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Are climate change damages on winter wheat overstated? Evidence from China

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Abstract

In this paper, we perform a comprehensive analysis of the impacts of climate change on winter wheat, one of the most widely planted crops, using data in China. We allow the climatic impacts to differ across seasons (growing stages) and regions with different climates in our panel data model. We find that heat in the fall and freezing days in the spring are the most evident drivers of yield reductions. We also find evidence of substantial adaptations in response to these damages. More importantly, our findings suggest that existing studies could have possibly overstated the climate change damages on winter wheat yields due to the omission of the potential benefit from the reduction of freezing days. For instance, our results indicate a yield reduction of 0.5% under a uniform 1 ºC warming scenario compared with a reduction of 3-5% found in existing studies, which is consistent with our results (a yield reduction of 5.5%) if the freezing effects were omitted in the model. The overestimation of climate change damages on winter wheat is robust to Shared Socioeconomic Pathway scenarios (SSPs) with which even yield gains are expected.

Keywords: Climate change; winter wheat yield; freezing days

Introduction

Climate change has been shown to impose negative effects on the economy (Burke et al., 2015; Dell et al., 2012), and the agricultural sector is expected to experience the most evident challenges (Deschênes and Greenstone, 2007; McCarl et al., 2008; Schlenker and Roberts, 2009). Better understandings of climate change effects on crop production are pivotal for developing suitable adaptation strategies (Liu et al., 2016). This is particularly relevant for emerging economies, which are usually characterized by a large population, a vulnerable agricultural system, and a less secure food supply.

In this work, using county-level agriculture and climate data collected in China from 1981-2015, we conduct a comprehensive analysis of the climate change impacts on winter wheat yields, one of the most widely planted crops globally (Food and Agriculture Organization of the United Nations, 2018).

Since winter wheat has a long growing period (generally from September to May), we first divide it into three seasons: fall, winter, and spring corresponding to distinct growing stages. We use piece-wise regressions to empirically identify the lower and upper temperature thresholds separately for each season (Tack et al., 2015). This allows us to construct a rich set of degree day variables, with which we use a panel data model with fixed effect to reveal the variations of yield responses to climate across seasons (growing stages) (Chen et al., 2016; Chen and Gong, 2020; Zhang et al., 2017). More importantly, we explicitly take into account the freezing days (temperatures below 0 ºC) in our model, which have mixed effects on yield development.

We also interact the key climate variables with dummy variables representing cold/warm regions to examine the variation of climate impacts across regions which could shed light on possible adaptation effects (i.e. hot regions may be less vulnerable to warming damages because they have adapted to the hot climate in the long run). Finally, based on the empirical estimations, we project future yield consequences under a variety of climate change scenarios.

We have three key findings. First, in terms of the variation of yield responses across seasons, we find that temperatures over 24 ºC in the fall and freezing days in the spring are the most evident drivers to yield loss with reductions of 11.4% and 11.3% per 10 degree days increase, respectively. We also find that heat is less harmful in regions with hot fall and freezing damages are smaller in regions with cold spring, which support our hypothese of adaptations. Our results pass a battery of robustness checks, such as with alternative growing periods, inclusion/exclusion of certain seasons, different temperature threshold setups, a wider geographic coverage, and statistical inference derived from bootstrapping.

Second and more importantly, our yield projections suggest that existing climate change evaluations on winter wheat could have overstated the damages due to the overlook of potential benefits stemming from the reduction of freezing days. For instance, under a 1 ºC uniform warming scenario (relative to 1981-2015), our projection accounting for the freezing effects suggests a much lower yield reduction of 0.5% compared with a reduction of 3-5% found in existing crop simulation models and statistical analysis (Asseng et al., 2015; Liu et al., 2016; Wilcox and Makowski, 2014) in which the freezing effects were not explicitly modeled. Furthermore, our projection in the absence of freezing effects (a yield reduction of 5.5%) is quite consistent with those existing studies in terms of the overestimation of climate change damages. On the other hand, our projections with the Shared Socioeconomic Pathway scenarios (SSPs) even suggest possible yield gains - as we expect a yield increase of 4.5% in 2040-2060 relative to 1970-2000 under SSP126.

Third, despite the adaptations to heat and freezing damages, yield projections performed at the county level show that, in terms of the *overall* climate change impacts, the north regions exhibit more damages than the south counterpart under both uniform warming scenarios and the SSP scenarios. Thus shifting the planting areas to such regions could be a possible direction for adaptation. More interestingly, for most emerging economies that have limited resources for climate change adaptation, lending more agricultural resources from summer crops (more prone to projected heat extreme increase in summer) to winter wheat (if applicable) might also be desirable for securing food supply in future climate.

Our work contributes to the existing literature in four important ways. First, our analysis is based on statistical models and adds new evidence to the current climate change assessments on winter wheat which were largely derived from crop simulation models. Although crop simulation models are constructed to reflect the key processes governing crop growth and yield, these models are plagued by uncertainties associated with model parameters (Asseng et al., 2013; Lobell and Asseng, 2017)[1], and projections from individual crop model are unlikely to represent the real crop responses to climate change[2].

Statistical models using long-term and large-spatial-scale empirical data can handle inherent uncertainties via statistical inference and/or bootstrapping and have become increasingly common in recent years due to the growing availability of data on both climate and crops[3]. Additionally, the flexibility of statistical models allows them to accommodate very fine-scaled data and uncover important effects that might have been overlooked in crop simulation models.

Second, the existing *statistical* analysis of the relationship between winter wheat and climate variables relies on either a mean temperature or a degree day variable (calculated based on a base temperature of 0 ºC) that is averaged or accumulated over the *entire* growing period (Asseng et al., 2015; Lobell et al., 2011; Xiong et al., 2014; Yi et al., 2016; Zhang and Huang, 2013). As a result, cross-season (i.e. growing stages) variability in climate impacts would not be accounted for, which is especially important for winter wheat given that its growing period spans across three different seasons corresponding to distinct growing stages. Moreover, using average temperature may overlook the impacts of extreme incidences (Lobell et al., 2011); and using a simple base temperature of 0 ºC for constructing degree day variables may not be appropriate because temperature thresholds could vary across seasons (Lesk et al., 2016; Tack et al., 2015), as we will empirically show in the cross-validation analysis.

In contrast to previous studies, we leverage fine-scaled observations of hourly temperatures[4] and the temperature thresholds are empirically estimated separately for each season using piece-wise regressions. Following that, we build a rich set of degree day variables (we show in the summary statistics that degree day variables constructed from hourly temperatures perform better than that

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[1] In fact, most of the assessments of climate change were conducted at a few agricultural sites. In this regard, those studies are also questioned about their external validities. A few exceptions are (Lv et al., 2013) and (Rosenzweig et al., 2014), in which the authors applied the crop simulation models to high-resolution raster data.

[2] Recent studies recommend to consider the median of an ensemble of simulation models as an accurate estimate, rather than relying on the results of an individual model. See examples in (Asseng et al., 2015, 2013; Liu et al., 2016; Schauberger et al., 2017).

[3] The statistical analysis also has weakness. For instance, it is unable to explicitly reflect the fertilizing effects of CO2. Another common concern is the difficulty of distinguishing the effects of highly correlated weather variables. See (Auffhammer and Schlenker, 2014; Hsiang, 2016; Lobell and Asseng, 2017) for detailed reviews.

[4] In fact, we are not aware any of empirical studies in China that used hourly temperature variation to estimate the climate change effects, regardless of which crops were investigated.

of daily temperatures in representing extreme incidences, particularly heat) and allow the yield responses to varying across seasons in our panel data model. More interestingly, we also allow the yield responses to varying across regions with different climates to shed light on possible adaptation effects. Our preferred model outperforms a suite of alternative specifications that were used in previous studies in terms of the out-of-sample predictions.

Third, while the climate change impacts on crop productivity have been extensively investigated in developed nations (Burke and Emerick, 2016; Deschênes and Greenstone, 2007; Mendelsohn et al., 1994; Schlenker and Roberts, 2009), solid evidence is still rare for developing countries (Chen and Gong, 2020; Pironon et al., 2019; Schlenker and Lobell, 2010). Using data collected from China, our work attempts to inform other emerging economies with similar agricultural and climatic characteristics.

More importantly, with only 7% of the world's arable land, China feeds over 22% of the world population (Piao et al., 2010). Understanding the impacts of climate change on Chinese agricultural productivity not only matters for domestic food supply but is also critical for stabilizing the international market, as China has become the largest food importer in terms of cereals (Food and Agriculture Organization of the United Nations, 2019).

Fourth, our work is closely related to (Tack et al., 2015) focusing on winter wheat growth in Kansas, a state in the United States. Our work focuses on a wider geographic area in China. We constructed a different model from that in (Tack et al., 2015) and we argue that our preferred specification is more robust from a biological stand of point. Moreover, in addition to yield projections with uniform warming scenarios as in (Tack et al., 2015), we also performed projections with SSP scenarios to depict a general picture of the climate change impacts on winter wheat.

Winter wheat in China

Wheat (winter wheat plus spring wheat) is the third most planted grain crop in China with 23.7 million planted hectares and 133.6 million tons of production in 2019, following corn and rice (National Bureau of Statistics, 2019). Most of the wheat in China is winter wheat accounting for over 90% of total wheat production (Zhang et al., 2017)[5]. North China Plain (NCP) produces over 71% of total winter wheat in China. The geographic coverage of NCP varies in the literature but normally consists of seven cities and provinces, including Beijing, Tianjin, Hebei, Henan, Shandong, Anhui, and Jiangsu.

In this study, we primarily focus on a sub-region of the NCP[6], which is considered the most suitable region for growth and produces most of the winter wheat (Zhao, 2010). It covers the south part of Hebei, most of Henan, the entire Shandong, and the north part of Anhui and Jiangsu (see the map in figure A1 in the appendix). Additionally, we chose this region based on several considerations.

First, this region has an arguably uniform growing period and crop pattern (winter wheat + summer corn). Winter wheat is usually planted in later September and early October and harvested in June (Asseng et al., 2015; Guo et al., 2010; Zhang et al., 2015). Thus, we define the baseline growing period as from October to May. We also performed robustness checks with alternative growing seasons including September to May and September to June.

Second, rainfall in this region is greater than the north part of NCP and we can arguably consider winter wheat is rain-fed in this region (Zhang and Huang, 2013; Zhao, 2010). We intend to focus on rain-fed winter wheat because we do not have high-quality data on irrigation, which plays an important role in evaluating the impacts of weather conditions on yields (Schlenker et al., 2005; Tack et al., 2017). If the crop is heavily irrigated, omitting the effects of irrigation could attenuate the estimation of the impacts of extreme incidences, particularly extreme heat (Troy et al., 2015).

Nevertheless, we performed robustness checks with larger geographic coverage and the results are

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[5] The National Bureau of Statistics did not provide information on the types of winter wheat (i.e. hard red, hard white, etc.) According to (He, 2001), most of the winter wheat in China are hard white.

[6] This sub-region is also known as the "Huang-Huai-Hai" plain.

consistent with the baseline estimates.

For winter wheat in China, the long growing period of Oct-May can be further divided into three seasons: fall (Oct-Nov), winter (Dec-Feb), and spring (March-May) coinciding with three different growing stages (Tan et al., 2018; Xiao et al., 2018; Zhou et al., 2018).

The fall season represents the vegetable growth stage covering the emergence and tillering of winter wheat. This stage is sensitive to high temperatures which would hinder the winter wheat from preparing dormancy for the coming winter (Porter and Gawith, 1999).

As temperatures decrease winter wheat enters dormancy in the winter season. (Liu et al., 2016) indicated that winter wheat is insensitive to weather through most of the winter season, however, this stage is still critical for yield development because the transformation of vegetable growth to reproductive growth is completed during this stage (University of Wisconsin-Extension, 2018). Climate extreme events could impose significant damages on crops. For instance, high temperatures could awake winter wheat from dormancy and thus make it susceptible to frost in early spring (Holman et al., 2011).

Winter wheat resumes growth in the spring season. This growing stage (March-May) covers jointing, booting, and flowering thus is regarded as the most temperature-sensitive period (Dreccer et al., 2018; Liu et al., 2016; Šebela et al., 2020; Tan et al., 2018; Zampieri et al., 2017). Agronomy studies have found that freezing in early spring could be dramatically harmful to grain development (Xiao et al., 2018).

The data

In this paper, we compiled a data set consisting of county-level winter wheat yield data and fine-scaled weather data spanning from 1981 to 2015.

Yield data. County-level yield data (in tons/hectare) were obtained from the database of the Institute of Agricultural Information at the Chinese Academy of Agricultural Science (Yi et al., 2016). To refine the yield data, we restrict to counties that have more than 10 years of yield observations. However, relaxing this restriction did not significantly change the regression results. In total, we have 352 counties and 8867 observations in our sample.

The spatial and temporal variations of yield data are shown in figure 1 below. Yields are higher in the middle part of our study region (largely the eastern part of Henan and the north Anhui, and Jiangsu), whereas the yields in the western part (largely western Henan) are lower, presumably due to the shortage of rainfall. On the other hand, the average yield in our study region has steadily increased from 2.2 tons/ha in 1981 to 6.3 tons/ha in 2015. We also observe that there exists a huge jump in average yields from 2.4 tons/ha in 1989 to 3.7 tons/ha in 1990. To address this, we performed a robustness check with data restricted to 1990-2015. The results are consistent with that derived from the full sample, except that we observed smaller damages associated with heat and freezing days in the regression excluding the data from the 1980s.

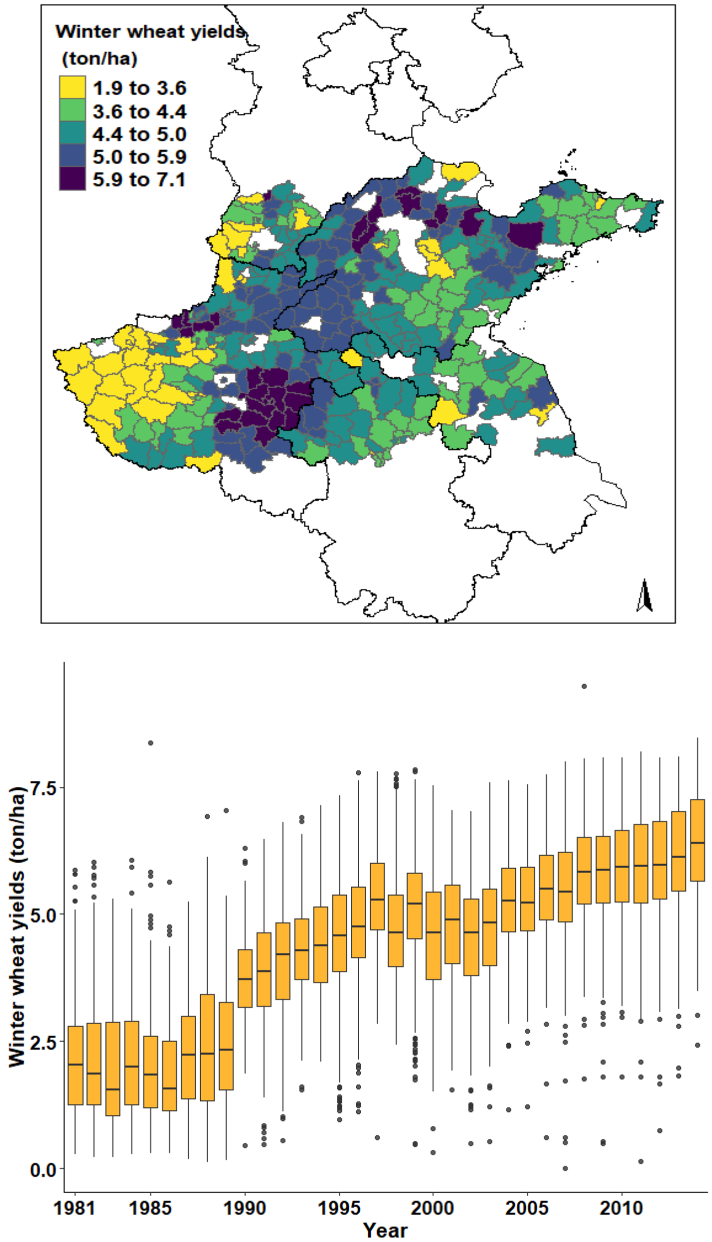

Figure 1 The spatial and temporal variation of winter wheat yield in our study region. (a) The map on the top shows the county-level yield averaged across 1981-2015. White areas in the map indicate no data (the urban areas). (b) The boxplot at the bottom depicts the trends of winter wheat yields. Each box is defined by the upper and lower quartile of county-level yields in the respective year, and the mean is depicted as the horizontal bar. The endpoints for the whiskers represent the respective quartile +/- 1.5 times the interquartile range, and dots indicate yield outside of the range.

Weather data. We collected temperature and precipitation data from two different sources.

The daily minimum and maximum temperature were downloaded from the China Meteorological Data Service Center (CMDC) affiliated with the National Meteorological Information Center of China (Chen and Gong, 2020). The initial data were gridded in a spatial resolution of 0.5°×0.5° (approximately 56km * 56km at the equator). We converted the gridded daily temperature to county-level by weighted-averaging over grid cells that overlap each county following (Auffhammer et al., 2013; Burke et al., 2018).

Unlike most previous studies, which relied on daily or monthly average temperature, we go further by exploring variations in hourly temperature. An advantage of hourly temperature is that it performs better in representing extreme incidences (Schlenker and Roberts, 2009). For instance, extreme hot/cold may occur in a day with moderate mean temperature. In this case, daily temperature may not be able to capture such extreme events.

To obtain hourly temperature, we interpolated the daily minimum and maximum temperatures using a sine function, as described in (Luedeling, 2020)[7]. The hourly temperatures are then used to construct a rich set of degree day variables based on the temperature thresholds estimated separately for each season. For instance, if the upper threshold for fall is estimated at 20 ºC, one hour of 30 ºC contributes to 30-20=10 degree "hour". Finally, the degree day are obtained by dividing the degree "hour" by 24.

In this work, we primarily employ degree day variables to estimate the relationship between climate and winter wheat yields, but we also perform out-of-sample cross validations with alternative temperature specificaitions.

The monthly precipitation data were collected from the China Meteorological Forcing Dataset, developed by (He et al., 2020)[8]. This dataset is arguably the first high spatial-temporal resolution gridded near-surface meteorological dataset and is one of the most widely used climate datasets

[7] The manipulation of hourly temperatures was performed using the R package "chillR". The workhorse is the "stack_hourly_temps" function which employs a sine curve for daytime temperatures, with nighttime cooling represented by a logarithmic decay function. It also should be addressed that differences in daylength between locations were accounted for by computing sunrise and sunset times based on geographic latitudes See technical details in (Luedeling, 2020).

[8] Unfortunately, this dataset did not provide daily minimum and maximum temperature, otherwise we would have used it to derive hourly temperature.

for China. The initial monthly precipitation data were gridded in a spatial resolution of 0.5°×0.5°, and we converted to county-level following the same procedure for the gridded temperature data. In line with the literature, the county-level monthly precipitation data are *aggregated over seasons* to construct seasonal precipitation variables (Chen et al., 2016; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Zhang et al., 2017).

Figure 2 below shows the general trends in seasonal temperature and precipitation from 1981 to 2015. We observed obvious upward trends in all three seasonal temperatures, particularly in the winter and spring. Precipitation is more fluctuated, and we did not detect any significant trends.

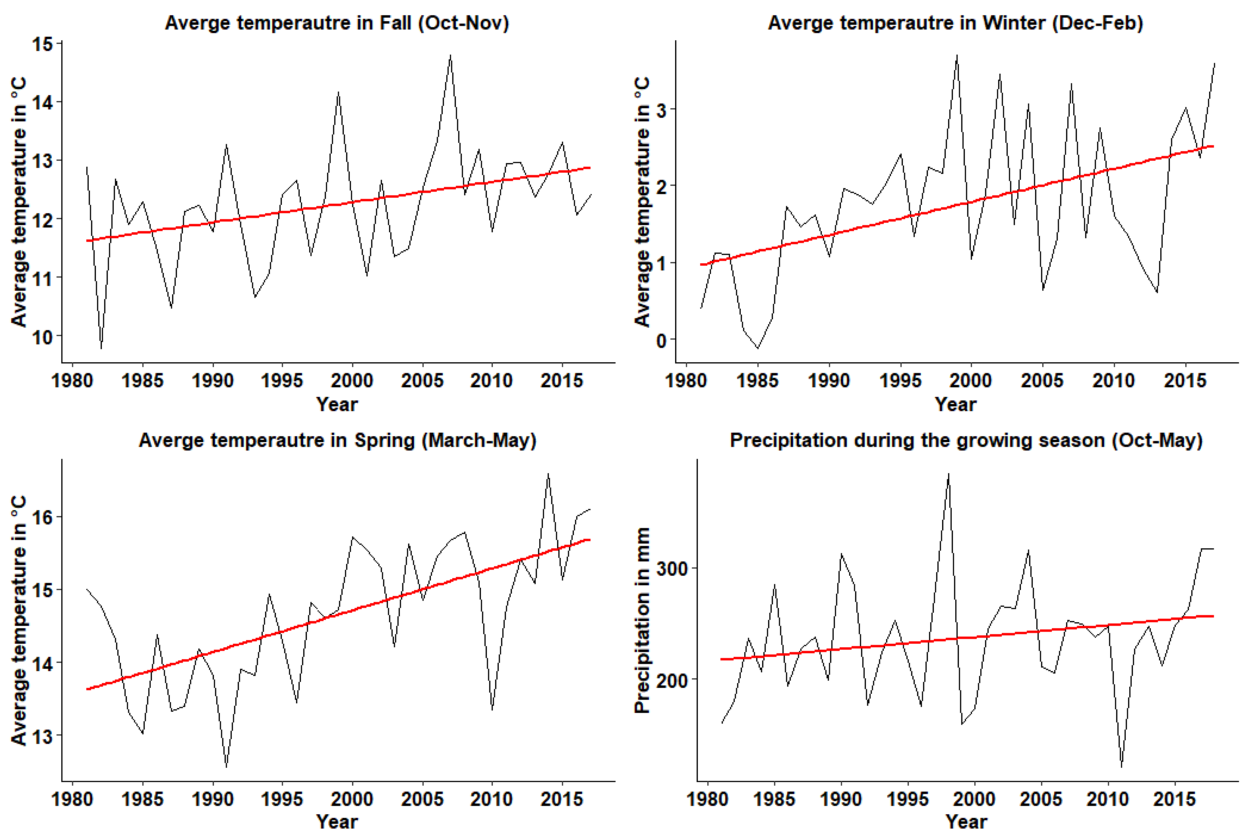

Figure 2 The trends in seasonal temperature and growing-period precipitation.

Empirically estimating temperature thresholds for constructing degree day variables: what is considered too cold/hot?

When calculating degree days for winter wheat, a large body of literature adopts a simple base temperature of 0 ºC, i.e. a daily temperature of 8 ºC contributes to 8-0=8 degree days (Dreccer et al., 2018; Yang et al., 2015; Yi et al., 2016). Also, the degree day variables are calculated over the *entire* growing period. However, this could be problematic given that different growing stages require distinct optimal temperature intervals (Porter and Gawith, 1999; Tack et al., 2015). Moreover, since extreme heat is less frequent during the winter wheat growing period compared with that for summer crops (e.g. corn and soybean), it is still debatable about the maximum temperature tolerance of winter wheat.

Also somewhat surprisingly, most existing studies omitted the impacts of freezing (temperatures below 0 ºC), which are critical and can have mixed effects on winter wheat. For instance, agronomic studies show that freezing temperatures in spring could impose significant damages on winter wheat yields (Xiao et al., 2018), whereas mild freezing in the early winter could help winter wheat to harden the shell of the seed and thus isolate winter wheat from even lower temperatures during the winter season (Porter and Gawith, 1999).

Following (Tack et al., 2015), we employed piece-wise regressions to *empirically* identify the temperature thresholds for fall, winter, and spring, respectively. We set the lower temperature threshold and upper temperature threshold (i.e. bracketing the optimal temperature interval) both above zero for the fall and spring seasons[9], while the freezing degree days (temperatures below 0 ºC) were calculated independently. That means we have four degree day variables for the fall and spring seasons, namely, freezing degree days (*Frez*), degree days between zero and the lower threshold (*DDlow*), degree days between the lower threshold and the upper threshold (*DDmed*), degree days above the upper temperature threshold (*DDhigh*). We hypothesize that *DDmed* as the

[9] Following (Tack et al., 2015), the lower threshold was restricted to be at least 5 ºC below the upper threshold to ensure that the temperature interval is not too narrow. (Tack et al., 2015) also imposed additional restrictions such as the lower threshold to be at least 5 ºC above zero and 10 ºC below the maximum observed temperature and the upper threshold is restricted to be 5 ºC below the maximum. Our piece-wise regressions are insensitive to these additional restrictions.

optimal interval gives the best supports for winter wheat growth, whereas *Frez*, *DDlow*, and *DDhigh* would hinder yield development. We loop over all possible threshold combinations and pick up the one which has the best fit (the highest r squared) in the piece-wise regressions.

The setup for the winter season is different. Specifically, to make agronomic sense, we set the lower threshold slightly *below* zero and the upper threshold *above* zero. In this case, we only have three degree day variables, i.e. the degree days below the lower threshold (*DDlow*), degree days between the lower threshold and the upper threshold (*DDmed*), degree days above the upper temperature threshold (*DDhigh*). Similar to spring/fall configures, *DDlow* and *DDhigh* would be harmful. What's different for the winter season is that the moderate temperature interval (*DDmed*), even when it's partially under 0 ºC ('freezing'), is beneficial to yield development as it supports the transformation from vegetable growth to reproductive growth. In other words, only the *temperatures below the identified lower threshold are considered too cold.*

Nevertheless, we also tested an alternative setup for the winter season in which we only established an upper threshold above zero. In this case, we have a freezing degree day variable measuring temperatures below 0 ºC, a medium degree day variable reflecting temperatures above 0 ºC but below the upper threshold, and an upper degree day variable representing temperatures above the upper threshold.

The estimated temperature thresholds are shown below in table 1. The thresholds for fall and spring are 17-24 ºC and 25-30 ºC, respectively. The thresholds for the winter season are -5-8 ºC. The temperature threshold for the alternative setup is estimated at 8 ºC. Our results are largely consistent with the thresholds estimated in (Tack et al., 2015) where the authors focused on winter wheat in the state of Kansas in the United States. The difference is that (Tack et al., 2015) adopted the same threshold setup for winter as for fall and spring and estimated temperature thresholds of 5-10 ºC for the winter season.

Table 1 The estimated temperature thresholds

Season	Thresholds (in ºC)
Fall (Oct-Nov)	17 and 24
Winter (Dec-Feb)	-5 and 8
Spring (March-May)	25 and 30

More importantly, our estimated cutoffs are largely consistent with results from field experiments. In a review of temperature and the growth of winter wheat, (Porter and Gawith, 1999) concluded that the photosynthesis rates in winter wheat have been optimized at 25 ºC, and declining at temperatures lower than 15 and higher than 30 ºC. (Cao and Moss, 1989) found that the optimal temperature for fall (leaf emergence) ranges from 21.3 to 24.3 ºC, and temperatures higher than 25 ºC tend to inhibit leaf appearance (Slafer and Rawson, 1995). The maximum tolerance of temperatures for the winter season was identified at 10-12 ºC (Halevy, 1985; Narciso et al., 1992; Petr, 1991).

In addition to the baseline growing period of Oct-May, we also estimated the temperature thresholds with alternative periods such as Sep-May and Sep-June. The estimated thresholds are rather consistent with that of Oct-May (see table A1 in the appendix).

The econometric model

There are two approaches for empirically estimating the impacts of climate change on the agricultural sector (crop yields, land values, etc.): cross-sectional model (one observation per county) and panel data model (multiple observations across multiple years per county) with fixed effects. The advantages of the former are that it takes account of the long-term climate change adaptions (such as crop mix, crop calendar, agricultural facilities, etc.) because it directly compares outcomes across different climatic regions (i.e. the cross-sectional variation) at which farm practices have been optimized for its climate in the long run[10]. However, it is plagued by endogeneity issues such as omitted variable bias, i.e. soil quality and other time-invariant but location-specific characteristics (Deschênes and Greenstone, 2007; Hsiang, 2016; Mendelsohn et al., 1994; Schlenker et al., 2006).

On the other hand, recent studies leaned towards the panel data model, which is able to alleviate the omitted variable bias to some extent by introducing location-specific fixed effects (Chen et al., 2016; Dell et al., 2012; Schlenker and Roberts, 2009; Zhang et al., 2017), which control for all time-invariant characteristics that could confound the estimates. Nonetheless, the panel regression relies on short-term time-series variations, i.e. comparing yield changes across years for each location. In this respect, the panel data model tends to reflect the effects of *weather shocks* (year-to-year weather variation) on the outcomes[11]. As a result, it does not fully take into account the long-term adaption as in the cross-sectional model (see detailed reviews in (Blanc and Schlenker, 2017) and (Kolstad and Moore, 2020) and theoretical work in (Hsiang, 2016)), though short-term adaptations (i.e. fertilizer use and irrigation) can be accounted for in panel models.

[10] For readers who are interested in this topic, see theoretical discussions in (Hsiang, 2016). The underlying assumption is that agricultural activities are assumed to be optimized at the current climate. For example, colder counties have adapted to the cold climate in the long run and so do the warmer counties. In this spirit, within a cross-sectional framework, warmer counties provide references of potential outcomes for colder counties when the climate gets warmer. If we further assume the colder counties are able to fully employ the adaptations currently taken by warmer counties, we are able to say that the estimated climate change effects take account of the long-term adaptations. The readers are also encouraged to go over the reviews in (Blanc and Schlenker, 2017) and (Kolstad and Moore, 2020).

[11] According to (Hsiang, 2016), if the outcome is a solution to a maximization problem (such as profits) which is continuous and differentiable in the dimension of all adaptation strategies (which is unlikely to hold), the marginal effect of the climate is exactly same as the marginal effect of weather shocks.

The baseline econometric model

In this work, we employ a panel data framework and use the rich set of degree day variables constructed from the estimated temperature thresholds to identify the winter wheat yield responses to climate across different seasons. Our panel data model with fixed effects takes the form below.

$$y_{it} = \delta_i + \alpha_1 t_{it} + \alpha_2 t_{it}^2 + \sum_s f_s(\mathbf{w}_{it}^s; \boldsymbol{\beta}^s) + \varepsilon_{it} \tag{1}$$

i and t denote county and year, respectively. s denotes seasons of fall, winter, and spring. y_{it} is the log of winter wheat yields. δ_i indicate the fixed effects that absorb all time-invariant factors that only differ between counties, such as soil quality and other geographic features. t_{it} and t_{it}^2 are the linear and quadratic terms of time trends representing the technology development over time (see the yield trends shown in figure 1). ε_{it} is the error terms and we cluster it at the county-level to take account of arbitrary serial correlations within the county. $f_s(\mathbf{w}_{it}^s; \boldsymbol{\beta}^s)$ includes all the climate variables which we define below.

$$\begin{aligned} f_s(\mathbf{w}_{it}^s; \boldsymbol{\beta}^s) = {} & \beta_{s1} Frez_{it}^s + \beta_{s2} DDlow_{it}^s + \beta_{s3} DDmed_{it}^s + \beta_{s4} DDhigh_{it}^s + \\ & \beta_{s5} Prec_{it}^s + \beta_{s6} (Prec_{it}^s)^2 \qquad \text{for } s = \textit{fall} \text{ and } \textit{spring}. \end{aligned} \tag{1.a}$$

$$\begin{aligned} f_s(\mathbf{w}_{it}^s; \boldsymbol{\beta}^s) = {} & \beta_{s1} DDlow_{it}^s + \beta_{s2} DDmed_{it}^s + \beta_{s3} DDhigh_{it}^s + \\ & \beta_{s4} Prec_{it}^s + \beta_{s5} (Prec_{it}^s)^2 \qquad \text{for } s = \textit{winter}. \end{aligned} \tag{1.b}$$

For s = fall and spring, $Frez_{it}^s$, $DDlow_{it}^s$, $DDmed_{it}^s$, and $DDhigh_{it}^s$ denote the freezing degree days, the degree days between zero and the lower threshold, the degree days between the lower threshold and the upper threshold (optimal range), and the degree days above the upper threshold, respectively. Degree day variables for winter are defined to be slightly different because we do not have an independent freezing degree day variable. The $DDlow_{it}^s$, $DDmed_{it}^s$, and $DDhigh_{it}^s$ variables in winter have similar meanings as in the fall and spring seasons. $Prec_{it}^s$ and $(Prec_{it}^s)^2$ are the linear and quadratic terms of seasonal precipitations.

The examination of possible adaptation effects

Knowing how farmers adapt to climate is critical to understand the “actual” effects of climate change in the future (Burke and Emerick, 2016). However, empirical estimates of adaptation effects are scarce, partially because most of adaptation strategies are not directly observable/ measurable. Even though they can be observed, it’s difficult to enumerate and capture all feasible options in the model (Moore and Lobell, 2014).

Nonetheless, the adaptation effects can be indirectly revealed by comparing the estimates from the cross-sectional model with that from the panel data model, i.e. the differences between these two are attributed to effects of adaptations (see a theoretical justification in (Dell et al., 2009)). This could hold only when the estimates of the cross-sectional model are not confounded by unobserved characteristics, which is a relatively strong assumption and difficult to empirically test.

To relax this restriction, several hybrid approaches have been developed in the literature, such as the long-difference models and the multistage models (Kolstad and Moore, 2020). The long-difference model is essentially a cross-sectional comparison of changes over time (a long period) in which unobserved characteristics are canceled out (Burke and Emerick, 2016; Chen and Gong, 2020)[12]. The multistage method models the county-level response as a function of local climate (Auffhammer, 2018; Butler and Huybers, 2013; Carleton et al., 2020; Heutel et al., 2020).

These approaches exploit cross-sectional variations and thus require a large number of counties (over 1000 counties in most of the applications) to obtain reliable estimates. Unfortunately, we only have 352 counties in our sample which are insufficient for reliable cross-sectional regression estimates[13]. Nonetheless, in this paper, we allow the yield response to climate to vary between hot regions and cold regions by interacting the climate variables with dummy variables (this is actually a special case of the multistage model).

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[12] Moreover, findings using the long-difference method are mixed. For instance, studies on the climate effects on yields (Burke and Emerick, 2016) and growth (Dell et al., 2012) concluded that the long-difference approach returned almost identical results as from the panel data model, suggesting limited effectiveness of adaptation. On the other hand, in the agricultural productivity context, (Chen and Gong, 2020) indicated that long-run adaptation revealed from the long-different approach has offset 37.9% of the short-run effects of extreme heat estimated from the panel data model. Similar adaptation effects in the agriculture sector were also observed in Europe (Moore and Lobell, 2015).

[13] We ran the long-difference regressions with multiple specifications. The results are sensitive to the choose of period over which we average the data. These results can be obtained from the authors upon request.

The basic idea is that heat could be less harmful in hotter regions because these regions have adapted to the climate, so are colder regions which could be more robust to freezing damages (Butler and Huybers, 2013; Dell et al., 2012).

To test these hypotheses, we interact the key climate variables with a dummy variable that represents hotter/colder regions. Here the key climate variables (*DDhigh_fall* and *Frez_spring* to be more precise) are determined based on the baseline regression results which exhibit the most evident damages to winter wheat yield.

Taking the *DDhigh_fall* as an example, to construct the associated dummy variable, we first average the observation over years to obtain the mean value. The dummy variable "*hot*" is set to be 1 in counties with *above-median DDhigh_fall* and 0 otherwise. Similarly, we set up a dummy variable "*cold*" for freezing damages in the spring, which is 1 in counties with *above-median Frez_spring* and 0 otherwise. Formally, we have:

$$\beta_{s4} DDhigh_{it}^{s} \text{ in eq (1.a)} \Rightarrow \beta_{s4}^{1} DDhigh_{it}^{s} + \beta_{s4}^{2}(hot * DDhigh_{it}^{s}) \quad \text{for } s = fall \tag{1.c}$$

$$\beta_{s1} Frez_{it}^{s} \text{ in eq (1.a)} \Rightarrow \beta_{s1}^{1} Frez_{it}^{s} + \beta_{s1}^{2}(cold * Frez_{it}^{s}) \qquad \text{for } s = spring \tag{1.d}$$

Where $\beta_{s4}^{1} + \beta_{s4}^{2}$ measures the yield responses to heat at counties with hot fall and β_{s4}^{1} measures the impacts on counties with cold fall. Similarly, $\beta_{s1}^{1} + \beta_{s1}^{2}$ tells us the impact of freezing days in counties with cold spring, whereas β_{s1}^{1} indicates the effects on counties with warm spring.

The adaptation hypotheses to be tested are:

$$\begin{aligned} &H_s(0): \beta_{s4}^{1} + \beta_{s4}^{2} > \beta_{s4}^{1} \qquad \text{for } s = fall \\ &H_s(0): \beta_{s1}^{1} + \beta_{s1}^{2} > \beta_{s1}^{1} \qquad \text{for } s = spring \end{aligned} \tag{2}$$

In addition to "*hot*" and "*cold*" dummy variables, we also built a dummy variable of "*wet*" based on the precipitations during fall/spring. We then interact this "*wet*" variable with *DDhigh_fall* and *Frez_spring* respectively to see whether the damages differ between wet and dry regions.

The summary statistics of key variables

The summary statistics of key variables are shown in table 2 below. We also present the degree day variables constructed from daily temperatures in the table to demonstrate the superiority of hourly temperatures in representing extreme incidences (particularly heat). For instance, the maximum and mean of *DDhigh_fall* calculated from hourly temperatures are 2.5 and 0.5 (in the unit of 10 degree days) respectively, whereas they are as low as 0.9 and 0.01 if calculated from daily temperatures. The differences are also evident for *DDhigh_spring*. Furthermore, the variations of degree day variables calculated from hourly temperatures are much greater than that from daily temperatures.

Table 2 The summary statistic of key variables across 8867 observations (year, county)

Statistic	Min	Max	Mean	St. Dev.
Panel one: Summary statistics of yield and precipitation variables				
Yield (in tons/ha)	0.01	9.5	4.7	1.7
Prec_fall (in mm)	0.002	343.4	62.0	47.9
Prec_winter (in mm)	0.002	321.5	43.5	37.2
Prec_spring (in mm)	9.0	483.3	124.3	66.2
Panel two: Degree day variables using hourly temperatures (in 10 degree*days)				
Frez_fall	0.0	8.6	0.4	0.7
DDlow_fall	23.3	88.6	66.7	8.1
DDmed_fall	0.0	12.4	4.6	1.8
DDhigh_fall	0.0	2.5	0.4	0.5
DDlow_winter	0.0	23.1	2.1	2.4
DDmed_winter	20.9	45.8	32.2	3.0
DDhigh_winter	0.001	12.4	2.7	1.8
Frez_spring	0.0	7.9	0.3	0.5
DDlow_spring	63.8	159.1	131.2	13.0
DDmed_spring	0.0	5.7	2.2	1.0
DDhigh_spring	0.0	2.2	0.3	0.3
Panel three: Degree days variables using daily temperatures (in 10 degree*days)				
Frez_fall	0.0	6.7	0.2	0.5
DDlow_fall	16.0	74.8	49.9	8.2
DDmed_fall	0.0	13.2	2.9	2.2
DDhigh_fall	0.0	0.9	0.01	0.1

DDlow_winter	0.0	16.2	0.6	1.1
DDmed_winter	9.0	37.6	23.2	4.4
DDhigh_winter	0.0	7.3	0.9	1.1
Frez_spring	0.0	6.7	0.1	0.3
DDlow_spring	62.2	156.8	127.4	10.8
DDmed_spring	0.0	3.2	0.4	0.5
DDhigh_spring	0.0	0.35	0.002	0.02

Note that: We used the same temperature thresholds as in hourly temperatures to construct degree day variables from daily temperatures.

Empirical results

We first report the regression results from our baseline model. We then show out-of-sample cross-validations with a suite of alternative model specifications to demonstrate the performance of the preferred model. We also present a battery of robustness checks. Following that, we examine future yield consequences under various climate change scenarios. Lastly, we discuss the heterogeneity of climate change effects which provides us possible adaptation strategies.

Regression results from the baseline model

Yield responses vary across seasons

Figure 3 below shows the regression results from the panel data model. Each bar presents the coefficients associated with the respective degree day variables. The tabulated results can be found in table A2 (column 3) in the appendix. The results are largely in line with our expectations. We consistently observe positive effects within the identified optimal temperature range. And we observe negative effects with temperatures outside of the optimal intervals, as well as negative effects with freezing temperatures.

In terms of the responses across the season, heat in the fall and freezing in the spring are identified as the most significant drivers to yield losses. In the fall season, additional 10 degree days of temperatures over 24 ºC are associated with 11.4% of yield reduction. On one hand, high temperatures in the fall will increase the water demand for the emergence and tillering of winter wheat. On the other hand, excess heat would prevent wheat from altering the metabolism to adjust for cold temperatures in the coming winter (so-called “hardening”) (Porter and Gawith, 1999). Similarly, additional 10 degree days of freezing degree days in the spring tend to reduce yields by 11.3%, which is qualitatively consistent with that in an agronomy study (Xiao et al., 2018). Finally, for the winter season, cold temperatures below -5 ºC and hot temperatures above 8 ºC would impact the dormancy and both have negative effects on yields, though the former is statistically insignificant.

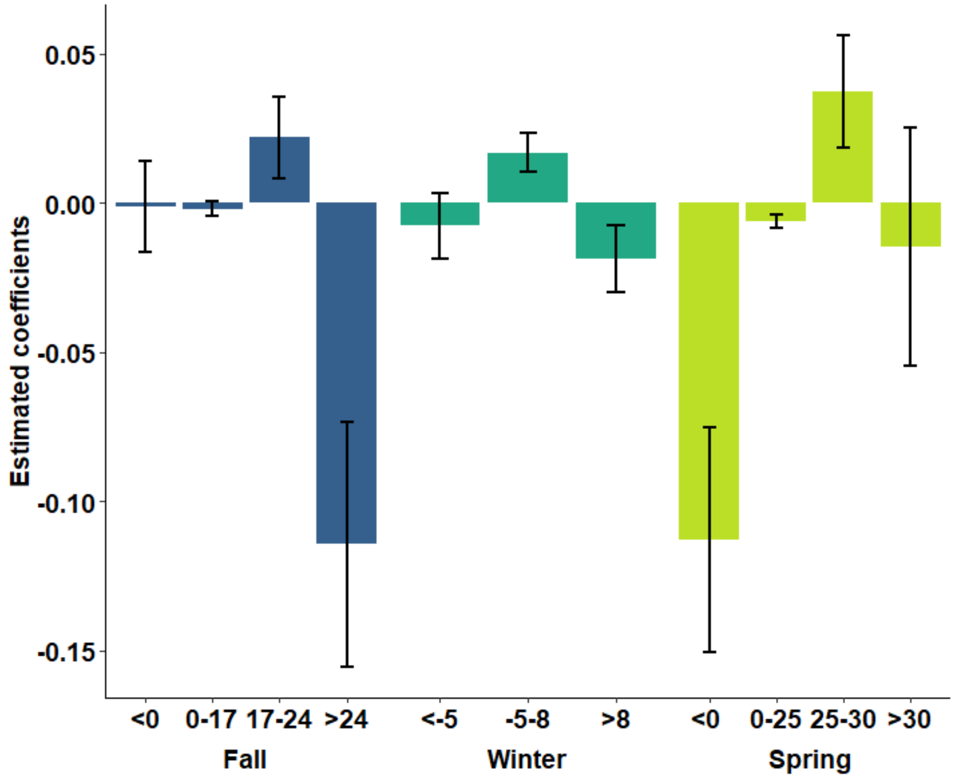

Figure 3 Winter wheat's responses to temperatures across different seasons. Note: The x-axis indicates the degree day variables (expressed in the unit of 10 degree days) constructed from the corresponding temperature thresholds. Bars show the estimated coefficients of the respective degree day variables and the 95% confidence intervals using standard errors clustered at the county level.

Notably, we do not observe statistically significant damages of heat in the spring, which contradicts findings in (Tack et al., 2015) where the authors indicated that springtime exposure above 34 ºC is associated with the largest yield reduction. This contradiction is probably attributable to several reasons. While (Tack et al., 2015) focused on the state of Kansas in the United States where they identified an upper threshold of 34 ºC for spring, we cover a larger geographic area and estimated an upper threshold of 30 ºC for spring. The degree day variable above 34 ºC was non-zero in over 75% of the observations in (Tack et al., 2015), while this number is only 39% in our sample.

Similar results to ours were found in (Schauberger et al., 2017) in which for US winter wheat of large geographic coverage, a negative response to high temperature is neither observed (in statistical analysis) nor simulated (in an ensemble of nine crop models) under historical conditions since critical temperatures are rarely exceeded during the entire growing season.

The discussion above also leads to another important question that the evaluation of climate change impacts is particularly sensitive to geographic coverage. To get reliable climate change assessments, extra attention should be paid not only to the quality of data but to the selection of representative study regions. Results derived from one region cannot be directly generalized to a different region with distinct climatic and agricultural characteristics.

Apart from the temperatures, precipitations exhibit an inverted U shape relationship with winter wheat yield in fall and spring, and the turning points were estimated to be at 134.6 mm (accumulated in a season) and 188.3 mm, respectively, beyond which the larger precipitation leads to yield reductions. Note that the mean rainfall in these two seasons in our sample is respectively 62.0 mm and 159.1 mm, indicating a significant shortage of rainfall in fall. We do not detect statistically significant effects of precipitation in the winter season. These findings are quite consistent with farm practices. Normally, irrigation is applied after sowing in the Fall to meet the water demand for the emergence of winter wheat.

Testing the adaptation hypothesis

Results from the baseline model suggest that yield responses to climate vary significantly across seasons. In this section, we examine whether yield responses vary across regions with different climates. Particularly, we are interested in whether the adaptation hypotheses that we constructed in the model part hold or not.

Table 3 below shows the results of models with dummy interactions. For brevity, we only present the coefficients on key climate variables and their interactions with dummy variables. Column 1 shows the results from the baseline model (i.e. the model without interactions). Column 2-3 refers to the results with degree day dummies (*hot_fall* and *cold_spring*) and precipitation dummies (*wet_fall* and *wet_spring*), respectively. Column 4 shows the results with all interactions. The bottom four rows summarize the impacts of climate variables for hot and cold regions, respectively.

We can see that the results support our hypothesis about adaptations, that is heat is less harmful in counties with hot fall, and freezing damage is less evident in regions with cold spring. Additional 10 degree days above the upper threshold in the fall reduce yields by 7.6% in hot regions, while the reduction increases to 16.3% in cold regions. Similarly, 10 freezing days lead to a yield reduction of 9.8% in regions with cold spring, whereas the damage is 39.1% in regions with warm spring (column 2). Moreover, the differences in freezing damages between regions with cold and warm spring are substantially larger than the difference in heat damages found in regions with hot and cold fall.

In terms of the interactions with the "*wet*" dummy variables, we do not detect changes in yield responses across wet/dry regions (column 3). The variation of yield response to hot/cold regions is robust to the inclusion/exclusion of the interactions with "wet" dummies (column 2 vs. column 4).

Table 3 Results of possible adaptation effects

	Winter wheat yields			
	(1)	(2)	(3)	(4)
DDhigh_fall	-0.114***	-0.163***	-0.130***	-0.167***
	(0.021)	(0.033)	(0.027)	(0.036)
Frez_spring	-0.113***	-0.391***	-0.123***	-0.437***
	(0.019)	(0.051)	(0.022)	(0.057)
*DDhigh_fall * Hot_fall*		0.087***		0.081***
		(0.026)		(0.025)
*Frez_spring * Cold_spring*		0.293***		0.320***
		(0.053)		(0.055)
*DDhigh_fall * Wet_fall*			0.026	0.018
			(0.022)	(0.020)
*Frez_spring * Wet_spring*			0.029	0.057*
			(0.035)	(0.031)
County fixed effect	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Quadratic time trend	Yes	Yes	Yes	Yes
Observations	8,867	8,867	8,867	8,867
Adjusted R^2	0.527	0.530	0.527	0.530
Heat damages in regions with hot fall	-	-0.076	-	-0.086
Heat damages in regions with cold fall	-	-0.163	-	-0.167
Freezing damages in regions with cold spring	-	-0.098	-	-0.117
Freezing damages in regions with warm spring	-	-0.391	-	-0.437

Note: Standard errors were clustered at the county-level and are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Our results suggest sizeable adaptation effects in response to the most evident drivers of yield reductions (heat in the fall and freezing in the spring). Possible adaptation strategies could be heat/cold-tolerant varieties. However, it is worth noting that the adaptation effects should be interpreted with caution. What we revealed is the differences in *short-term* responses across regions with different climates because the results were still derived from panel data models. The interpretation of long-term adaptation only holds when long-term adaptations impact (at least partially) the yield responses via changing the short-term responses (see the theoretical justification in (Hsiang, 2016)). In this regard, it's appropriate to interpret the differences in responses across regions as a lower bound of adaptation.

Model performance and robustness checks

To examine the performance of our baseline model, we conducted out-of-sample cross validations for a suite of alternative model specifications.

Specifically, we randomly chose 80% of data points from our full sample. The estimated model is then used to predict the yield for the rest 20% of our sample (Fan et al., 2020; Schlenker and Roberts, 2009). The root mean squared errors (RMSE) is calculated from the predictions and the process was repeated 1000 times. We compare the RMSE of our baseline model with that of four alternative specifications:

(1) a model with temperature and precipitation averaged over the *entire* growing period;

(2) a model with seasonal temperature and seasonal precipitation;

(3) a model with simple freezing degree day and growing degree day (based on a single threshold temperature of 0 ºC), calculated over the *entire* growing period;

(4) similar as in (3), except that the two degree day variables are calculated for each season (fall, winter, and spring) separately.

Figure 4 shows that the baseline model has the smallest RMSE. That indicates our preferred model outperforms the other four alternatives in predicting yields. One of the most striking results is that the model with simple average temperature ("simple tavg" in figure 4) performs very well and it can even outperform the more "sophisticated" seasonal degree day model ("seasonal dd" in figure 4). This highlights the fact that models using degree day variables calculated based on a single threshold temperature of 0 ºC, a wide practice in literature, are inappropriate for winter wheat at least.

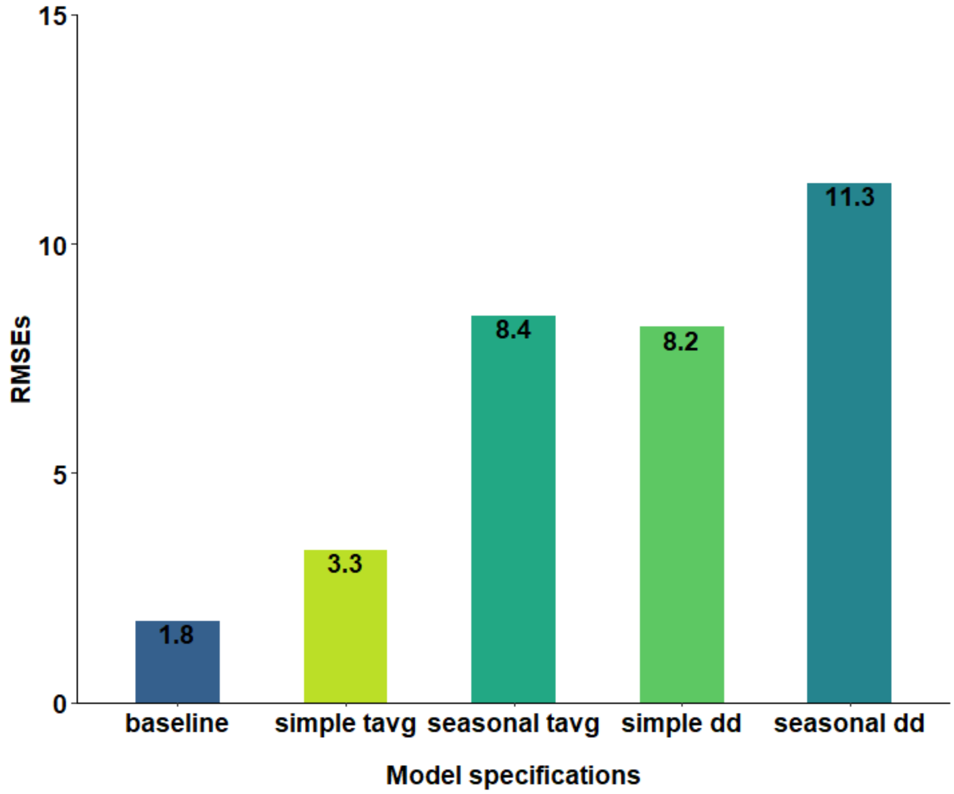

Figure 4 Out of sample prediction comparison for multiple model specifications. "simple tavg" refers to the model with average temperature and precipitation over the entire growing period; "seasonal tavg" refers to the model with seasonal temperature and seasonal precipitation; "simple dd" denotes the model with freezing degree day variable and growing degree day variable (based on a base temperature of 0 ºC) calculated over the entire growing period; analogously, "seasonal dd" indicates the model with seasonal degree day variables. The numbers in the bars are RMSEs calculated following the steps described in the text.

In addition to the cross-validations with alternative model specifications, we also performed a variety of robustness checks.

To address the sudden yield jump observed in 1989-1990 (see figure 1), we ran the regression with data restricted to 1990-2015. The results are shown in table A2 (column 1) in the appendix and are rather consistent with that derived from the full sample, except that fewer damages were detected with heat and freezing days in the former regression possibly due to adaptation overtime.

To examine whether our results are sensitive to the selection of growing period, we ran regressions with Sep-May (figure A2) and Sep-June (figure A3), respectively. The results are quite consistent with our baseline estimates with Oct-May. One exception is that in the regressions with Sep-June, we observed statistically significant negative effects of temperatures over 30 ºC in the spring. This could possibly because we have more temperatures over 30 ºC due to the inclusion of June. It leads to a concern of climate change damages in the future as we are expected to experience more heatwaves (Hong et al., 2019). On the other hand, given winter wheat is usually harvested in June, we speculate that these negative effects could be attributed to the impacts of heat on labor productivity (Graff Zivin and Neidell, 2014; Kjellstrom et al., 2009). This speculation is further supported by the fact that farm operation in China is still labor-intensive because the size of the farm managed by individual households is relatively small, which is quite different from the United States where farm operations heavily rely on machinery. A recent study in China shows that a 1 ºC increase in the mean temperature will reduce an average rural resident's time allocated to farm work by 7% (Huang et al., 2020).

To examine whether our baseline results are sensitive to the inclusion/exclusion of certain seasons in the model, we performed regressions independently with each season and the results are shown in table A3 in the appendix. The results are consistent with our baseline estimates. One exception is that we observed a statistically significant negative effect of DDhigh in the model with spring only.

To test the robustness of our baseline winter temperature thresholds setup (-5-8 ºC), we ran regressions with winter degree day variables derived from the alternative setup in which only one temperature threshold was established (8 ºC. See the temperature thresholds estimation part for more details). The results are shown in figure A4 and are consistent with our baseline estimates.

We also relaxed the restriction on our study region to have wider geographic coverage, i.e., the entire seven provinces and municipalities including Hebei, Beijing, Tianjin, Henan, Shandong, Anhui, and Jiangsu (8856 observations vs 11893 observations). The results are shown in table A2 (column 2) in the appendix and again are consistent with our baseline estimate. Nonetheless, as we discussed previously, our primary study region was narrowed down to address the concerns about the confounding effects of irrigation and differences in the growing seasons.

Finally, we also performed statistical inference using pair bootstrapping with replacement to address the uncertainties associated with the baseline estimates. Pseudo bootstrapping samples were randomly drawn from the original sample with replacement. Coefficients were estimated with the bootstrapping sample. This was repeated by 1000 times to establish distributions of coefficients. Standard errors were then constructed from those distributions. The resulted confidence intervals are provided in table A5 in the appendix and it turned out that the clustering standard errors performed very well in terms of addressing the uncertainties.

Future projection: Are the warming damages overstated?

Climate change characterized by global warming increases the intensity and duration of heatwaves and could impose significant damages to crop yields. However, another consequence of climate change is the possible reduction of freezing days. This may not concern climate change impacts for summer crops but matters for winter wheat. As we have seen in figure 3, early spring freezing imposes significant negative effects on winter wheat yields. On the other hand, winter wheat also suffers from the heat in the fall. Thus, it is not immediately clear what the overall impacts of climate change would be for winter wheat.

To examine which effect dominates, we project yield consequences with and without freezing variables under a range of uniform warming scenarios (1 to 5 ºC temperature increase in relative to 1981-2015) to make our results comparable with previous studies (Asseng et al., 2015; Liu et al., 2016; Tack et al., 2015). Specifically, we first applied uniform temperature increase to all counties across the entire growing period, and then we recalculated the degree days to obtain the changes (see table A5 in the appendix). Following that, we combined our estimates with the changes in degree days to project yield consequences. Additionally, we also conduct yield projections with Shared Socioeconomic Pathways (SSPs) scenarios to depict a general picture of climate change's impact on winter wheat yields.

Yield projections with uniform warming scenarios

The uniform warming results are shown in figure 5. In the figure, “baseline” denotes the yield projections derived from the baseline model with all degree day variables included. The “omit freezing” indicates the yield projection without the consideration of freezing variables (*Frez_fall*, *DDlow_winter*, and *Frez_spring*).

We want to emphasize two findings here. First, the potential benefits stemming from the reduction of freezing days tend to largely offset the damages of excess heat. Ignoring this would dramatically overstate the damages of warming on winter wheat. For instance, under a 1 ºC uniform warming scenario, projections in the absence of the freezing effects show a yield reduction of 5.5% whereas projections accounting for the freezing effects show a much lower reduction in yield (0.5%). The overestimation of warming damages is observed in all other uniform warming scenarios as shown in figure 5[14].

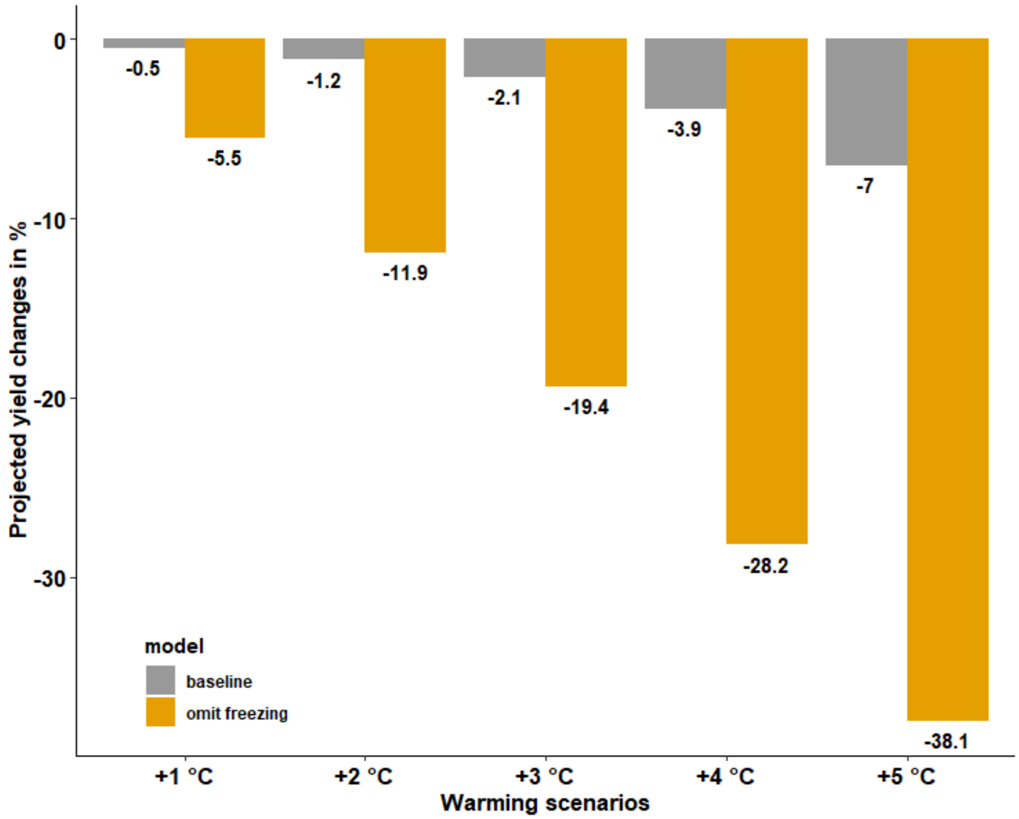

Figure 5 Projected yield consequences under a range of uniform warming scenarios. Note: "baseline" denotes the yield projections derived from the baseline model with all degree-day variables included. The "omit freezing" indicates the yield projection derived from the model in which freezing variables were excluded (Frez_fall, DDlow_winter, and Frez_spring). Numbers in the figure are yield reductions in percentage.

Second, the "omit freezing" projections are consistent with previous findings in which freezing impacts were not explicitly considered. For instance, an ensemble projection made by 30 crop simulation models at 30 agricultural sites indicated a yield reduction of 6% (compared with our

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[14] We also show the projection results with the alternative winter temperature threshold setup (see figure A5 in the appendix). The results are largely consistent with that shown in figure 5.

5.5% yield reduction) under a 1 ºC uniform warming scenario (Asseng et al., 2015). Additionally, (Liu et al., 2016) obtained consistent projections from crop models and statistical regressions[15]. For winter wheat in China, their estimated yield reduction was 3.0% under a 1 ºC uniform warming scenario. These estimates relied on either crop models with daily (monthly) temperature (Asseng et al., 2015; Liu et al., 2016) or statistical regressions with temperatures averaged over the *entire* growing period (Liu et al., 2016). In such cases, impacts of extreme incidences (including freezing and heat) are overlooked and variations of temperature responses across seasons are neglected. The consistency between our "omit freezing" projections with these previous work supports the importance of considering freezing effects and its changes in evaluating climate change impacts on winter wheat yields.

Yield projections with Shared Socioeconomic Pathways scenarios

To shed light on the yield consequences under more plausible climate change scenarios, we conducted the yield projections with SSPs data from the WorldClim database (Fick and Hijmans, 2017). The database provides climate model output of past and future climate data at a monthly temporal resolution and a variety of spatial resolutions. We downloaded historical monthly temperature data (1970-2000) and future temperature projection data (2041-2060) derived from the IPSL-CM6A-LR climate model at a spatial resolution of 4.6 km * 4.6 km. The gridded data were converted to county-level by weighted-averaging over grid cells that overlap each county. Following that, changes in monthly mean temperature (2041-2060 relative to 1970-2000)[16] were calculated and applied to historical hourly temperatures, and degree day variables were recalculated. Finally, changes in yield were estimated under a variety of SSPs scenarios (SSP126, SSP 245, SSP 370, and SSP 585).

The results are shown in figure 6. Again, the warming damages are overestimated if the effects of freezing days are omitted. Moreover, unlike projections under uniform warming, the results with

[15] By performing a meta-analysis of process-based crop model simulations, (Wilcox and Makowski, 2014) concluded a 3.3 + 0.8% declined in wheat yield with a 1 ºC increase in local temperature. Based on historical regressions and simulation studies, (Fischer et al., 2014) reported an average of 5.9% wheat yield decline with 1 ºC warming.

[16] Ideally, we should measure the temperature changes in 2041-2060 relative to 1981-2015. Unfortunately, the database does not provide the model output of 1981-2015. Note that one cannot directly compare the output of climate models with historical observations (Auffhammer et al., 2013). In other words, when calculating temperature changes, both temperatures in 2041-2060 and temperatures in 1981-2015 should be output of climate models. Nonetheless, we averaged the model output of 1970-2000 and the output of 2021-2040 (under the SSP126) to represent the temperatures of 1981-2015. Using these as base temperatures, we redid the SSP projections and the results (see figure A6) are consistent with that in figure 6.

SSP scenarios suggest overall yield gains. For instance, the projection with the full set of variables under SSP126 shows a yield increase of 4.5% while the projection omitting freezing effects indicates a yield reduction of 7.8%. The yield improvement is also observed in the rest of the SSP scenarios.

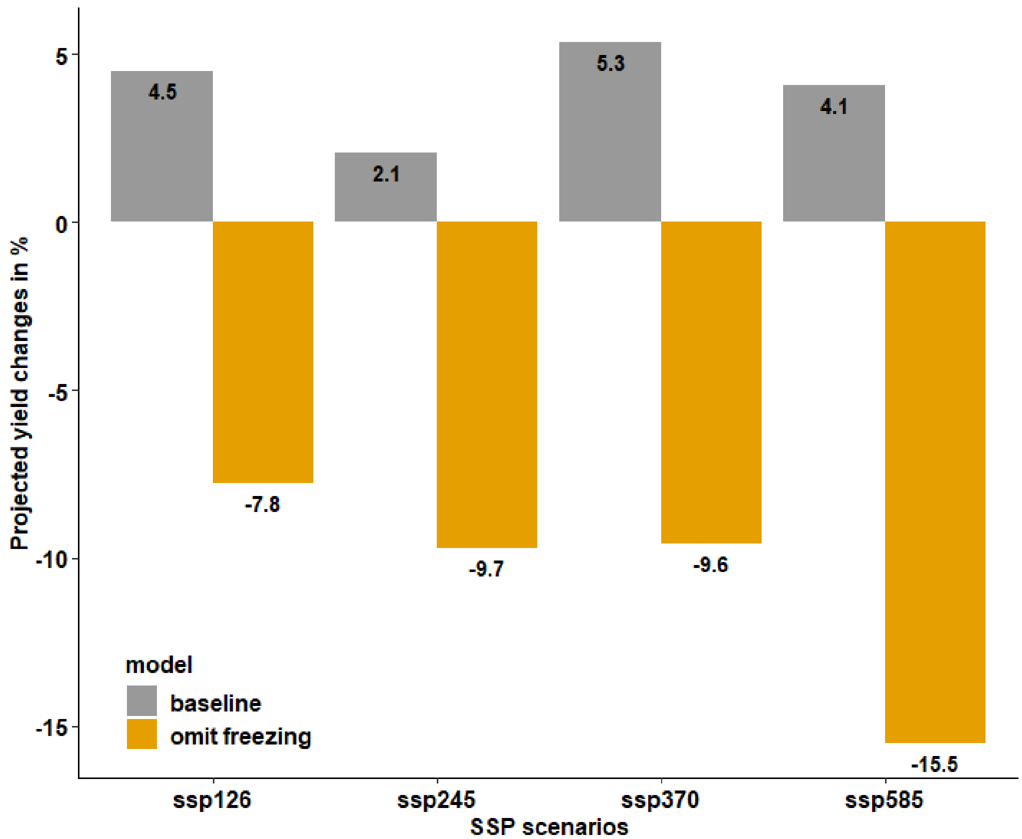

Figure 6 Projected yield consequences under SSP scenarios. Note: Similar as in figure 5, "baseline" denotes the yield projections derived from the baseline model with all degree-day variables included. The "omit freezing" indicates the yield projection derived from the model in which freezing variables were excluded (Frez_fall, DDlow_winter, and Frez_spring). Numbers in the figure are yield reductions in percentage.

The difference in projections between SSPs and uniform warmings could be because climate change-induced temperature increases are unlikely to be uniform across seasons, i.e., we may expect more evident temperature increases in the winter and spring seasons. See the evidence in figure 2 where we plot the historical trend of seasonal temperatures from 1981 to 2015.

Although the projections with SSP scenarios suggest positive effects of climate change on winter wheat yields, the inherent uncertainties associated with the projections should be addressed, such as the uncertainties in climate change data as well as the uncertainties in our empirical models. For instance, our model failed to detect statistically significant negative effects of heat (temperatures over 30 ºC) in the spring, because temperatures rarely exceed the threshold. However, this may not hold under the future climate, in which case heat in the spring could become a more evident threat to yields. Moreover, uncertainties in the climate data could be exacerbated as our projections highly depend on climate change impacts on specific seasons and hourly temperatures. Nonetheless, this could be a research avenue for future studies.

Yield projections at the county level: the north region tends to suffer more from future climate change

The yield projections in the previous section show that, on average, the overall climate change damages are relatively low under a variety of scenarios. In this section, we further assess the spatial heterogeneity of the climate change effects, that is we show the yield projections at the county level. This is of great importance because even under uniform warming scenarios, the changes in degree day variables are likely to differ across seasons and counties.

It should be noted that despite the different responses between hot and cold regions we revealed in previous sections, we performed county-level projections using the empirical results from the baseline model without any dummy interactions. This is because, in addition to the key variables (*DDhigh_fall* and *Frez_spring*), the rest of the climate variables also play important roles in the projection. We intend to show the disparity of the *average* climate impacts across counties.

The results with uniform warming scenarios are presented in figure 7 below. The northern regions, particularly the southern part of Hebei, are more susceptible to climate change damages and have the most evident yield reduction in any of the warming scenarios. Under a uniform warming of 1-2 ºC, most counties in this region are expected to experience yield reduction between 0-5%. The west part of our study region (mostly in Henan province) exhibits a similar pattern as in the north region and both regions are characterized by a shortage of rainfall.

The southeast region (north part of Anhui and Jiangsu provinces) and the coastal part of Shandong province, which have a warmer climate and more abundant rainfall, are projected to gain benefits under moderate warming scenarios. For instance, 1 ºC warming tends to increase yields by 0-5%. Yet under warming of 4-5 ºC damages outweigh benefits and consequently lead to considerable yield reductions. County-level projections with SSPs show a similar pattern yet are more dispersed in space (see figure A7 in the appendix). For instance, yield reductions are expected in the north part in all the SSP scenarios, whereas yield gains are observed in the south part.

Evidence from statistical analysis (Butler and Huybers, 2013) and field experiments (Ristic et al., 1996) for some summer crops (i.e. corn) suggest the existence of a spatial pattern of climate change impacts. That is hotter regions are less sensitive to extreme heat than the cooler counterpart partly because hotter regions have adapted to the hot climate (though such findings were not observed in (Schlenker and Roberts, 2009)). Winter wheat has a different story. As we have shown in previous sections, yield responses to temperature differences across seasons, and winter wheat is vulnerable to both heat in the fall and freezing in the spring. In this spirit, the overall climate change impacts are more important, because climate change not only alters the frequency and intensity of extreme incidences but changes the distribution of moderate temperatures. Our county-level projections show that in terms of the overall effects, north regions tend to experience more evident warming damages than the south and coastal regions. This spatial presentation is consistent with the findings in (Lv et al., 2013), in which the authors concluded that under rain-fed conditions, the future wheat yield tends to decrease in the northern regions while increases in the southern regions.

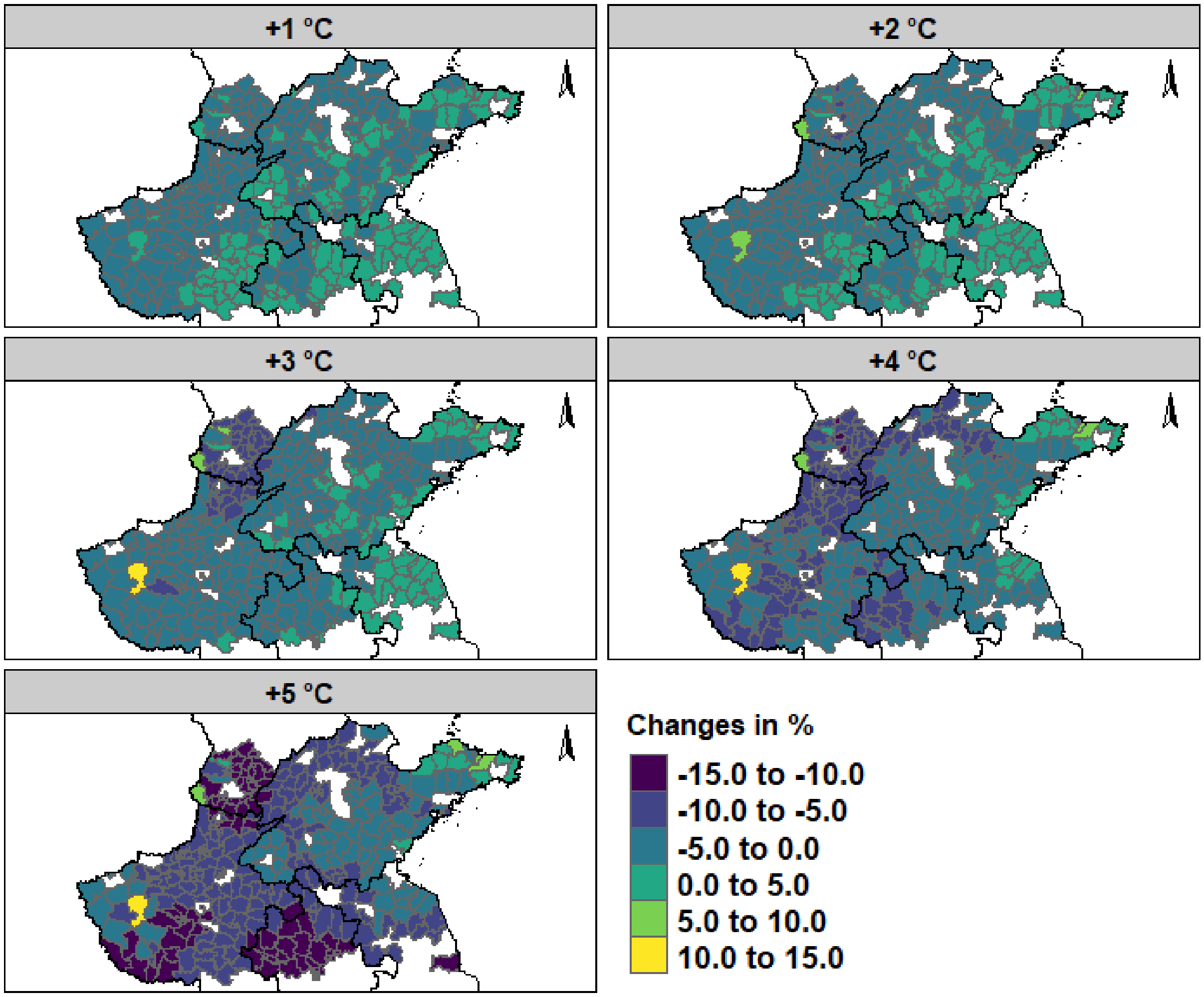

Figure 7 Yield consequences at the county level under uniform warming scenarios. Note: Yield projections were conducted following the same steps in figure 5, except that the projections were shown at the county level.

Conclusion

The agriculture sector is among the most susceptible sectors to climate change. Temperature and precipitation directly enter the production function and are determinants to crop yields. Investigating the impacts of climate change on agricultural productivity is important for developing effective and efficient adaptation strategies which are critical for emerging economies. In this paper, we performed a comprehensive analysis of climate change on winter wheat, the first domesticated and one of the most widely planted food crops globally (Food and Agriculture Organization of the United Nations, 2018).

Specifically, we divided the long growing period of winter wheat into three seasons, fall (Oct-Nov), winter (Nov-Feb), and spring (March-May), corresponding to different growing stages. We first ran piece-wise regressions to identify the appropriate temperature thresholds separately for each season to construct a rich set of degree day variables. Following that, we ran the panel data model with fixed effects to estimate different yield responses to climate across seasons. We explicitly modeled the impacts of heat as well as the impacts of freezing days. We also examine the variation of responses across regions with different climates to reveal possible local adaptations.

Our findings indicate that heat (temperatures over 24 ºC) in the fall and freezing days (temperatures below 0 ºC) in the spring are the most important drivers to yield reductions. 10 degree days increase in temperatures over 24 ºC in the fall and 10 degree days increase in temperatures below 0 ºC in the spring would decrease yield by 11.4% and 11.3%, respectively. Furthermore, the results support our hypotheses of long-turn adaptations. That is heat is less harmful in regions with hot fall and freezing damages are substantially smaller in regions with cold spring. Our preferred model passed a variety of robustness checks and more importantly outperformed a suite of alternative model specifications that were used in previous studies.

The comparison between the separate regressions with observations from 1981-2000 and 2001-2015 reveals a lower bound of adaptation effects to some extent. 10 degree days increase in temperatures above 24 ºC in the fall tends to reduce yield by 14.7% in 1981-2000, whereas the reduction decreases to 4.6% in 2001-2015. The freezing days in the spring season show a yield reduction of 10.3% in 1981-2000, while the effect is reversed to a 0.2% yield gain in 2001-2015.

Finally and most importantly, our yield projections with various climate change scenarios highlight the importance of accounting for the potential benefits stemming from the reduction of freezing days. If such effects were omitted, the assessment of climate change impacts on winter wheat will lead to significantly overstated damages. For instance, our findings suggest that projections omitting the freezing effects indicate a yield reduction of 5.5% under a 1 ºC uniform warming scenario. This number decreases to 0.5% when the freezing effects are accounted for in the projections. The overestimation of warming damages is observed in the rest of uniform warmings (2-5 ºC) and is robust to SSP climate change scenarios, in which case overall yield gains are expected (i.e. a yield increase of 4.5% under SSP126). County-level yield projections show that warming damages are less evident in regions with a warmer and wetter climate. For developing countries, adaptation strategies such as applying irrigation in the fall, moving the major planting areas to warmer regions could be appropriate.

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Appendix

Title: "Are climate change damages on winter wheat yields overstated? Evidence from China"

Date: March 3rd , 2021

Supplementary tables

Table A1 Estimated temperature thresholds for alternative growing periods

September to May	
Season	Thresholds (in ºC)
Fall (Sep-Nov)	17 and 24
Winter (Dec-Feb)	-5 and 8
Spring (March-May)	25 and 30
September to June	
Season	Thresholds (in ºC)
Fall (Sep-Nov)	18 and 23
Winter (Dec-Feb)	-5 and 8
Spring (March-June)	25 and 30

Table A2 Regression coefficients with observations from 1990-2015, the full NCP, and the baseline estimates, respectively

	Winter wheat yields		
	1990-2015	Full NCP	Baseline estimates
	(1)	(2)	(3)
Frez_fall	-0.001 (0.005)	0.004 (0.007)	-0.001 (0.008)
DDlow_fall	-0.002** (0.001)	-0.0002 (0.001)	-0.002 (0.001)
DDmed_fall	0.011*** (0.004)	0.015** (0.006)	0.022*** (0.007)
DDhigh_fall	-0.022* (0.012)	-0.103*** (0.019)	-0.114*** (0.021)
DDlow_winter	0.005 (0.003)	-0.009*** (0.003)	-0.008 (0.006)
DDmed_winter	0.005*** (0.002)	0.013*** (0.003)	0.017*** (0.003)
DDhigh_winter	-0.005 (0.003)	-0.014*** (0.005)	-0.019*** (0.006)
Frez_spring	-0.046*** (0.010)	-0.116*** (0.014)	-0.113*** (0.019)
DDlow_spring	-0.0003 (0.001)	-0.007*** (0.001)	-0.006*** (0.001)
DDmed_spring	0.024*** (0.006)	0.026*** (0.008)	0.037*** (0.010)
DDhigh_spring	-0.076*** (0.013)	0.007 (0.017)	-0.015 (0.020)
County fixed effect	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes
Quadratic time trend	Yes	Yes	Yes
Observations	7,433	11,893	8,867
Adjusted R^2	0.288	0.526	0.527

Note: Column (1) indicates the regression results with data restricted to 1990-2015. Column (2) presents the results with full NCP coverage, i.e. the entire seven provinces and municipalities including Hebei, Beijing, Tianjin, Henan, Shandong, Anhui, and Jiangsu. Column (3) shows our baseline estimates. Standard errors were clustered at the county-level and are shown in the parenthesis.

Table A3 Regression coefficients with separate seasons and all seasons, respectively

	Winter wheat yields			
	Only fall	Only winter	Only spring	Full season
	(1)	(2)	(3)	(4)
Frez_fall	-0.015* (0.008)			-0.001 (0.008)
DDlow_fall	-0.004*** (0.001)			-0.002 (0.001)
DDmed_fall	0.034*** (0.005)			0.022*** (0.007)
DDhigh_fall	-0.125*** (0.017)			-0.114*** (0.021)
DDlow_winter		-0.010* (0.005)		-0.008 (0.006)
DDmed_winter		0.008*** (0.003)		0.017*** (0.003)
DDhigh_winter		-0.008 (0.005)		-0.019*** (0.006)
Frez_spring			-0.119*** (0.021)	-0.113*** (0.019)
DDlow_spring			-0.006*** (0.001)	-0.006*** (0.001)
DDmed_spring			0.047*** (0.008)	0.037*** (0.010)
DDhigh_spring			-0.039** (0.016)	-0.015 (0.020)
County fixed effect	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Quadratic time trend	Yes	Yes	Yes	Yes
Observations	8,867	8,867	8,867	8,867
Adjusted R^2	0.518	0.515	0.521	0.527

Note: Column (1) – (4) corresponds to separate regressions for fall, winter, spring, and all seasons, respectively. Standard errors were clustered at the county-level and are shown in the parenthesis.

Table A4 Confidence intervals constructed from clustering and bootstrapping, respectively

	Winter wheat yields	
	Clustered at county-level	Bootstrapping
	(1)	(2)
Frez_fall	-0.001 (-0.017, 0.014)	-0.001 (-0.017, 0.014)
DDlow_fall	-0.002 (-0.004, 0.0004)	-0.002 (-0.005, 0.0004)
DDmed_fall	0.022*** (0.008, 0.036)	0.022*** (0.008, 0.036)
DDhigh_fall	-0.114*** (-0.155, -0.073)	-0.114*** (-0.155, -0.074)
DDlow_winter	-0.008 (-0.019, 0.003)	-0.008 (-0.019, 0.003)
DDmed_winter	0.017*** (0.010, 0.023)	0.017*** (0.010, 0.023)
DDhigh_winter	-0.019*** (-0.030, -0.007)	-0.019*** (-0.030, -0.008)
Frez_spring	-0.113*** (-0.151, -0.075)	-0.113*** (-0.153, -0.073)
DDlow_spring	-0.006*** (-0.009, -0.004)	-0.006*** (-0.009, -0.004)
DDmed_spring	0.037*** (0.018, 0.056)	0.037*** (0.018, 0.056)
DDhigh_spring	-0.015 (-0.055, 0.025)	-0.015 (-0.053, 0.024)
County fixed effect	Yes	Yes
Linear time trend	Yes	Yes
Quadratic time trend	Yes	Yes
Observations	8,867	8,867
Adjusted R^2	0.527	0.527

Note: Confidence intervals of 95% are shown in the parenthesis. Column (1) indicates the confidence interval calculated using clustered standard errors whereas column (2) displays the confidence intervals constructed from the bootstrapping.

Table A5 The average changes in degree day variables under uniform warming scenarios

Warming scenarios	Fall				Winter			Spring			
	Freezing	*DD_low*	*DD_med*	*DD_high*	*DD_low*	*DD_med*	*DD_high*	*Freezing*	*DD_low*	*DD_med*	*DD_high*
+1 °C	-0.15	4.71	1.10	0.24	-0.80	1.56	0.92	-0.16	8.09	0.77	0.21
+2 °C	-0.25	8.97	2.49	0.58	-1.30	4.16	2.24	-0.24	16.02	1.65	0.51
+3 °C	-0.32	12.94	4.10	1.03	-1.62	7.52	3.95	-0.29	23.73	2.66	0.94
+4 °C	-0.36	16.58	5.93	1.62	-1.82	11.44	6.11	-0.32	31.18	3.81	1.52
+5 °C	-0.37	19.65	7.83	2.33	-1.93	15.29	8.53	-0.33	37.75	4.99	2.20

Note: Changes in degree days are measured in 10 degrees*days.

Supplementary figures

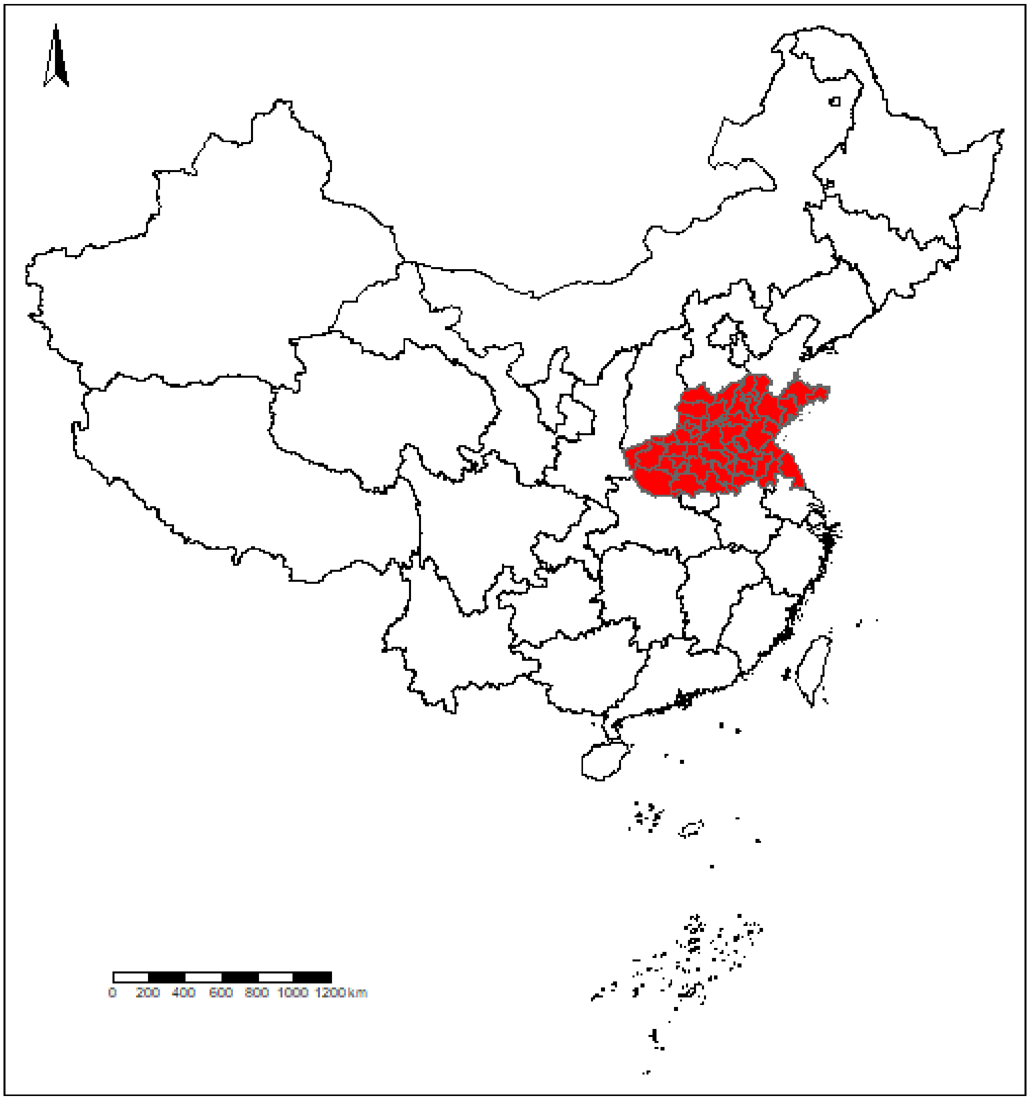

Figure A1 The study region. Note: This region (also known as the "Huang-Huai-Hai" plain) mainly covers the south part of Hebei, most of Henan, the entire Shandong, and the north part of Anhui and Jiangsu.

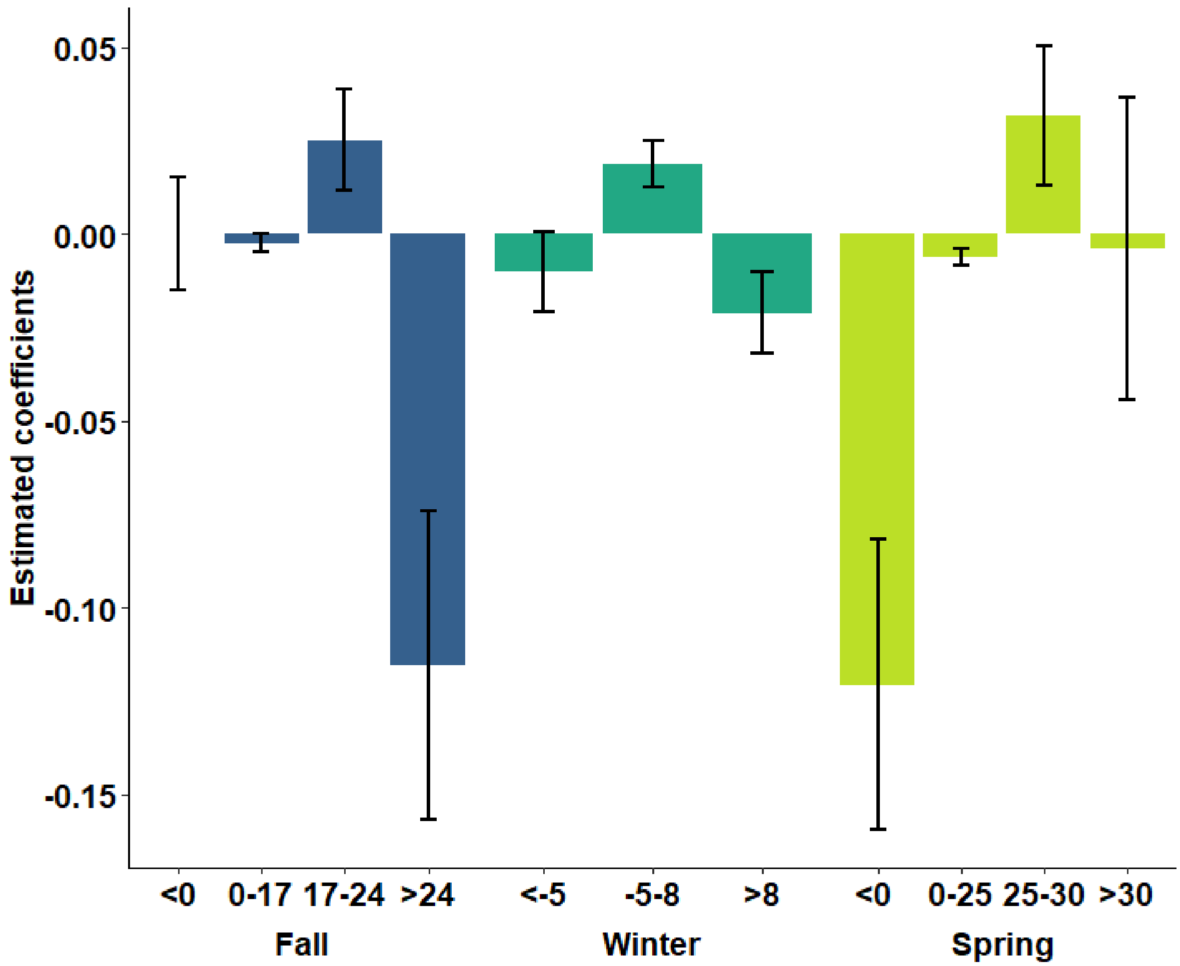

Figure A2 The robustness check with a growing season of Sep-May. Note: The x-axis indicates the degree day variables constructed from the associated temperature thresholds. Bars show the estimated coefficients of the respective degree day variables and the 95% confidence intervals using standard errors clustered at the county-level.

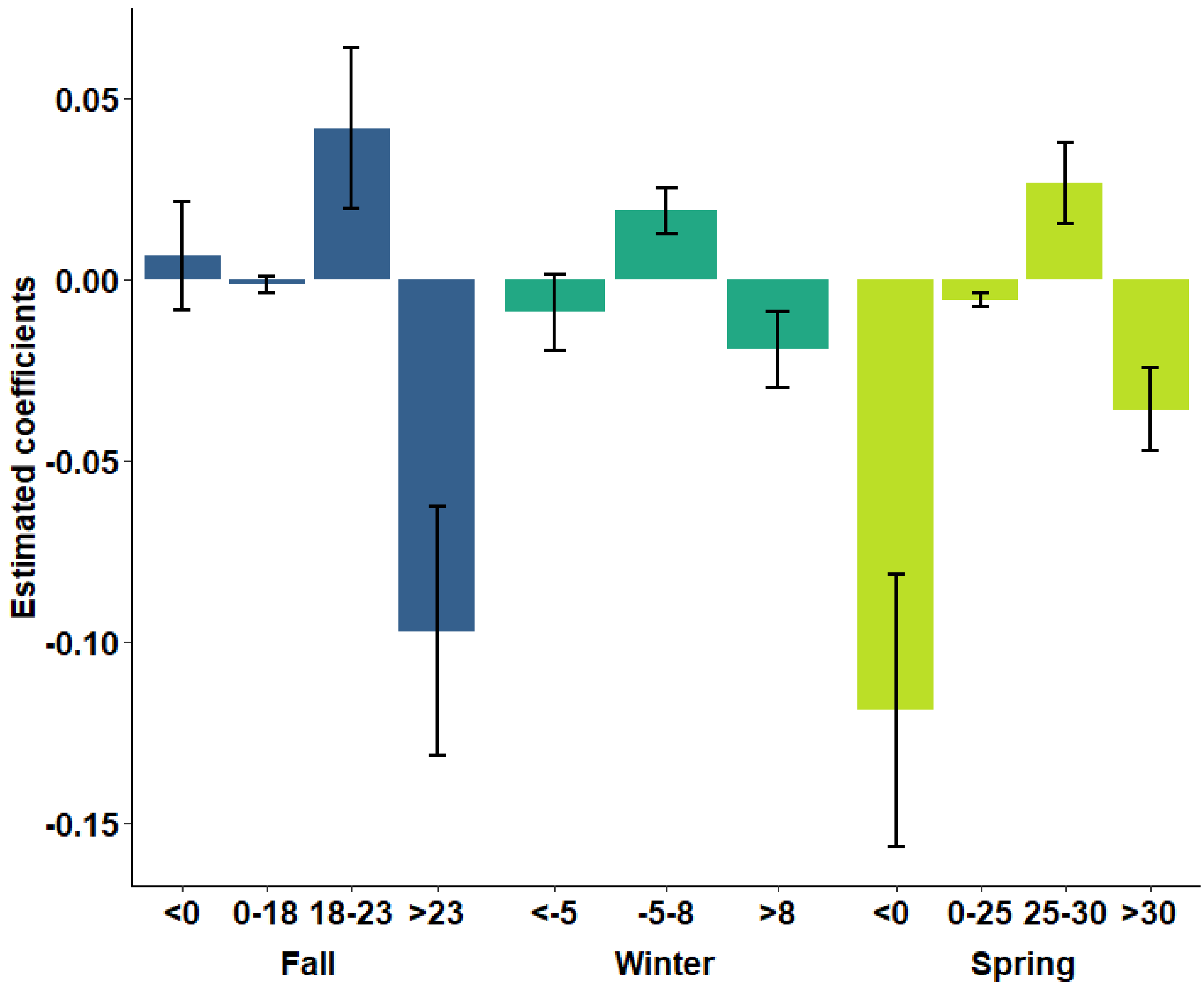

Figure A3 The robustness check with a growing season of Sep-June. Note: The x-axis indicates the degree day variables constructed from the associated temperature thresholds. Bars show the estimated coefficients of the respective degree day variables and the 95% confidence intervals using standard errors clustered at the county-level.

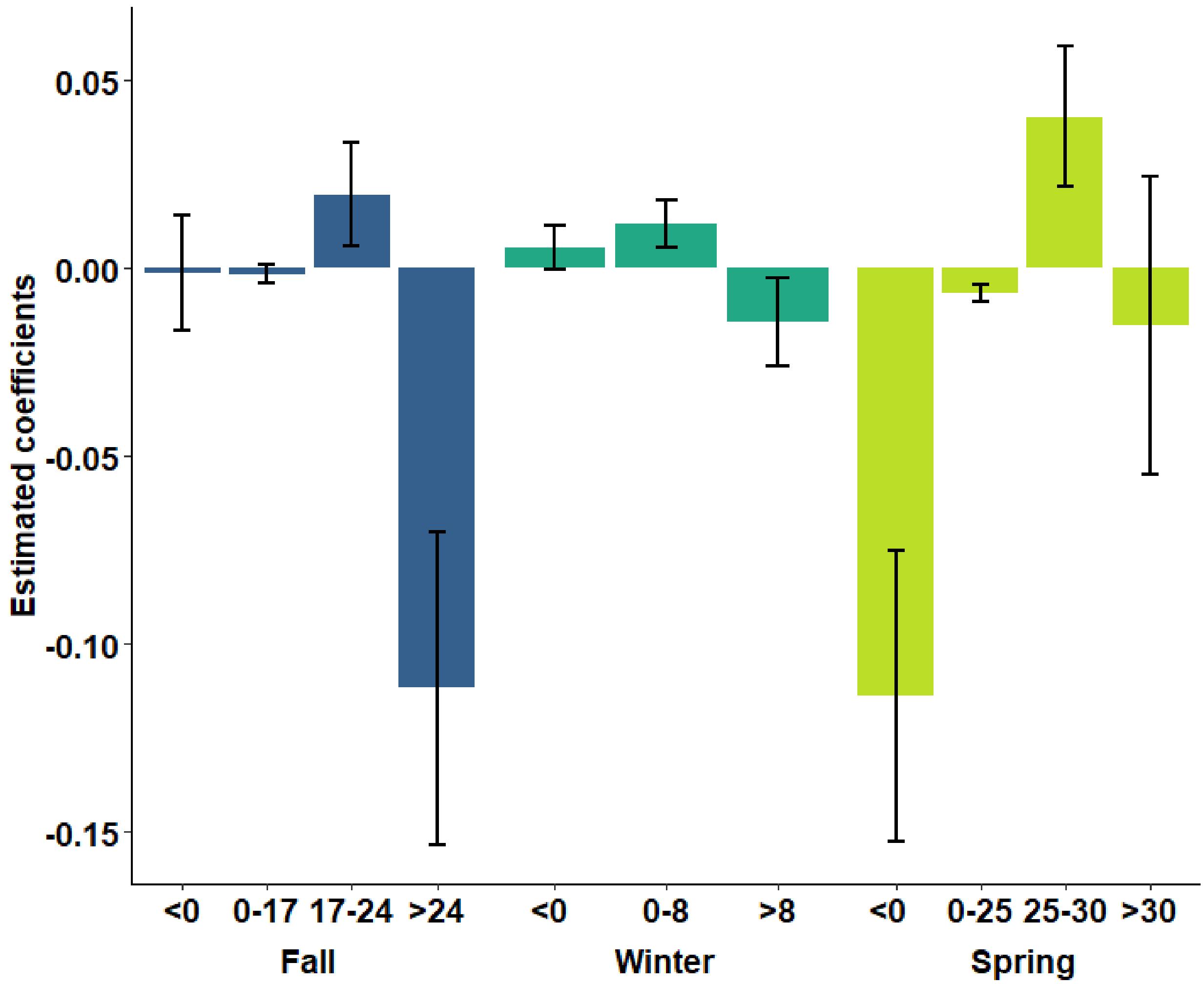

Figure A4 The robustness check with an alternative winter temperature threshold setup. Note: The x-axis indicates the degree day variables constructed from the associated temperature thresholds. Bars show the estimated coefficients of the respective degree day variables and the 95% confidence intervals using standard errors clustered at the county-level.

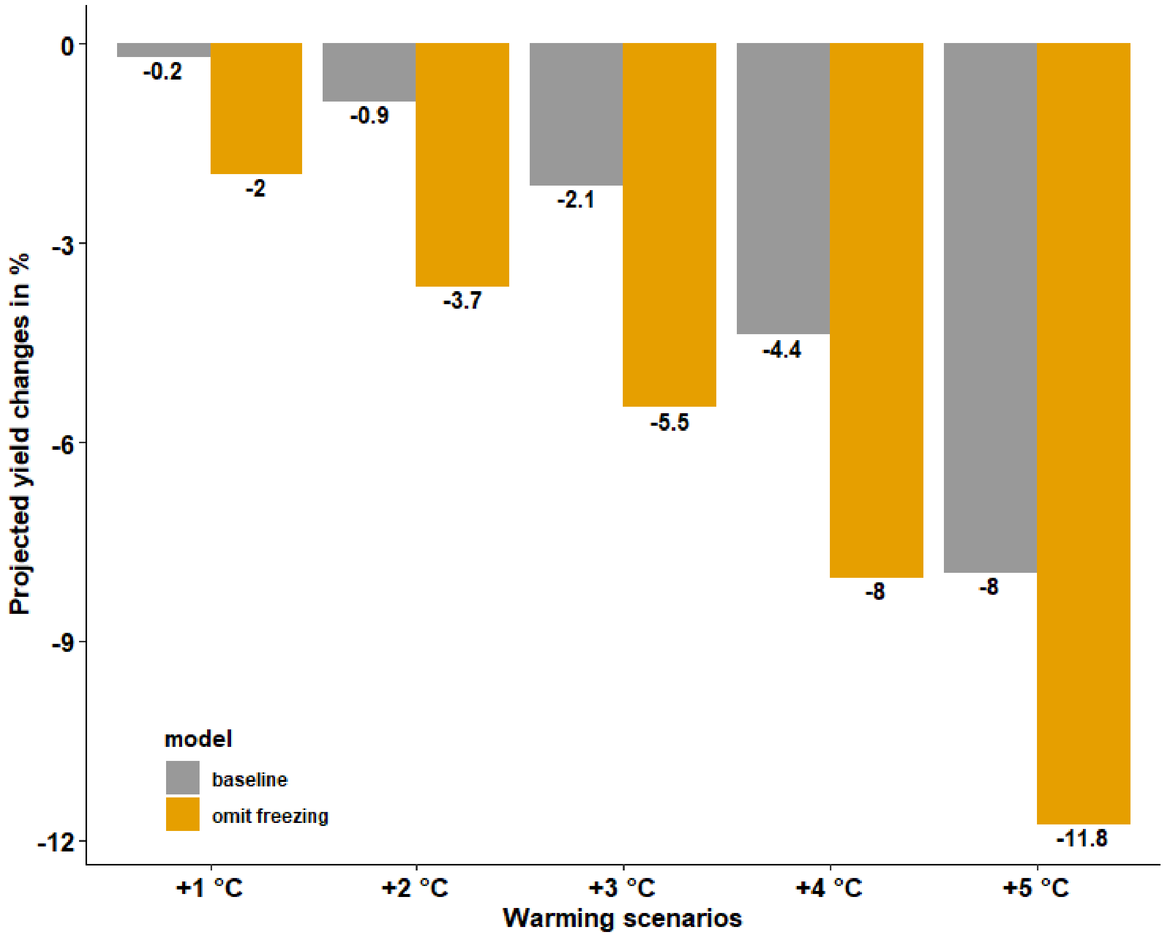

Figure A5 Projected yield consequences with an alternative winter temperature threshold setup. Note: these results were derived following the same steps in figure 5 in the text.

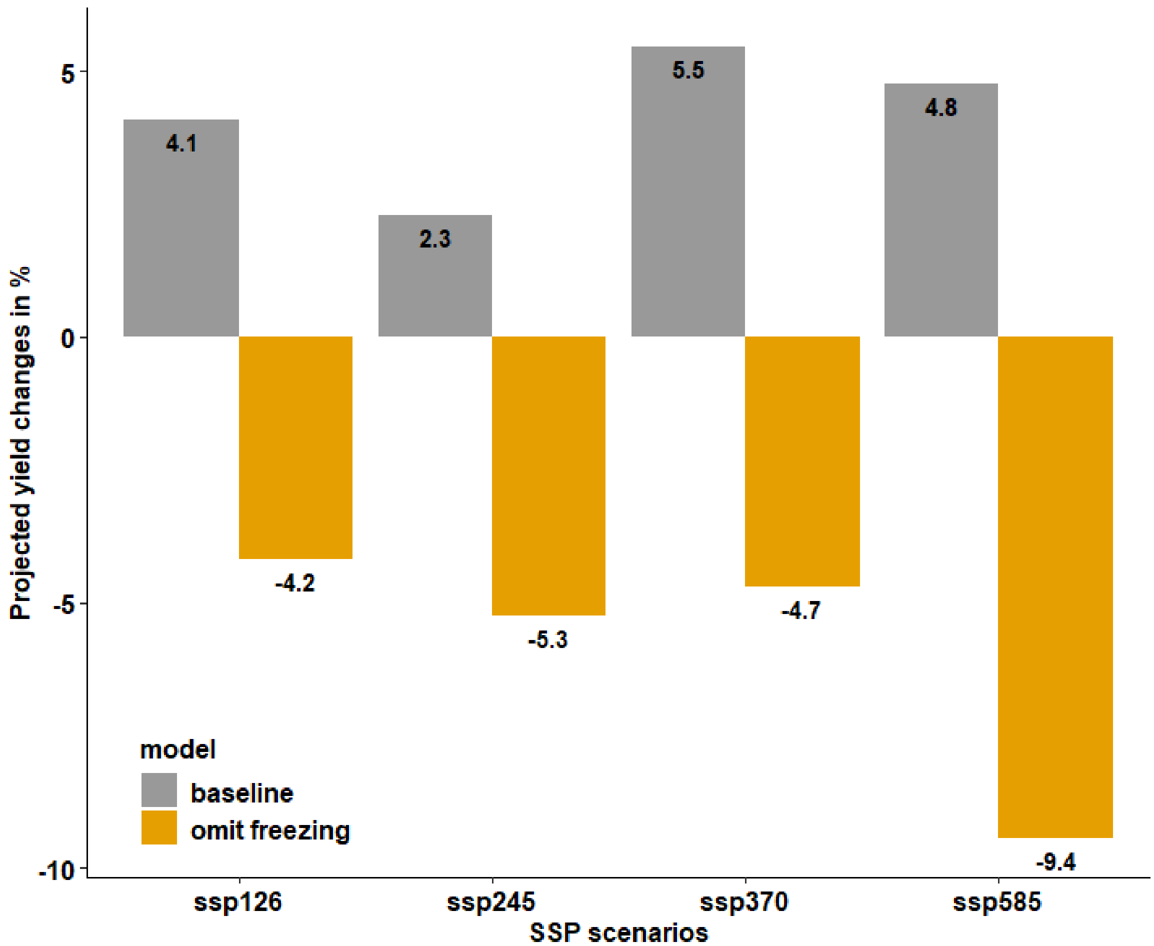

Figure A6 Projected yield consequences under an alternative SSP scenario specification. Note: In this figure, the base for calculating temperature changes is the mean of temperatures between 1970-2000 and the temperatures of 2021-2040 (under the SSP126). Everything else is similar as in figure 6 in the main text.

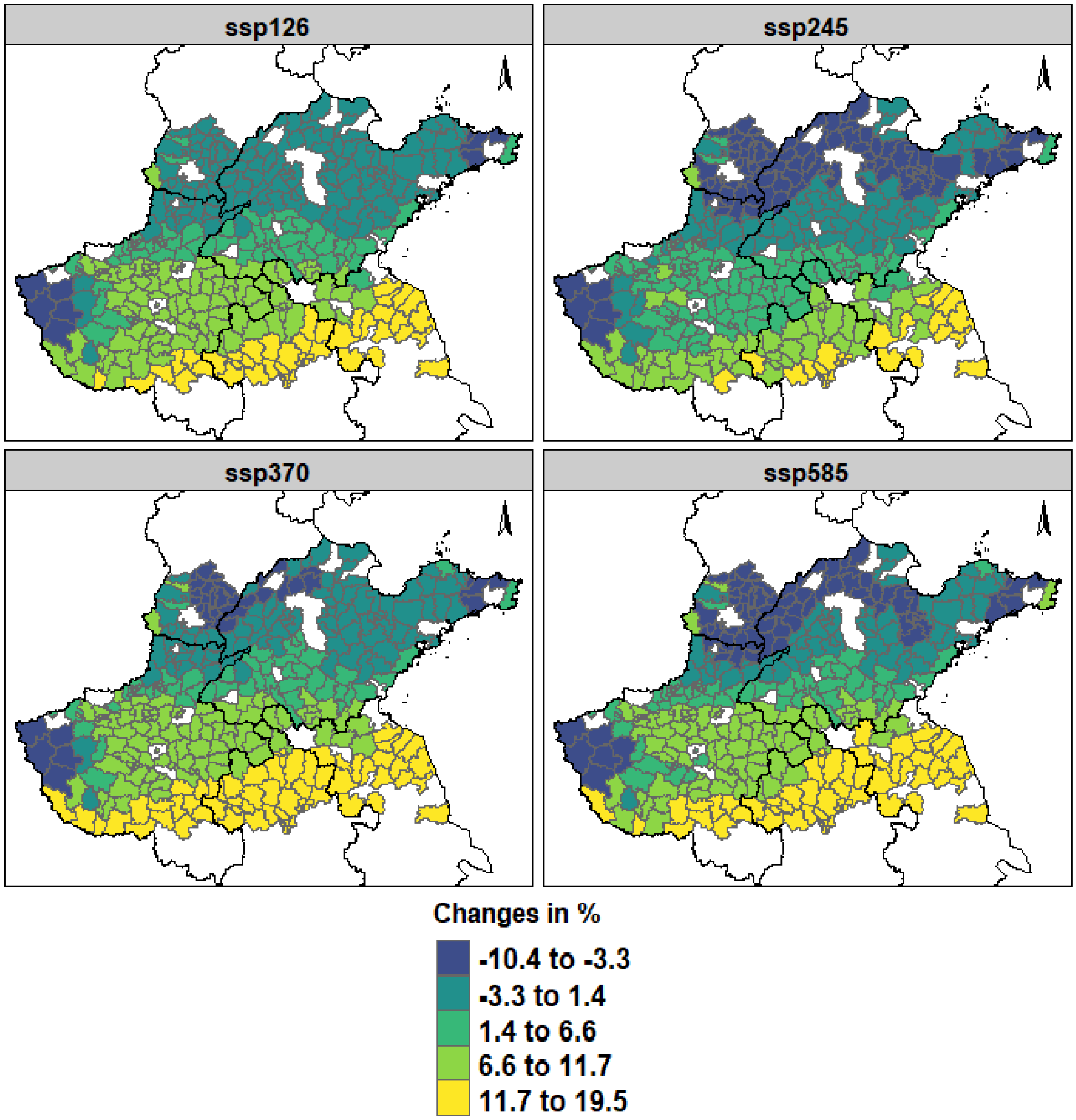

Figure A7 Yield projections with SSP scenarios at the county level. Note: Yield projections were conducted following the same steps in figure 6 in the main text, except that the projections were calculated at the county level.