Rising temperature threatens China’s cropland

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Abstract

The rising demand for calories and protein together with urbanization, pose significant challenges to China’s food security. The determination of policy actions requires accurate estimates of climatic impacts on both crop yields (intensive margin) and cropland area (extensive margin). However, the analysis of the latter has been limited, especially in developing countries. Here, we assess the impact of temperature on land use in China by matching high-resolution satellite data on land use with daily weather data from 1980 to 2010. We find that extremely hot weather (daily average temperature above 30 °C) has a long-lasting effect on reducing cropland in China. Combining climate projections from 39 downscaled climate models, we predict that climate change is likely to reduce China’s cropland area by 2.09%–25.51% under IPCC’s slowest and fastest-warming scenarios by the end of this century. In addition, we find that non-irrigated land is more susceptible to rising temperatures in the short term; however, irrigated land is subject to a similar impact in the long term. This result suggests that the adaptive effect of irrigation could be limited under persistent rising in temperature.

1. Introduction

Sustaining food security has become a major development goal worldwide as the global population is rapidly increasing, more crops are being converted into biofuels, and newly developing economies are switching to more resource-intensive food such as meat. Climate change has emerged as a new threat to global food security (Schmidhuber and Tubiello 2007, Godfray et al 2010). Changes in climatic conditions, such as higher temperatures and shifted precipitation patterns, negatively affect the production of staple food crops (Deschenes and Greenstone 2007, Lobell et al 2008, Schlenker and Roberts 2009, Welch et al 2010, Lobell et al 2013, Roberts et al 2013, Burke and Emerick 2016, Ortiz-Bobea et al 2021). Continued global warming increases the frequency, and intensity of heatwave and drought, putting the crops on the cultivatable land in jeopardy (Schauberger et al 2017, Lesk et al 2021). Besides crop yields (intensive margin), long-term and gradual climate change will also fundamentally affect cropland area (extensive margin) as cropland becomes less arable and less profitable (Larson 2013).

The threat to food security due to climate change is particularly severe in China. On the one hand, the production of three staple crops in China–rice, wheat, and corn–is vulnerable to climate change (Wang et al 2009, Chen et al 2016, Zhang et al 2017). On the other hand, China is struggling to maintain at least 1.2 million km² of cropland; the so-called ‘red line’ is arguably the minimum amount of cropland needed to feed the Chinese people (Kong 2014). Although China is the third-largest country globally in terms of land area, almost half of the land is not suitable for agriculture. Climate change is likely to complicate the protection of cropland that is being threatened by rapid economic growth and urbanization. Despite its importance, only a few studies have estimated climatic impacts on cropland in developed countries (Auffhammer et al 2006, Haim et al 2011, Fezzi et al 2015, Mu et al 2017, Ortiz-Bobea et al 2019, Cui 2020,
Sloat et al. 2020, Zaveri et al. 2020, Aragón et al. 2021). Very little is known about the magnitude of the climate change effect on cropland and its implications for food production in China.

To fill this research gap, we construct a unique dataset that combines high-resolution satellite data on land use with daily weather data and climate forecasts to estimate the impact of temperature on land use in China with climate econometric models. In particular, the satellite data on land use report the areas of six land types—cropland (irrigated and non-irrigated), forest land, grassland, waterbody, developed land, and barren land—at a resolution of the 10 × 10 km grid in the years of 1980, 1995, 2000, 2005, and 2010. Ideally, we would compare two identical grids, treat one with a warmer temperature and compare its cropland change to the other control grid. Practically, we can approximate this experiment using the longitudinal structure of our data and compare a grid itself between hotter and cooler years. In addition, we control for: (a) all constant differences between grids, such as geographic location; (b) all common contemporaneous shocks within each province, such as technological progress, policy change, and crop prices shocks; (c) other weather variables, including precipitation, relative humidity, sunshine duration, and wind speed. Because weather fluctuations within a given locality are typically exogenous to factors that otherwise determine cropland, we could isolate the weather effects on cropland from other socio-economic-ecological factors without explicitly controlling them.

We use three methods to measure the long-term effect of temperature on land use. The first method is a distributed-lag model, which widely adopted by the climate-economy literature, is very flexible in estimating long-term effects (Dell et al. 2012). The second method is a period-averaged model, in which we average temperature bins from lagged years to the contemporaneous year. Lastly, we use the long differences model (Burke and Emerick 2016), which regresses the differenced temperature bins on the differenced land area between the 1980s and 2010s.

We find that extremely hot weather (daily average temperature above 30 °C) has a long-lasting effect on reducing cropland in China. In particular, if climate change increases the temperature of one day from 15 °C–20 °C to above 30 °C permanently, it reduces cropland area by a total of 1.01% in ten years. The results are robust across all three models. In addition, we find that non-irrigated land is more susceptible to rising temperatures in the short term (less than five years); however, irrigated land is subject to a similar impact in the long term (more than five years). This result suggests that the adaptive effect of irrigation could be limited under persistent temperature increases. We find insignificant temperature effects for forestland, grassland, waterbody, and barren land. However, the effect of extremely hot weather on developed land (used for urban and rural residence, infrastructure, and industry) is significantly positive, and it suggests that some lost cropland has been converted to developed land. Finally, combining climate projections from 39 downscaled climate models, we predict that climate change is likely to reduce China’s cropland area by 2.09%–25.51% under intergovernmental panel on climate change (IPCC)’s slowest and fastest-warming scenarios by the end of this century. This suggests that climate change could threaten China’s cropland. China, the world’s largest CO$_2$ emitter, could take more aggressive climate actions in its interest.

2. Data and methods

2.1. Land data

The land data are from China’s land-use/cover data- sets (CLUDs), provided by the Data Center for Resources and Environmental Sciences at the Chinese Academy of Sciences. CLUDs were updated from 1980 to 2010, with standard procedures based on Landsat thematic mapper and enhanced thematic mapper plus (TM/ETM+) images at a spatial resolution of a 30 × 30 meter grid (Liu et al. 2005, Liu et al. 2014). The accuracy of CLUDs is above 94.3%, which can meet the requirement of the user mapping accuracy on the 1:100 000 map scale. We did not use the original resolution of 30 × 30 meter grids due to a lack of high-resolution historical and future weather data. Instead, we use the resolution at 10 × 10 km grids.

The data report the percentages of six main land categories: cropland, forest land, grassland, waterbody, developed land, and barren land in 1980, 1995, 2000, 2005, and 2010. The primary focus of this paper is cropland, which is further classified as irrigated or non-irrigated cropland. Supplementary information (SI) table S1 reports the summary statistics for cropland and developed land area in square kilometers. On average, cropland accounts for 18% of total land, and 70% of cropland is non-irrigated. Developed land accounts for around 2% of the total land in China.

Figure 1 shows the geographic distribution of China’s cropland (panel a), irrigated (panel b) and non-irrigated cropland (panel c), and developed land (panel d) in 2010. The color shows the percentage of each land type in a 10 × 10 km grid. Non-irrigated land is mostly located in the north and northeast, including Heilongjiang, Inner Mongolia, Shandong, Hebei, and Henan. In contrast, irrigated land is mostly located south, particularly in Jiangsu, Anhui, Sichuan, Hunan, and Hubei. Overall, most cropland in China is non-irrigated, and these main grain production areas are also under rapid industrialization and urbanization. SI figures S16–S19 show the land-use change of cropland, irrigated cropland, non-irrigated cropland, and developed land from 1980 to 2010.
2.2. Weather and climate prediction data

The weather data are drawn from China Meteorological Data Service Center (http://data.cma.cn/en). It has published daily weather data, including maximum and minimum temperatures, precipitation, relative humidity, wind speed, and sunshine duration, for over 800 weather stations across China since 1951. We use the kriging spatial prediction method (Cressie and Wikle 2015) to covert weather data on each day from each station to a $10 \times 10$ km grid to match with the land use data.

To measure the non-linear effects of temperature, we follow the bins approach (Deschênes and Greenstone 2011) and divide daily average temperature (average between daily maximum and minimum temperatures) into $5^\circ C$ bins starting from minus $10^\circ C$ to above $30^\circ C$. The bin $15^\circ C$–$20^\circ C$ serves as the reference group. We then count the number of days within each bin. We use the annual mean plus a quadratic term for relative humidity, wind speed, and sunshine duration; we also use the annual total with a quadratic term for precipitation. Note that we use weather variables for all days in a year. In comparison, the literature that measures weather effects on crop yields only considers the weather in the growing seasons. This is mainly because we do not know which crops are planted in each grid.

SI table S1 reports the average number of days within each $5^\circ C$ temperature bin in China from 1970 to 2010, and most days lie within $10^\circ C$–$25^\circ C$. On average, China has 1.89 extreme hot days with a daily average temperature above $30^\circ C$ per year. SI table S1, panel c further reports the average for precipitation, relative humidity, sunshine duration, and wind speed.

The climate prediction data are drawn from the Coupled Model Intercomparison Project 5 (Taylor et al. 2012). We obtain the mean prediction on daily average temperature from 39 climate models under Representative Concentration Pathways (RCPs) 2.6 (slowest scenario), 4.5, 6.0, and 8.5 (fastest scenario) for each $2.5^\circ C \times 2.5^\circ C$ grid for each month over the period 1970–2010 and 2070–2099. We then calculate the temperature difference in each month-grid between two periods and convert it from a $2.5^\circ C \times 2.5^\circ C$ grid to a $10 \times 10$ km grid using the area-to-point downsampling (Kyriakidis 2004) method to match with historical weather data. We add the difference to the observed daily time series from 1970 to 2010. This shifts the mean of daily temperature and keeps its
variance to predict the number of days within each temperature bin (Auffhammer et al 2017).

2.3. Climate econometric model

We have developed three econometric models to estimate the effect of temperature on land area. The first model, the baseline model, is a distributed-lag model. Let i index 10 × 10 km grid and t index year (1980, 1995, 2000, 2005, and 2010). The natural log of cropland area in year t is a function of

\[
\ln y_{it} = \alpha + \sum_{b} \left( \sum_{j=0}^{J} \beta_{bT^b_t-j} \right) + \sum_{j=0}^{J} (\gamma_j W_{it-j}) + \delta_i + \lambda_{pt} + \varepsilon_{it},
\]

where \( T^b_t \) is the number of days in temperature bin b. Daily average temperature (the average between daily maximum and minimum temperatures) is specified as 5 °C bins starting from below minus 10 °C to above 30 °C, with 15 °C–20 °C as the reference. This specification allows for flexible temperature-land relationships (Deschenes and Greenstone 2011). The vector of other weather variables, \( W \), includes total precipitation, average relative humidity, average wind speed, and average sunshine duration, in both linear and quadratic terms. Both \( T^b_t \) and \( W \) are included with \( J \) lags, where \( J \) ranges from 0 to 10 years. We do not further extend ten year lags as we believe ten years is a reasonable long-term exposure window. This is also consistent with Dell et al (2012), who used a ten year distributed lagged model to study the long-term climate-economy relationship.

We use \( \delta_i \), grid fixed effect, to control for time-invariant grid-specific characteristics such as geographic location and soil quality. We use year-by-province fixed effect, \( \lambda_{pt} \), to control for common shocks within each province in a year, such as technological progress, policy change, and crop price shocks. The unobservable error term \( \varepsilon_{it} \) is clustered at the county level (the size of a typical county is 50 × 50 km) to allow for arbitrary spatial and serial correlations within each county. Our results are robust if standard errors are clustered at a grid level (table S8), by-year-province level (table S9), and both grid level and year-by-province level (table S10).

The distributed lag model can generate unbiased estimates of climatic impacts (Dell et al 2012). The regression of this model will be run separately for \( J \) times, with \( J \) from 0 to ten years of lag. The parameter of central interest is \( \sum_{j=0}^{J} \beta_{bT^b_t-j} \), which measures the \( J \)-year cumulative effect of temperature bin b on cropland area. Suppose climate change permanently shifts one day within 15 °C–20 °C to temperature bin b. Other things being equal, it will change cropland area by \( \sum_{j=0}^{J} \beta_{bT^b_t-j} \) in percentage points, accounting for both contemporaneous and lagged effects up to \( J \) years.

The second model is a period-averaged model that uses the averages of each weather variable in contemporaneous and lagged years. Specifically, the natural log of area for grid \( i \) in year \( t \) is a function of

\[
\ln y_{it} = \alpha + \sum_{b} \beta_{bT^b_t} + \gamma' \bar{W}_{i} + \delta_i + \lambda_{pt} + \varepsilon_{it},
\]

where

\[
\bar{T}^b_t = \frac{1}{J+1} \sum_{j=0}^{J} T^b_{t-j},
\]

and

\[
\bar{W}_{i} = \frac{1}{J+1} \sum_{j=0}^{J} W_{it-j}.
\]

In the model, all weather variables are calculated using the average of \( J \) lagged years, with \( J \) from 0 to 10 years. The other notations are the same as those in equation (1). The parameter of central interest is \( \beta_{bT^b_t} \), which measures the \( J \)-year cumulative effect of temperature bin b on cropland area. The regression of equation (2) will be run separately for \( J \) times, with 0–10 years of lag.

The third model is a long differences model following Burke and Emerick (2016):

\[
\Delta \ln y_{it} = \alpha + \sum_{b} \beta_{bT^b_t} \Delta \bar{T}^b_t + \gamma' \Delta \bar{W}_{i} + \lambda_p + \varepsilon_{it}.
\]

In this form, \( \Delta \ln y_{i} \) measures the difference in log of land area between 1980 and 2010, i.e. \( \Delta \ln y_{i} = \ln y_{i,2010} - \ln y_{i,1980} \). Ideally, we want to use the average of log land area spanning several years across two long periods, such as the average over the period 1978–1982 and 2008–2012, but the land data are only available in 1980 and 2010. Correspondingly, \( \Delta \bar{T}^b_t \) and \( \Delta \bar{W}_{i} \) measure the difference in averaged temperature and other weather variables between 1980 and 2010, such that

\[
\Delta \bar{T}^b_t = \frac{1}{J+1} \sum_{j=0}^{J} T^b_{2010–j} - \frac{1}{J+1} \sum_{j=0}^{J} T^b_{1980–j},
\]

and

\[
\Delta \bar{W}_{i} = \frac{1}{J+1} \sum_{j=0}^{J} W_{2010–j} - \frac{1}{J+1} \sum_{j=0}^{J} W_{1980–j}.
\]

The province fixed effect in equation (3) is denoted by \( \lambda_p \). The other notations are the same as those in equation (1). The regression of equation (3) will be run separately for \( J \) times, with 0–10 years of lag. The parameter of central interest is \( \beta_{bT^b_t} \), which measures the \( J \)-year cumulative effect of temperature bin b on cropland area. The difference between equations (2) and (3) is that the latter uses longer variation.
3. Results

3.1. Historical impact of temperature on cropland area

We start by estimating the effect of temperature on cropland area while controlling for precipitation, relative humidity, wind speed, sunshine duration, and various fixed effects (see equation (1)). To account for the nonlinear effect of temperature, we calculate the number of days within each 5 °C intervals ranging from below −10 °C to above 30 °C using daily average temperature. SI figure S1 plots the historical (1970–2010) and predicted (2070–2099) histograms under four RCPs, ranging from the slowest (RCP 2.6) to the fastest (RCP 8.5) warming scenario. It shows that climate change shifts temperature distribution to a higher range. As a result, more extreme hot weather, with a daily average temperature above 30 °C, is likely to occur. For example, annual extreme hot days will increase from 2 to 22 days on average in China under the fastest-warming scenario by 2070–2099.

The estimated relationships between temperature and cropland area, with 95% confidence intervals, are shown in figure 2 and table S3. The estimate is interpreted as the J-year cumulative effect of temperature on cropland, with J denoting the lags up to ten years. Take the result of the ten year model (lag 10) as an example. If climate change increases the temperature of one day from 15 °C–20 °C to above 30 °C permanently, it will reduce cropland area by a total of 1.01% in ten years. Since heat and extremely hot weather will rise significantly under climate change (see SI figure S1), this estimate implies the significant risk of cropland loss.

The temperature-cropland relationship is nonlinear. Generally, temperature below 30 °C has a limited effect; temperature above 30 °C has a statistically significant (p < 0.01) and economically large effect on cropland loss. In addition, the negative effect of extremely hot days increases when more lags are included, suggesting temperature has a long-lasting cumulative effect. Except for the temperature, the effects of other variables—precipitation, relative humidity, sunshine duration, and wind speed—are generally insignificant, except only for a few specifications (see SI table S2).

We conducted a few robustness checks on our main model, the long-difference model, using 50% and 25% samples. The subsample was generated by splitting samples using the year-by-province as the strata. Table S6 shows that the results of the 50% and 25% samples are robust for the entire country. Moreover, we conducted a censored regression model as a robustness check because quite a few grids only have a small area of cropland. The results are shown in table S7, which are robust to the main regression shown in table S3, particularly for the extremely hot temperatures. Our results are robust to alternative climate econometric models. Our baseline model includes both contemporaneous and lagged weather variables (equation (1)). Alternatively, we calculate the average number of days in each temperature bin over various lagged periods (equation (2)). The results that use these period-averaged temperature bins are very similar to the baseline model (see SI figure S2 and table S4). We also employ the long-difference approach (equation (3)). In this approach, we calculate the average number of days in each temperature bin before 1980 and 2010, respectively, and then regress the difference in log cropland area on the difference in each temperature bin between the two periods. The long-difference approach is similar to the period-averaged model, except we use the period-to-period variation in a longer time framework over 30 years. The results of the long-difference approach are also very similar to those of the baseline specification (see SI figure S3 and table S5).

Our results are also robust to alternative measures of daily temperature. In the baseline model, we construct bins using daily average temperature. Alternatively, we construct bins using daily maximum and minimum temperatures (see SI figures S4 and S5). To better use the variation in tails, we define extremely hot weather as the daily maximum temperature above 35 °C and daily minimum temperature above 25 °C. With different temperature measurements, our main conclusion still holds, although the magnitude of the effect varies. Lastly, we test for different functional forms of the dependent variable. The baseline model uses the logarithm of cropland area as the dependent variable, and thus the estimated coefficient is interpreted as a change of cropland in percentage points. Alternatively, the original cropland is included, so the estimates are measured in km². The results are still robust (see SI figure S6).

3.2. Heterogeneous effects of temperature on cropland

The temperature may have heterogeneous effects on irrigated and non-irrigated cropland. Using the baseline model with ten year lagged weather variables, the cumulative effect of temperature for each land type is shown in figure 3. We find similar effects for irrigated and non-irrigated cropland, suggesting the adaptive effect of irrigation is limited at a decadal scale. In SI figures S7 and S8, we plot the coefficients for irrigated and non-irrigated cropland separately using lags from 0 to 10. The effect of extremely hot weather on irrigated cropland is statistically insignificant (p > 0.1) in the first five years but becomes significantly (p < 0.01) negative from then on. This indicates that irrigation can mitigate the negative effect of temperature rises in the short term (less than five years) but not in the long term (more than five years).

Figure 3 also plots the cumulative response function in ten years between daily average temperatures and land area for other land types. We find
Figure 2. Estimated response function between cropland area (natural log) and daily average temperature using the distributed-lag model. Each point estimate represents the cumulative effect of each temperature bin on cropland area for up to ten years. Temperature bin 15 °C–20 °C is the reference group, and the unit is the percentage point. The control variables include second-order polynomials in annual cumulative precipitation, annual mean relative humidity, wind speed, sunshine duration, grid fixed effect, and year-by-province fixed effect. The shaded area in light blue denotes the 95% confidence intervals after adjusting for serial and spatial correlation within each grid.

Figure 3. Estimated response function between the different land-use area (natural log) and daily average temperature using the distributed-lag model with ten year lags. Each point estimate represents the cumulative effect of each temperature bin on the different land areas with ten year lags. Temperature bin 15 °C–20 °C is the reference group, and the unit is the percentage point. The control variables include second-order polynomials in annual cumulative precipitation, annual mean relative humidity, wind speed, sunshine duration, grid fixed effect, and year-by-province fixed effect. The shaded area in light blue denotes the 95% confidence intervals after adjusting for serial and spatial correlation within each grid.

Insignificant effects ($p > 0.1$) for forest land, grassland, waterbody, and barren land. However, the effect of extremely hot weather on developed land (used for urban and rural residence, infrastructure, and industry) is positive and statistically significant ($p < 0.01$). It suggests that some lost cropland has
Figure 4. Predicted impacts of climate change (2070–2099) on cropland area under the mean projection from 39 climate models under four RCPs. The climate impacts are calculated using the estimated regression coefficients of temperature on cropland area multiplied by the predicted temperature change. The unit is a percentage point. The whiskers denote the 95% confidence intervals after adjusting for spatial and serial correlation within each grid.

3.3. Future impact of climate change on cropland area and food production

We predict the impacts of climate change by the end of this century (2070–2099) on cropland (irrigated and non-irrigated) using the historical response function between land area and temperature, as well as a set of downscaled climate models. To account for uncertainties in climate models (Burke et al. 2015), we use the average projection from 39 downscaled climate models from the Coupled Model Intercomparison Project 5 (Taylor et al. 2012). We focus on RCPs 2.6, 4.5, 6.0, and 8.5 in the IPCC's Fifth Assessment Report (AR5). RCP 2.6 is the slowest warming scenario, while RCP 8.5 is the fastest, with RCPs 4.5 and 6.0 in the middle.

We use the following method to do the climate prediction. First, we obtain the mean prediction of daily average temperature from 39 climate models for each month-grid over the periods 1970–2010 and 2070–2099. Second, we calculate the temperature difference in each month-grid between the two periods. Third, we add the difference to the observed daily time series from 1970 to 2010. This shifts the mean of daily temperature but also keeps its variance. Fourth, we calculate the predicted change in each 5 °C temperature bin. Finally, we multiply estimated coefficients from equation (3) by the predicted change in each bin and ultimately aggregate the prediction on each bin to project the impacts of climate change on cropland.

Figure 4 depicts the estimated impacts in percentage points and 95% confidence intervals under the four RCPs. We find that climate change is likely to reduce China's cropland by 2.09%–25.51%, depending on the RCPs. The estimates are statistically significant at 5% significance level under RCPs 4.5, 6.0, and 8.5. The predicted negative climate effects are similar for irrigated (2.06%–19.44%) and non-irrigated (2.95%–19.49%) cropland.

Our model also predicts the impacts of climate change on cropland for each grid under different RCPs. Figure 5 shows that most areas of China may see decreases in cropland area as a result of climate change this century, whereas the northeast, southwest, and Tibet Plateau areas may experience some net increase in cropland, particularly in RCPs 2.6 and 4.5. The negative effects are pronounced in China's most productive agricultural regions, including the North China Plain, Yangtze River Delta, Pearl River Delta, and Sichuan Basin, and climate change threatens food production in these regions. The impacts of climate change on irrigated and non-irrigated cropland are
Figure 5. Predicted impacts of climate change (2070–2099) on cropland area for each grid under the mean projection from 39 climate models under four RCPs. The climate impacts are calculated using the estimated regression coefficients of temperature on cropland area multiple by the predicted change in temperature in each grid. The unit is km².

shown in SI figures S14 and S15. We find that both irrigated and non-irrigated cropland tend to be negatively affected by temperature rise.

Using the relationship between climate and cropland, we can conduct a back-of-the-envelope calculation of the impact on food production. China produced 497 million tons of cereals in 2010 (www.fao.org/faostat/en/data). If we assume agricultural productivity remains constant, a 25.51% loss in cropland area reduces cereals production by 126.78 million tons or about 5% of global cereals production in 2010. China imported 5.69 million tons of cereals in 2010. To compensate for the loss of cereals production, China needs to increase cereals imports by 22 times, which is 37% of global exports of cereals.

Considering that climate change also has an adverse effect on agricultural productivity, the loss of food production will be even larger. Zhang et al (2017) estimate that climate change is likely to decrease the yields of three major crops in China—rice, wheat, and corn—by 36.25%, 18.26%, and 45.10%, respectively. Using the average crop yield loss (33.20%) and assuming the worst-case scenario of cropland loss (25.51%), climate change is likely to reduce China’s total crop production by up to 50.24% by the end of this century. To compensate for this loss, China needs to import 250 million tons of cereals, which is nearly 10% of global cereals production and 74% of global cereals exports in 2010. This will have a profound impact on the global food market.

Although this business-as-usual projection method is widely used in the climate-economy literature (Ortiz-Bobea et al 2021), it bears several caveats. First, most climate-economy estimates based on historical data used short-term weather fluctuations, while climate change is permanent and gradual. We believe our estimates from equations (1)–(3) partly alleviate this concern as we use three dynamic models to incorporate long-term temperature impacts.

Second, this projection assumes no price effect, constant population, economic growth, urbanization, and technology development. Here we discuss the possible effects if we change assumptions. If hot weather continues to impact cropland negatively, crop prices may be higher, and thus more investment may be made, and we may overestimate the cropland impacts. In terms of population, China’s population is predicted to decrease from 1.38 billion in 2016 to 1 billion in 2100 (United Nations 2015), which will relieve the pressure on crop demand in China. However, the global population is projected to increase from 7.44 billion in 2016 to 11.2 billion in
2100 (United Nations 2015), implying keener competition with China for crop imports on the global market.

In terms of economic growth and urbanization, our projection may underestimate the true impact of climate change on cropland if the rate of economic growth and urbanization keeps increasing since it will speed up the conversion of cropland to developed land, although the ‘red line’ policy may mitigate the effect. As for technology development, our projection may overestimate the impact if heat-tolerant crops can be bred and promoted in the future.

4. Discussion

We find that extremely hot weather significantly reduces China’s cropland. Climate change shifts the temperature distribution to the right tail and leads to extremely hot temperatures. Under the fastest-warming scenario, climate change is likely to reduce China’s cropland by 25.51% by the end of this century. Since China had 1.78 million km$^2$ of cropland in 2017, the loss is equivalent to 0.45 million km$^2$ of cropland, almost as large as the total land area of Spain or Thailand and larger than California.

We also find that adaptation through irrigation is unlikely to offset the negative effect: these croplands are either converted into developed land or become unsuitable for cropping in the long term. This conclusion is consistent with the previous findings in the U.S. that farmers are generally not able to adapt to climate change by maintaining the same crop yields in the long term (Schlenker and Roberts 2009, Burke and Emerick 2016).

High temperatures could affect cropland through two channels. The first channel is the active adjustment to high temperatures. If high temperatures lower agricultural productivity, cropland may be converted to developed land for better value. The second channel is the passive adjustment to high temperatures. Extreme weather events such as heatwaves or droughts may degrade cropland and make it unsuitable for cropping. For example, Lesk et al (2016) found that production losses due to extreme weather disasters were associated with a reduction in both harvested area and yields. Moreover, a global study by Zhao et al (2017) investigated the impact of temperature on yields of wheat, rice, maize, and soybean, which are the main caloric intake in China. The result consistently showed a negative temperature impact on crop yield on the global scale. China’s ‘red line’ policy, which has aimed to protect 1.2 million km$^2$ of cropland since 2006, can limit the active conversion of cropland to developed land through heavy regulations on land use. However, this policy cannot prevent high temperatures from making the cropland completely unsuitable for cropping. This may mean the Chinese government will need to augment the ‘red line’ policy by introducing measures to guarantee a return on croppings, such as providing subsidies to farming or increasing investment in infrastructure such as irrigations and dams to deal with extreme weather events. For example, Tack et al (2017) found that irrigation can offset heat impacts in a similar short-run heat shock impact model.

Most importantly, our results suggest that China should be more incentivized to reduce greenhouse gas (GHG) emissions in its interest. China is the world’s largest GHG emitter; China is also one of the most vulnerable countries in a warming world. Reducing GHG emissions is the ultimate approach to prevent further cropland loss to climate change.

Our method could be generalized to other settings. An international analysis could be implemented if fine spatiotemporal land data are available. However, two caveats exist in this study. First, we did not account for the CO$_2$ fertilization effect since increasing CO$_2$ levels might spur crop growth and yield, and we may overestimate the impact if the fertilization effect is significant. Second, we mainly estimate the climatic impacts on cropland through increased temperatures. It is also possible that the rise in sea level will reduce cropland in coastal areas. In this case, our results may underestimate the climatic impacts on cropland. We will leave these questions for future research.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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Author contributions

P Zhang, J Wang and J Zhang contributed to the study conception and design. Material preparation, data collection and analysis were performed by Y Wang and P Zhang. The first draft of the manuscript was written by P Zhang. J Wang and J Zhang commented on previous versions of the manuscript. All authors contributed equally to this work. The authors are listed alphabetically.

Ethics approval and consent to participate

Not applicable because the study does not report the results of studies involving humans and/or animals. Consent to participate is not applicable because the study does not report the results of studies involving humans and/or animals.

Consent for publication

Not applicable because the study does not report the results of studies involving humans and/or animals.

Conflict of interest

The authors declare no competing interests.

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