Also, spring and fall precipitation simulated by GISS ModelE with a regional nuclear war have negative changes through all 10 years. However, summer precipitation after year 1 simulated by GISS ModelE changes in the opposite direction with gradually positive anomalies from 0.01 mm/day (year 2) to 0.4 mm/day (year 8). In particular, national weather anomalies weighted by maize production in 2008 show strong summer precipitation increases of 0.4-0.8 mm/day after year 1 (Supplemental Material, Figure 4). In the WACCM simulation, precipitation shows a consistent reduction during 10 years with the largest anomaly of -0.8 mm/day in spring and summer of year 0 and anomalies gradually approaching zero at the end of 10 years (Figure 3b). Precipitation changes simulated by SOCOL vary more strongly than the other two models with positive changes in years 2, 3, 4 and 8, 9.

Climate changes due to a regional nuclear war between India and Pakistan (or any other conflict that put 5 Tg soot into the sub-tropical upper troposphere) would affect agricultural activity in China. The changes of year1 weather elements for the different provinces in China, averaged for all three models, are shown in Figures 4a-4c, and the agricultural responses (after the climate changes from each of the models are applied to the agricultural model separately for each crop, and the yield changes are averaged) are shown in Figures 4d-4f, and summarized in Table 2 and Figure 5. The three major grains, rice, maize, and wheat, show lower yields at most locations in China. Different regional climates lead to different responses of crop yield perturbed by the same injection event.

In general, rice yield in northern China is damaged significantly while in southern China the rice yield reduction is mild (Figure 4d). Temperature reduction in southern China is not as strong as that in northern China (Figure 4a), which causes less yield reduction in southern China and even yield increase in certain locations. However, since the natural variability of annual-average rice production in China is 12%, all four provinces that show positive changes are within this natural variability. Without changing the planting date (25 March) and without irrigation, rice grown in most regions of China (20 provinces) would suffer in a colder and drier environment with a yield decline of 5% to 98%, and 15 out of 23 provinces show a reduction larger than 12%.

There are two types of maize in this study: summer maize, which is planted on 9 June in northern China and spring maize, which is planted on 19 April in central and southern China. Maize yield declines in most of the provinces in southern and northern China, while in central China, several provinces show a slight yield increase after a regional nuclear war (Figure 4e). This response is partially due to the combination of temperature reduction and summer precipitation increase in certain provinces forced by climate change in GISS ModelE. Another reason for this positive change in Ningxia and Gansu (provinces 19 and 4 in Figure 4e) is that the control level of maize yield is low due to a relatively warm and dry environment, with no irrigation. When temperature goes down after the regional nuclear war, maize yield in Ningxia and Gansu increases compared with the control run. However, only three provinces (4, 19, and 21) have an increase greater than the natural variability (12%), while other provinces (provinces 1, 2, 6, 11, and 17) show decreases greater than 12%.

Wheat yield decreases in all 12 provinces studied. Four northern provinces are planted with spring wheat on 25 March and the other eight provinces are planted with winter wheat on 16 October (Figure 4f). Although winter wheat needs a few weeks of cold before being able to flower, persistent snow cover would be disadvantageous. In addition, if the fall temperature is too low, winter wheat cannot sprout before freezing occurs. Therefore, even winter wheat – a cold crop – shows a large negative impact from a regional nuclear war.

Grain production was calculated by multiplying grain yield in each province by the grain planting area in 2008 (Table 1). The control level of grain production is lower than the actual national grain production, since no irrigation is applied during the simulation and not all provinces in China are simulated. We ran 30 simulations for each nuclear war year, and compare the average rice production summed for the 25 provinces to the average and standard deviation of our control runs in Figure 5a. In year 1, rice production is reduced by 30 Mt (29%), falling well outside the control 1 standard deviation variability. Average rice production does not return to natural variability at the end of year 9. Similar to rice production, the strongest maize reduction is in year 1 with a value of 36 Mt (20%) of the average of three climate models. However, since climate forcing such as summer precipitation from the three climate models is different at major maize production locations (Supplemental Material, Figure 4), simulated maize production using different climate anomalies varies quite a bit. Maize simulations driven by climate anomalies of WACCM showed gradual recovery, but at the end of year 9, their maize production reduction is still 17% (Figure 5b). Chinese maize production forced by GISS ModelE only shows 11% reduction in the first two years after the regional nuclear war, and then is back to the level of the control run. This positive response of maize production forced by climate changes of GISS ModelE is mainly driven by its precipitation anomalies. We have switched climate forcing between GISS ModelE and WACCM – one variable one time, and precipitation itself can explain 64% of the difference between maize production forced by GISS ModelE and WACCM (Supplemental Material, Figure 7). Precipitation is also the controlling factor in maize simulation driven by the SOCOL climate anomalies. The strong maize production reduction in years 5-7 (Figure 5b) is due to strong summer precipitation reductions in major maize production regions during those years (Supplemental Material, Figure 4). During this period, simulations of spring wheat and winter wheat production driven by SOCOL climate anomalies show strong reductions as well (Figures 5c and 5d).

Different temperature anomalies predicted by three climate models induce different winter wheat production responses (Figure 5c). In SOCOL, the black carbon dispersion rate is faster than for GISS ModelE and WACCM, and hence surface temperature reductions last for a shorter period of time. Higher temperature (compared with GISS ModelE and WACCM) in fall insures that winter wheat can sprout before freezing, and the relative cold environment compared with the control condition benefits winter wheat before its flowering. Therefore, winter wheat production using SOCOL climate forcing shows no significant decrease due to a regional nuclear war. However, temperature reduction in the other two climate models continues through each of the first 9 years after the regional nuclear war, which causes winter wheat production to decline by 22.3 Mt (52%) and 29.4 Mt (69%) in year 1 for GISS ModelE and WACCM, respectively, and by 17.3 Mt (40%) and 20.8 Mt (49%) at the end of year 4. Spring wheat has different production changes among climate models as well (Figure 5d). Similar to maize, spring wheat dominated provinces show much weaker summer precipitation reduction in GISS ModelE compared with WACCM (Supplemental Material, Figure 6), which causes nearly no change in national spring wheat production when forced by GISS ModelE climate changes. The sudden drop of spring wheat production forced by SOCOL in years 4-6 is due to the combination of stronger summer precipitation reduction and less temperature reduction, which will enhance the evaporation and therefore reduce the water available in the soil.

Crop yield sensitivity to climate change is different under different agriculture practices. Therefore, we tested crop yield changes in response to a regional nuclear war under four different agricultural managements including the one we used above, which we call the default run (Table 2). Also control runs under the four agriculture managements were examined. In general, if auto irrigation is applied, the crop production shows less reduction compared with the default run (Figure 6) except for spring wheat, which indicates that for rice, maize and winter wheat, with auto irrigation a regional nuclear war has less impact on yields, but for spring wheat, auto irrigation makes the negative climate impact stronger. Since we are comparing crop yield under auto irrigation with the auto irrigated control run, the larger spring wheat reduction is because auto irrigation promotes spring wheat under the control run climate more than under the regional nuclear war climate. Although with auto irrigation, most crops show less reduction, the natural variability is largely reduced as well (Supplemental Material, Figure 8). Therefore, a regional nuclear war would cause significant crop production reduction in China during the first five years even with auto irrigation turned on (Table 2). Increasing fertilizer also reduces regional nuclear war impact on crops, especially for rice (Figure 6 and Supplemental Material, Figure 9). Additional 50 kg/ha nitrogen fertilizer would increase rice production by 17 Mt, which is 17% of the default control run. Planting crops 10 days later than the default run make no difference (Figure 6 and S Figure 10). Therefore, auto irrigation and more nitrogen fertilizer could help reducing the negative impacts on agriculture from a regional nuclear war, but even under these two agriculture practice scenarios, the crop production reductions are still significant during the first five years (Table 2).

However, those results contain uncertainties. Although there are three climate models that performed the same regional nuclear war experiment, more climate models are needed to better understand regional precipitation changes since the three climate models in this paper differ on regional precipitation changes, especially for the summer. Also, the downscaling method could make a difference in an agriculture impact study. Although our method is likely a good way to downscale temperature anomalies [*Hawkins* et al., 2013], creating precipitation input is more complicated and could produce differences, especially considering that precipitation is an important factor controlling the crop response in our study. In addition, we only used one crop model in this study and crop models with different climate sensitivities would produce different crop yield responses even under the same climate forcing and the same agriculture management [*Palosuo* et al., 2011; *Rötter* et al., 2011; *Asseng* et al., 2013].

Therefore, to make a robust conclusion, it would be valuable to have more climate models and crop models repeat this study.

3. Famine in China

By using three different state-of-the-art climate models, all forced by the same scenario of 5 Tg of soot in the upper troposphere [*Toon et al.*, 2007], we have produced a robust estimate of the impacts of a regional nuclear war on grain production in China (Table 2). These estimates warn of famine in China as a result.

China has only 9% of the world's cultivated land, but 22% of the world's population. With such a large fraction of the population, Chinese food demand and China's ability to meet it affect global food security [*Brown*, 1995; *Brown and Halweil*, 1998]. At present, the food supply seems secure in China because per capita grain production has been above 350 kg/capita for most years since 1980, which is close to the world average [*Halweil*, 2007]. At baseline, China is in a better position to withstand the effects of decreased food production than the poorer nations of the world. Caloric intake has risen significantly with the dramatic economic expansion of the last three decades and the average Chinese now consumes about 3000 calories per day [*Food and Agricultural Organization of the United Nations*, 2009]. The Chinese diet has also become more diversified with some decline in the proportion of calories obtained from grains and a rise in the amount obtained from fruits, vegetables and meat products, although cereals still account for more than 40% of caloric intake [*Cheng*, 2009]. In addition, expressed as days of food consumption, China has significantly larger reserves of grain than the world as a whole. In the summer of 2013, wheat reserves totaled nearly 167 days of consumption, and rice reserves were 119 days of consumption [*Foreign Agricultural Service*, 2013].

Despite this relatively strong position, China would be hard pressed to deal with the very large reduction in wheat projected in the new study. While rice (144 million tons per year) is the most important grain in China in terms of direct human consumption, wheat (125 million tons) is a close second and accounts for more than 1/3 of grain consumption [*Zhou et al.*, 2012], and China's wheat consumption amounts to 19% of world production [*Foreign Agricultural Service*, 2013]. As a 2012 Australian government study noted, "Security of supply for these two cereals is of uttermost importance in China and therefore food security in China often refers to 'grain security.' Not surprisingly, China pays much attention to ensuring a high-level of self-sufficiency in these two crops." [*Zhou et al.*, 2012]

A 38% shortfall in wheat production, coupled with a 15% decline in rice production for five years, would end China's state of self-sufficiency. Even the large reserves that China maintains would be exhausted within 2 years. At that point China would be forced to attempt to make massive purchases on world grain markets driving prices up even more. If, as expected, international hoarding made grain unavailable, China would have to dramatically curtail rice and wheat consumption.

The 15% decline in Chinese maize production for five years would further affect food security. Maize is actually China's largest grain crop, at 177 million tons in 2010 [*Zhou et al.*, 2012]. The vast majority is used, not for direct human consumption, but for animal feed. The decline in maize production would primarily affect the 20% of caloric intake currently provided by meat and poultry.

Taken together, the declines in rice, maize, and wheat would lead to a decline of more than 10% in average caloric intake in China. However, this is the average effect, and given the great economic inequality seen in China today the impact on the billion plus people in China who remain poor would probably be much greater. There are still 158 million people (12% of the total) in China undernourished in 2010-2012 [*Food and Agricultural Organization of the United Nations*, 2012]. It is clear that this dramatic decrease in food supply would cause profound economic and social instability in the largest country in the world, home to the world's second largest economy, and a large nuclear arsenal of its own.

4. Global implications

The data on Chinese grain production are particularly disturbing because of the possible implications for global production. Most of the world's wheat is grown in countries at similar latitudes to China, and the impact of climate disruption on wheat after limited nuclear war has not been studied in any other country.

Although this study is based on one crop model and focused on one region, we would expect similar agriculture responses all over the world because of the global climate changes after a regional nuclear war [*Robock et al.*, 2007b; *Stenke et al.*, 2013; *Mills et al.*, 2014]. The climate signal from the same nuclear conflict in this study would reduce maize and soybean yield in the United States as well [*Özdoğan et al.*, 2013]. We have not modeled the impact on wheat production in the U.S., but there is no reason to believe that it would not be similar to that in China. Therefore, even a regional nuclear war using less than 0.03% of the explosive yield of the current global nuclear arsenal would damage world agriculture production. Rice, maize and wheat are the major cereal crops in the world. With a large reduction of agriculture production after a regional nuclear war, countries would tend to hoard food, driving up prices on global grain markets. As a result the accessible food, the food that people could actually afford to buy, would decline even more than the fall in production. Hence there would be less food available on the market, with higher prices. Considering that at present there are 805 million people undernourished (791 million living in developing countries) [*FAO et al.*, 2014], which is 11% of the world population, those people will be under high risk of starvation.

A regional nuclear war could bring famine to developing countries and major disruptions to developed countries. While the direct effects of the use of nuclear weapons, blast, fire, and radiation, would be horrible, the indirect effects on food would affect far more people. It is beyond the scope of this paper to analyze how global food markets and political systems would respond to this shock, but recent events, such as the Arab Spring, show that even small changes in global food supply can have large repercussions [*Sternberg*, 2012; *Anonymous*, 2012; *Perez and Climatewire*, 2013]. These results also imply that the current level of nuclear arsenals in the world threaten global catastrophic consequences if even a small portion of them is used [*Robock et al.*, 2007b].

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Table 1. Province locations and agricultural data used in DSSAT simulations. Numbers refer to province locations in Figure 2. SW is spring wheat and WW is winter wheat. Latitudes, longitudes, and elevations are for weather stations used to force the model for the different crops for the evaluation. Climate model output was also extracted from these locations for the simulations. Crop area and production data are for 2008 [*Ministry of Agriculture of the People's Republic of China*, 2009].

No.	Province	Crop	Latitude (°N)	Longitude (°E)	Altitude (m)	Area (kha)	Production (kt)
1	Anhui	Rice	31.9	117.2	28	1700	11024
		Maize	31.9	117.2	28	705	2866
		WW	30.5	117.1	20	2347	11679
2	Beijing	Rice	39.8	116.5	31	0.4	3
		Maize	39.8	116.5	31	146	880
3	Fujian	Rice	26.7	118.2	126	2670	437
		Maize	24.5	118.1	139	136	37
4	Gansu	Rice	40.3	97.0	1526	6	38
		Maize	40.3	97.0	1526	557	2654
		SW	40.0	94.7	1139	290	1136
5	Guangdong	Rice	24.7	113.6	61	933	4750
		Maize	22.8	115.4	17	144	635
6	Guangxi	Rice	22.0	108.6	15	151	877
		Maize	25.3	110.3	164	490	2072
7	Guizhou	Rice	26.6	106.7	1224	686	4576
		Maize	27.3	105.3	1511	735	3912
8	Hainan	Rice	20.0	110.3	64	129	650
		Maize	19.1	108.6	8	17	70
9	Hebei	Rice	40.4	115.5	54	82	556
		Maize	39.4	118.9	11	2841	14422
		WW	38.0	114.4	81	2413	12205
10	Heilongjiang	Rice	44.6	129.6	241	2391	15180
		Maize	48.1	125.9	235	3594	18220
		SW	47.4	127.0	239	239	895
11	Henan	Rice	36.1	114.4	76	605	4431
		Maize	36.1	114.4	76	2820	16150
		WW	34.7	113.7	110	5260	30510
12	Hubei	Rice	30.3	109.5	457	1228	10892
		Maize	30.3	109.5	457	470	2264
		WW	30.3	109.5	457	1001	3292
13	Hunan	Rice	26.2	111.6	173	1255	8831
		Maize	27.5	110.0	272	241	1280

14	Jiangsu	Rice	34.3	117.2	41	2228	17688
		Maize	34.9	119.1	3	399	2030
		WW	34.3	117.2	41	2073	9982
15	Jiangxi	Rice	27.1	114.9	71	401	2680
		Maize	28.6	115.9	47	16	66
16	Jilin	Rice	45.1	124.9	136	659	5790
		Maize	43.9	125.2	236	2923	20830
		SW	43.9	125.2	236	6	18
17	Liaoning	Rice	42.4	122.5	79	659	5056
		Maize	41.5	120.5	170	1885	11890
		SW	42.4	122.5	79	10	49
18	Neimenggu	Rice	43.6	118.1	799	98	705
		Maize	40.2	104.8	1324	2340	14107
		SW	50.5	121.7	733	452	1540
19	Ningxia	Rice	38.5	106.2	1111	80	664
		Maize	38.5	106.2	1111	209	1499
		SW	37.8	107.4	1348	131	510
20	Shandong	Rice	37.5	117.5	12	131	1104
		Maize	37.5	117.5	12	2874	18874
		WW	36.6	109.5	96	3525	20341
21	Shaanxi	Rice	33.1	107.0	510	125	831
		Maize	37.4	122.7	48	1157	4836
		WW	33.1	107.0	510	1140	3915
22	Sichuan	Rice	32.1	108.0	674	2662	20254
		Maize	28.8	104.6	341	1729	8830
		WW	32.1	108.0	674	1507	4830
23	Tianjin	Rice	39.1	117.1	13	15	105
		Maize	39.1	117.1	13	160	843
24	Yunnan	Rice	25.1	101.3	1301	947	5775
		Maize	25.1	101.3	1301	1326	5296
25	Zhejiang	Rice	29.0	118.9	82	691	5099
		Maize	30.2	120.2	42	26	111

Table 2. Change of grain production during the decade after a regional nuclear war. Mean changes with forcing by the three climate models. These are means of the results shown in detail in Figure 5.

	First 5 years (%)				Second 5 years (%)			
	Default[1]	**AI[2]**	**F200[3]**	**P10[4]**	**Default[1]**	**AI[2]**	**F200[3]**	**P10[4]**
China maize	-15%	-9%	-15%	-20%	-12%	-4%	-12%	-15%
China middle season rice	-26%	-16%	-20%	-26%	-21%	-10%	-16%	-21%
China spring wheat	-26%	-36%	-25%	-26%	-20%	-28%	-17%	-18%
China winter wheat	-38%	-32%	-38%	-44%	-23%	-14%	-22%	-24%

[1]Crop simulations with no irrigation, 150 kg/ha nitrogen fertilizer applied at planting date, planting date fixed for each cultivar

[2]Crop simulations with auto irrigation turned on, 150 kg/ha nitrogen fertilizer applied at planting date, planting date fixed for each cultivar

[3]Crop simulations with no irrigation, 200 kg/ha nitrogen fertilizer applied at planting date, planting date fixed for each cultivar

[4]Crop simulations with no irrigation, 150 kg/ha nitrogen fertilizer applied at planting date, planting date is 10 days later than in the default runs

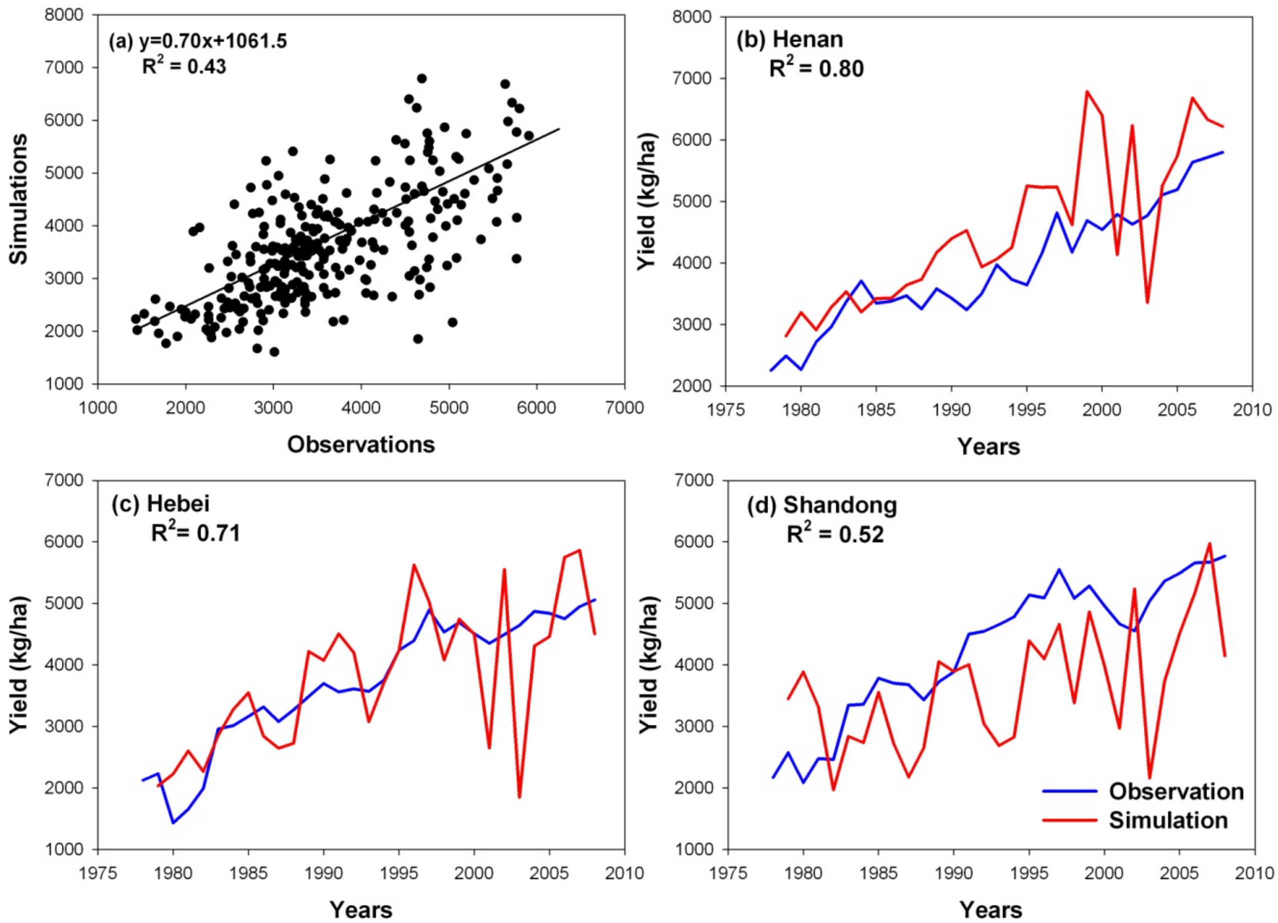

Figure 1. (a) Comparison of DSSAT simulated winter wheat yield (kg/ha) and observations for the eight provinces. R^2 is the coefficient of determination. Also shown are time series of simulated winter wheat yield and observations for the top three winter wheat production provinces: (b) Henan, (c) Hebei, and (d) Shandong (1979-2007).

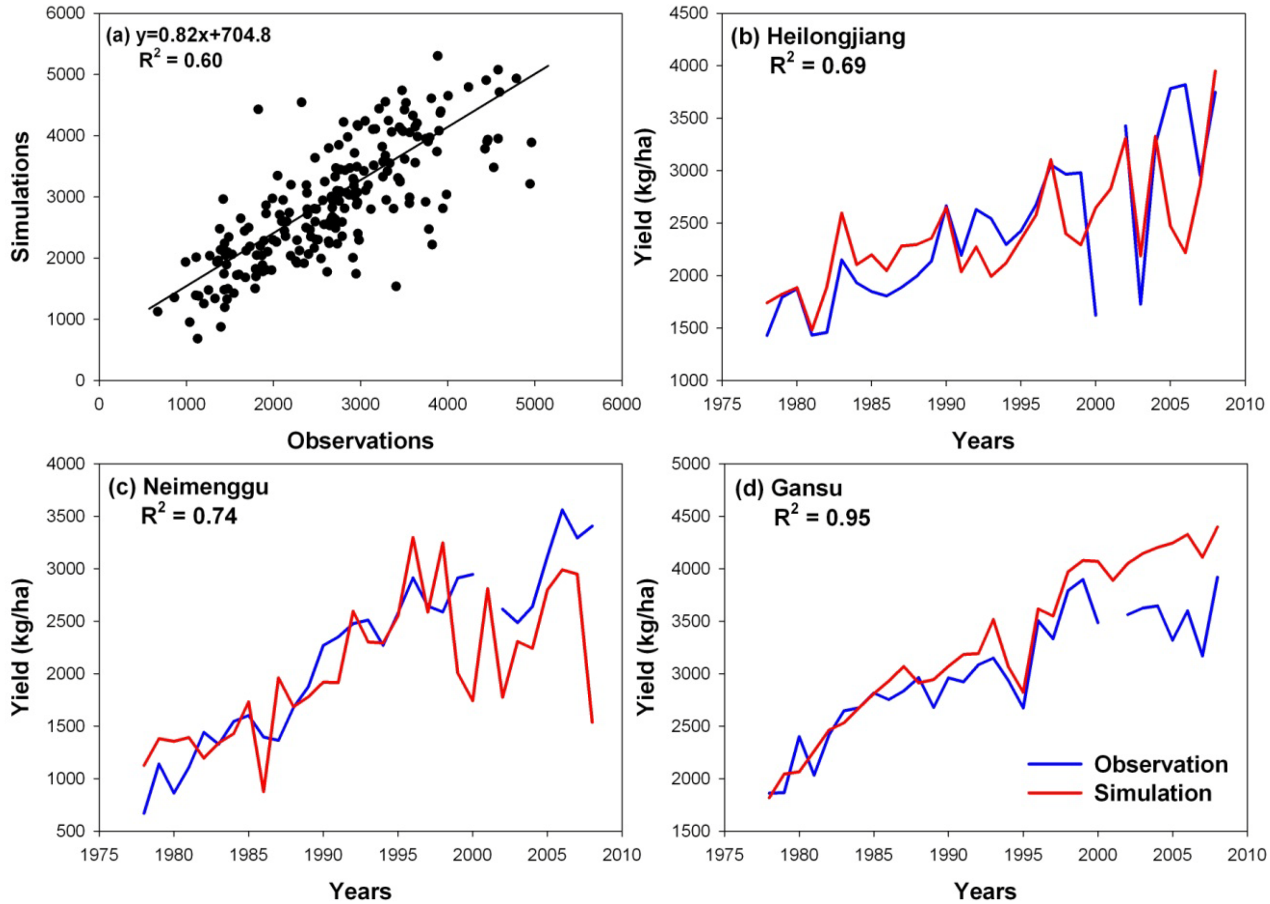

Figure 2. (a) Comparison of DSSAT simulated spring wheat yield (kg/ha) and observations for the four provinces. R^2 is the coefficient of determination. Also shown are time series of simulated spring wheat yield and observations for the top three spring wheat production provinces: (b) Heilongjiang, (c) Neimenggu, and (d) Gansu (1979-2007).

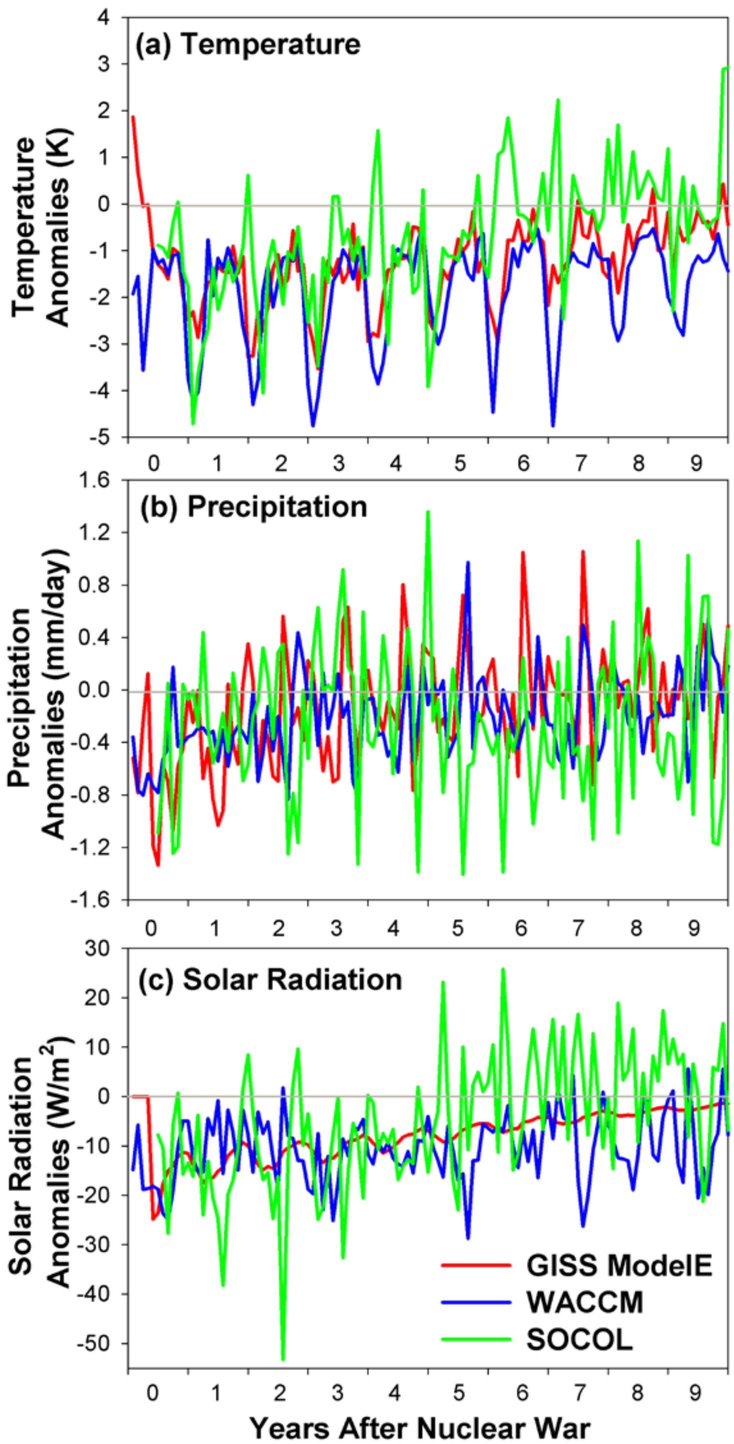

Figure 3. Monthly climate anomalies for (a) temperature, (b) precipitation, and (c) surface downwelling solar radiation, calculated as the simulated climate after a regional nuclear war minus the control run. All lines are the average of all 51 locations in China (Table 1). The regional nuclear war occurred in year 0, 1 May in GISS ModelE and SOCOL, and 1 January in WACCM.

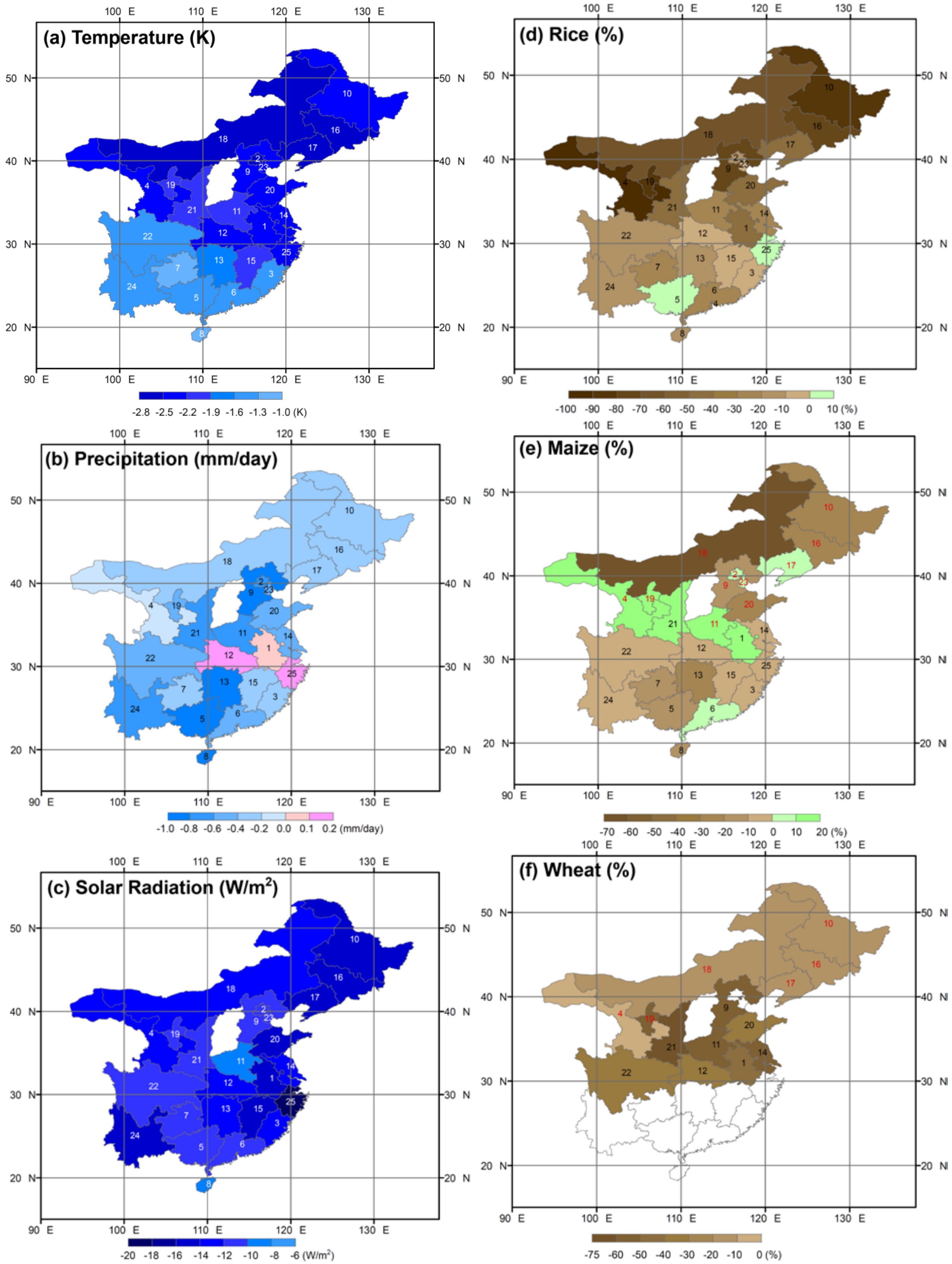
(a) Temperature (K)
-2.8 -2.5 -2.2 -1.9 -1.6 -1.3 -1.0 (K)
(b) Precipitation (mm/day)
-1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.1 0.2 (mm/day)
(c) Solar Radiation (W/m²)
-20 -18 -16 -14 -12 -10 -8 -6 (W/m²)
(d) Rice (%)
-100 -90 -80 -70 -60 -50 -40 -30 -20 -10 0 10 (%)
(e) Maize (%)
-70 -60 -50 -40 -30 -20 -10 0 10 20 (%)
(f) Wheat (%)
-75 -60 -50 -40 -30 -20 -10 0 (%)

Figure 4. Left panel: maps of climate anomalies between simulated climate after a regional nuclear war and the climate control runs (year 1) (a) temperature (b) precipitation and (c) surface downwelling solar radiation under all sky conditions. Blue indicates negative change, and pink indicates positive change. Right panel: maps of crop yield changes (%) for year 1 after a regional nuclear war (d) rice, (e) maize and (f) wheat. The average of the response of the DSSAT model to anomalies from all three climate models is shown. Brown indicates negative change, and green indicates positive change. See Table 1 for the list of provinces corresponding to the numbers. In (e), red numbers indicate summer maize and black numbers are spring maize. In (f), provinces with red numbers are planted with spring wheat, and provinces with black numbers are planted with winter wheat.

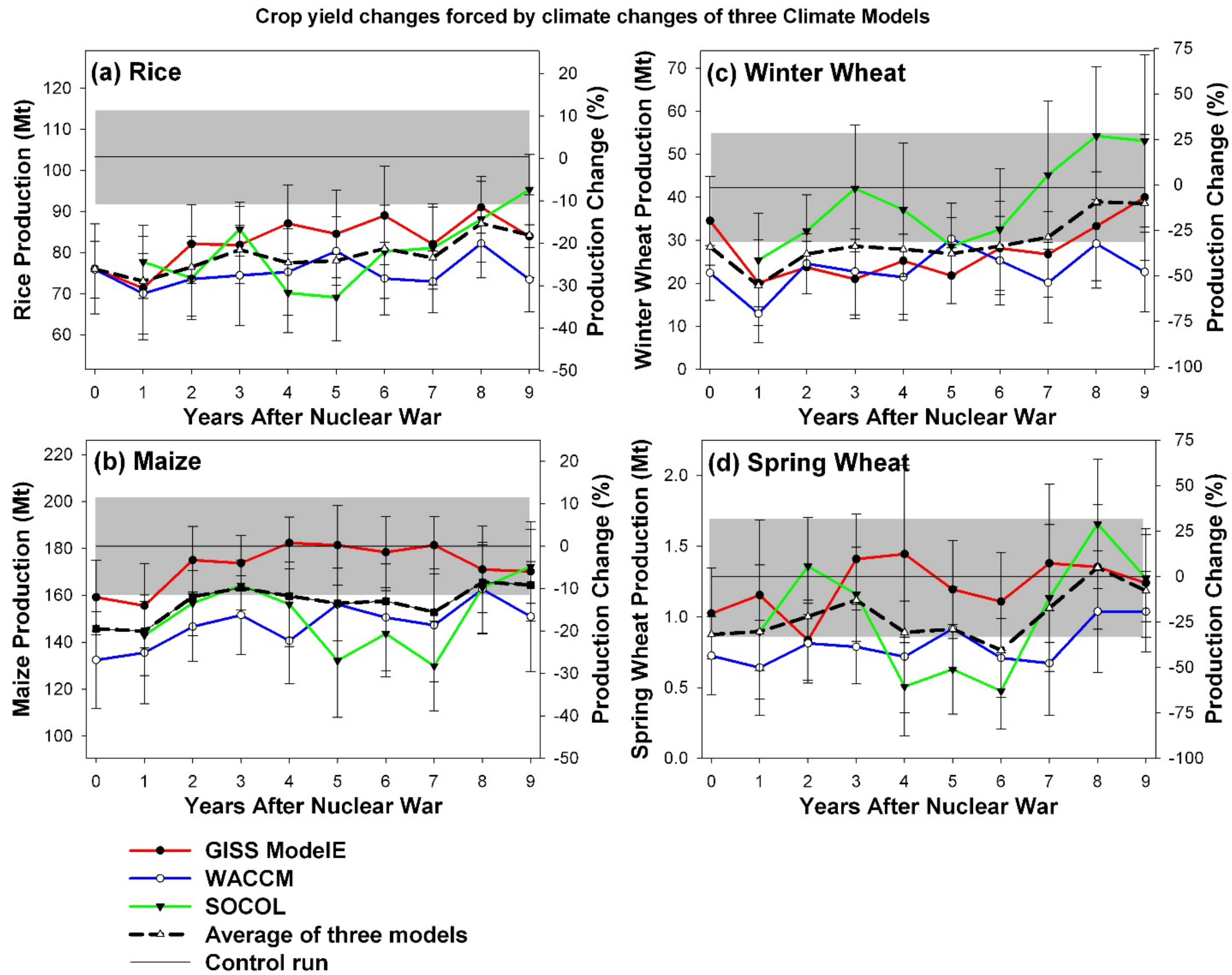

Figure 5. Chinese production (Mt) and percentage changes of the major grains: (a) rice, (b) maize, (c) winter wheat and (d) spring wheat. The error bars are one standard deviation of grain production simulated from climate forcing of three climate models including 30 climate conditions for each year. The gray area shows one standard deviation from the 30-year control run, illustrating the effect of interannual weather variations The scale for production changes (right side of each panel) is different for wheat (panels (c) and (d)) than for rice (a) and maize (b).

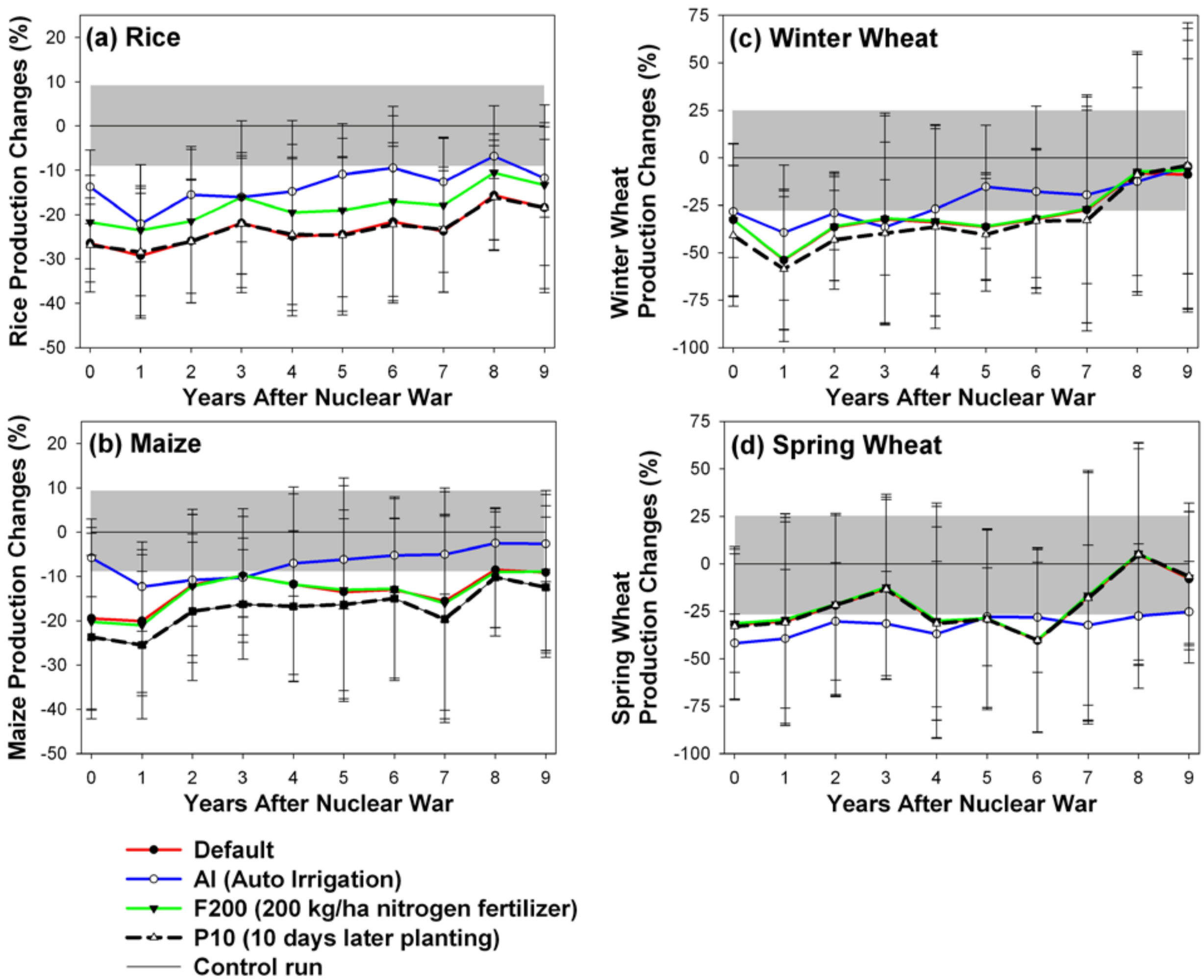

Figure 6. Percentage changes of the major Chinese grains: (a) rice, (b) maize, (c) winter wheat and (d) spring wheat under different agriculture management practices. Each line is the average of three crop simulations forced by three climate models. The error bars are one standard deviation of grain production changes driven by climate forcing of three climate models including 30 climate conditions for each year. The gray area shows the average of one standard deviation from the 4 control runs with different agriculture managements, illustrating the effect of interannual weather variations. The scale for production changes is different for wheat (panels (c) and (d)) than for rice (a) and maize (b).