Differentiated Agricultural Sensitivity and Adaptability to Rising Temperatures across Regions and Sectors in China

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Abstract

Prioritizing efforts that adapt agriculture to a warmer climate requires understanding how different regions and sectors of the agricultural system respond to warming. We assess the regional and sectoral responses in agriculture to rising temperatures using a rich and comprehensive panel of Chinese counties over more than two decades. We leverage temperature variations both from year to year and over multiple-year periods to separately identify short-run and intermediate-run responses. We find that temperature effects vary between northern and southern China, and between sectors (cropping, livestock, forestry, and fisheries). Warming's impacts are concentrated in the cooler northern region, where contemporaneous high temperatures depress both the cropping and livestock sectors but benefit the forestry sector. When intermediate-run adaptations are accounted for, the negative short-run impact of extreme temperatures on the cropping sector can be largely mitigated. But the mitigating effect is limited in the livestock sector. These findings inform the design and ranking of region and sector-specific policies and investments for agricultural adaptation to climate change.

Keywords: climate change, adaptation, temperature, agriculture

JEL codes: O13, Q12, Q51, Q54

1. Introduction

Climate change, one of the most pressing environmental challenges of our time, poses severe threats to global agricultural systems (Calzadilla et al., 2013; Shukla et al., 2019). Unfavorable climatic conditions can hinder the agricultural production that supplies food, fuel, clothing, and shelter to humans (Kirilenko and Sedjo, 2007; Hoegh-Guldberg and Bruno, 2010; Wheeler and Von Braun, 2013). These threats become more significant as global demand for agricultural products increases and diversifies with rising income and rapid urbanization (Tilman et al., 2011; Keating et al., 2014). The sustainability of future economic growth will crucially depend on the resilience and responsiveness of agriculture as the climate warms (Howden et al., 2007). Importantly, the different regions and sectors of the agricultural system vary in their sensitivity and adaptability to global warming. An understanding of these variations is needed to inform the development and prioritization of cost-effective adaptation strategies, especially in developing countries with resource and capability constraints.

This study focuses on China, the world's largest agricultural economy. China is the largest importer and the sixth largest exporter of agricultural products on the globe. In 2019, the total value of its agricultural output exceeded a trillion US dollars, and the total traded value of agricultural products (imports and exports combined) amounted to 230 billion US dollars (MOA, 2019; FAO, 2020). Over the past 70 years, China's annual mean land surface temperature has increased by an average of 0.26°C/decade, substantially exceeding the global average of 0.15°C/decade (CMA, 2021). The impact of rising temperatures on Chinese agriculture, and its ability to adapt to them, matter both for the country's vast domestic population and market, and for billions of people around the world.

In this paper, we provide a holistic empirical evaluation of regional and sectoral sensitivities and adaptabilities of Chinese agriculture to rising temperatures, based on a rich and comprehensive panel dataset drawn from approximately 2,500 counties over more than 20 years. In a panel fixed effect framework, we exploit within-county year-to-year variations in local land surface air temperature distribution to identify short-run temperature impacts on regional and sectoral specific agricultural output values, controlling for other weather variables and nonlinear regional trends. Guided by a conceptual model, we illustrate that the empirical estimates not only reflect physical impacts of temperature on agricultural products, but also carry information, though to a lesser extent, regarding direct and indirect price effects incurred by temperature deviations.

We find that temperature impacts on agriculture are in general more salient in northern China. An additional 24-hours with temperatures above 35°C would lower the aggregate output value of northern agriculture by about 4.95%, relative to the reference temperature range of 10-15°C. This reduction is mostly driven by induced value losses in the cropping and livestock sectors. Unlike in northern China, we do not find significant impacts of temperature on agricultural output values in southern China. These regional and sectoral heterogeneities are particularly meaningful since we would find generally insignificant temperature effects had we aggregated all the regions and sectors for our empirical examination.

We support the value-based sectoral and regional estimates with empirical estimates on the major products in each sector and each region, considering that direct physical impacts still constitute the primary channel through which temperature affects the aggregate output value. To this end, we assess the yield responses of six major crops in the cropping sector, including corn, wheat, rice, vegetables, soybeans, and oil crops. In the other three sectors, we examine the impacts of rising temperatures on the total production of individual products. Major products in the livestock sector include meat, milk, and eggs. In the forestry sector, we analyze several primary and processed timber products (raw logs, sawn logs, chipboard and plywood) and non-timber forest products. Our analysis of the fishery sector considers aquatic products in both freshwater and seawater. In all the four sectors in both northern and southern China, our product-level estimates in general support the value-based results, despite heterogeneities across different products.

Building on our estimated contemporaneous effects, we further explore value responses in the intermediate run, considering that (i) heat impacts may accumulate over years for certain agricultural products, and (ii) meaningful adaptive actions may be induced upon experiencing shocks. Here we rely on three different estimation strategies, including a moving-average specification, a distributed-lag model and a long-difference approach. Building on the empirical estimates obtained from the first two approaches, the contrasts between our short-run and intermediate-run sectoral estimates are contextualized with a set of projection simulations based on hypothetical uniform warming of 0.5°C, 1.0°C, 1.5°C, and 2.0°C, respectively. The results indicate that, although the cropping and livestock sectors in northern China are similarly affected by high temperatures in the short run, the cropping sector is much more resilient in the intermediate run than the livestock sector. The projection simulation based on the long-difference estimates further supports that intermediate-run adaptations can fully mitigate the short-run negative impact in the cropping sector, but the mitigating effect is much more limited in the livestock sector.

This paper contributes to the literature on understanding climatic impacts on agriculture. Previous research has extensively examined the implications of rising temperatures for the cropping sector.[1] However, empirical analysis of other sectors, such as livestock, forestry, and fisheries, remains scant (Carter et al., 2018), despite them jointly contributing nearly 40% of global agricultural output by value (The World Bank, 2020). Overlooking warming's implications for these sectors would preclude a general view of the agricultural system's likely evolution as climates change. Our analysis not only fills this gap by providing estimates on the livestock, forestry, and fishery

[1] There is a long literature on identifying temperature effects on yields and other related margins in the cropping sector, including Schlenker and Roberts (2009), Lobell et al. (2011), Tack et al. (2015), Chen et al. (2016), Miao et al. (2016), Gammans et al. (2017), Cui (2020a, 2020b), Chen and Gong (2021), etc.

sectors in addition to the cropping sector. Moreover, with a unifying framework, our sectoral estimates will allow decision makers to comprehend the relative responsiveness of agricultural sectors to rising temperatures, and to prioritize adaptive efforts and investments. It is also worth mentioning that, without our effort on collecting a comprehensive dataset on the world's largest agricultural economy, this holistic evaluation would not be feasible.

The estimation strategy we adopt in this paper takes advantages of both the Ricardian approach and the panel approach for identifying climatic impacts. Using agricultural output value as the outcome variable enables us to incorporate both direct physical impacts (supply-side) and indirect price effects (demand-side) of temperature on agriculture. It has a conceptual similarity with the existing hedonic studies (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007), while focusing on output values as the variable of interest has excused us from confounding effects arising from induced input adjustments.[2]

Our empirical analysis on the intermediate-run response also builds on the emerging literature on identifying agricultural adaptation to climate change. Our work falls into the group that requires estimates to implicitly account for adaptation.[3] Based on yield measures, Burke and Emerick (2016) devise the "long-difference" approach and find minimal long-run adaptation of US corn and soybean productivity to rising temperatures. Mérel and Gammans (2021) propose a novel estimation strategy to obtain estimates that reflect both short-run response and long-run adaptability.[4] In contrast to Burke and Emerick (2016), the empirical illustration in Mérel and Gammans (2021) suggests that meaningful yield adaptation exists for certain crops in the US and France. Our results on sectoral adaptability, in the context of China, echoes these findings as we

[2] Some recent studies have documented important input adjustments induced by temperature changes, including Jagnani et al. (2021), Aragón et al. (2021), Cui and Xie (2022), etc.
[3] We note that many recent empirical studies focus on explicitly identifying behavioral responses of specific adaptive margins. See Ortiz-Bobea (2021) for an excellent review.
[4] Other similar studies include, for example, Moore and Lobell (2014). It differs from Mérel and Gammans (2021) since the former infers adaptation through a "weather penalty" while the latter through a "climate penalty".

also find intermediate-run adaptability in the cropping sector. However, our findings suggest that cropping's adaptability to warming cannot be directly generalized to other agricultural sectors.

Our key results have important policy implications. In particular, the weaker adaptability in the livestock sector implies that immediate actions should be taken to mitigate the persistent negative impact of warming on this sector. Beyond this sectoral heterogeneity, the north-south regional differentiation in our results is informative for those making concrete adaptation plans for geographically vast countries like China, especially since previous empirical studies have focused exclusively on average temperature effects across the entire country (Chen et al., 2016; Zhang et al., 2016; Chen and Gong, 2021).[5]

The rest of the paper is organized as follows. Section 2 provides necessary background on China's climate and agriculture. Section 3 presents a conceptual model that illustrates the contents of information carried by the empirical estimates. Section 4 introduces our novel and comprehensive datasets. Section 5 discusses estimation of temperature effects on sectoral values, with supporting evidence based on the product-level estimates. The last section concludes.

2. Background

2.1 The North-South Divide

The Huai River-Qin Mountains line (approximately latitude 33° north) was initially proposed as the boundary between subtropical zone and warm temperate zone in China in 1958 by Zhu Kezhen, who was the main founder of China's modern atmospheric sciences and geographic sciences (Zhu, 1958). When drawing the boundary, the principal indicator that he considered was temperature and the division was based on (i) the contour with growing degree days of 4,500 ℃ above 10 ℃, and (ii) a frost-free period of 240 days. It was also the first time to use a rigorous approach for

[5] We note that the empirical studies on the US have paid more attention to the regional divide (the rainfed versus the irrigated) since the discussions in Schlenker et al. (2005).

defining China's temperature zones. From then on, the Huai River-Qin Mountains line has become the geographic divide between northern and southern China and has also been adopted for subsequent agricultural geographic divisions in China. For instance, China's National Agricultural Zoning Committee in 1981 officially adopted the Huai River-Qin Mountains line to define the north-south division of the eastern agricultural zones (CNAZC, 1981).

The Huai River-Qin Mountains line also approximately coincides with China's 0 ℃ January isotherm and the 800 mm isohyet (see the dotted line in Figure 1). There are significant divides in climate, agriculture, culture, and cuisine north and south of the Huai River-Qin Mountains line. With the exceptions of the Qinghai-Tibet plateau and the arid Northwestern regions, most of mainland China is under the influence of the East Asian Monsoon. During the summer, the prevailing winds in China's East Monsoon regions (EMR) are southerly and southwesterly, and the monsoon carries warm and moist air from the Indian and Pacific Oceans. However, much of the moisture falls in southern China before reaching the Huai River-Qin Mountains line. During the winter, strong and stable northwesterly winds, from the east flank of the Siberian high-pressure zone, bring cold, dry air to China's EMR.

[Figure 1 is inserted here]

As a result, most parts of northern China are considerably colder and drier than southern China (Figure 1). During the period 1995-2015, the annual average temperature in northern China varied between -3.4 ℃ (in the coldest county) and 16.5 ℃ (in the warmest county); this is considerably cooler than the equivalent county with annual averages between -0.4 ℃ and 27.2 ℃ in southern China. In terms of rainfall, while the north is relatively drier, precipitation is abundant throughout southern China.

It has been long thought that these climatic differences may have led to considerable differences in agriculture between northern and southern China (Cressey, 1934). For instance, winter wheat is primarily grown in the North China Plain, while Indica rice is mainly produced in southern China. A psychology study finds that the difference in crop choices can explain cultural differences between the residents of northern and southern China (Talhelm et al., 2014). Using a geographic regression discontinuity design based on the Huai River-Qin Mountains line, Wang (2015) find that China's market reform has been more successful in rice-growing regions than in wheat-producing regions. The successful market reform in southern China has greatly boosted the region's economic activities, enabling the region to be equipped with more resources when coping with climate extremes relative to northern China. Moreover, as a region that has been exposed to high temperatures for a long period of time, southern China might have developed some types of adaptation to mitigate thermal stress on the agricultural sector. All these factors may have contributed to the difference in the estimated relationships between temperature and agricultural outcomes. Several recent climatic and agronomic studies also suggest that there exist large differences in the impacts of climate change on China's agriculture north and south of the Huai River-Qin Mountains line (Zhang et al., 2018; Wu et al., 2021).[6]

The Huai River-Qin Mountains line has also been treated as the dividing line to study the geographic differences in outcomes other than agriculture between northern and southern China. For instances, there is suggestive evidence that manufacturing firms adapt to warming differently between two sides of the line (Chen and Yang, 2019). Other studies have also used the difference in heating policies between the two sides to study pollution consequences on life expectancies (Chen et al., 2013; Ebenstein et al., 2017).

[6] Our study differs from these two studies. While our focus is mainly on estimating the relationship between temperature and agricultural output values, Zhang et al. (2018) estimate regional heterogeneity on firms that include agricultural-related industries, but its analysis does not explicitly target on agriculture and Wu et al.(2017) only study the impacts of temperature on maize yield.

2.2 Sectors in China's Agriculture

Chinese agriculture is divided into four broad sectors: cropping, livestock, forestry, and fisheries. Figure 2 shows that, in many regions, cropping accounts for more than half of the nation's total agricultural output by value. Livestock is another major component in China's agricultural economy, contributing approximately one-third to the value of China's total agricultural output. Forestry and fishery outputs account for about 6% and 7% respectively of China's total agricultural output by value.

[Figure 2 is inserted here]

Cropping. China is a leading producer of rice, corn, wheat, vegetables, and soybeans. China produces approximately 30% of global rice production (see statistics reported in Supplementary Table S1). As a water-intensive crop, rice is mostly grown in the south. Wheat, the second most-prevalent field crop in China, has nearly two-thirds of its production in the North China Plain. China grows both spring wheat and winter wheat, with the latter accounting for over 90% of the nation's total wheat production. China is the world's second largest corn producer and the largest importer of soybeans. The vast majority (80% and 68%, respectively) of corn and soybeans are grown in northern China (National Bureau of Statistics, 2021). China contributes to roughly half of the global vegetable production, with its vegetable acreage being split evenly in northern and southern China.

*Livestock***.** China has been the world's largest livestock producer since overtaking the US and Europe in the early 1990s (Bai et al., 2018). Dominating the global pork market, China owns more than half of the global pig inventory, and produced nearly 55 million tons of pork in 2015 (FAO, 2021a). About 63% of China's pork production is concentrated along the Yangtze River (south of the Huai River), while the remaining pork is produced in the north. In 2015, the bulk of China's beef and mutton/lamb (68% and 72% respectively) were produced north of the Huai River, while about 56% of the poultry production in China occurs in the south (National Bureau of Statistics, 2021). Production of milk and eggs, mostly concentrated in the north, had reached 36.6 and 30.8 million tons, respectively, in 2015 (FAO, 2021a).

Forestry. China's forest area amounted to 208 million hectares in 2013. The northeastern region has the country's largest natural forest area, accounting for about 27% of the total forest area (National Forestry and Grassland Administration, 2014). China produces a wide variety of timber products, including both raw and processed timber, and a rich set of non-timber products, including tallow seeds, quince seeds, pine resin, tung oil seeds, and edible fungus. Approximately 43% of China's forestland is state-owned, while the remainder is collectively-owned. State-owned forests are mainly located in the northeastern and southwestern regions, and collectively-owned forestland is concentrated in the south.

Fisheries. China produces roughly one-third of the world's total fishery products, and most of China's fishery production is concentrated in the middle and lower Yangtze valley and the Pearl River Delta of southern China (FAO, 2021b). In 2015, China produced approximately 62 million tons of aquatic products, with seawater and freshwater products accounting for about 52% and 48% of the total aquatic production respectively (National Bureau of Statistics, 2021).

3. Conceptual Framework

We present a simple conceptual model to illustrate the content of information reflected in our empirical estimates discussed later. We define R as the aggregate output by value of a sector in a region, which sums over the output values of all products (indexed by g and $h \neq g$) in the sector of that region, i.e.,

$$R = \sum_{g} p_g\,(q_g, \boldsymbol{q}_h) q_g,$$

where $p_g(q_g, \boldsymbol{q}_h)$ denotes the market price of product g, which depends on its own production q_g and the outputs of other products $\boldsymbol{q}_h$. An exogenous change in temperature (w) affects the aggregate output value by affecting each specific product, i.e.,

$$\frac{\mathrm{d}R}{\mathrm{d}w} = \sum_g p_g \frac{\mathrm{d}q_g}{\mathrm{d}w} + \sum_g \left(\frac{\partial p_g}{\partial q_g} \frac{\mathrm{d}q_g}{\mathrm{d}w} + \sum_{h \neq g} \frac{\partial p_g}{\partial \boldsymbol{q}_h} \frac{\mathrm{d}\boldsymbol{q}_h}{\mathrm{d}w} \right) q_g = \sum_g p_g \left(\frac{\mathrm{d}q_g}{\mathrm{d}w} + \frac{1}{\eta_{gg}} \frac{\mathrm{d}q_g}{\mathrm{d}w} + \sum_{h \neq g} \frac{1}{\eta_{hg}} \frac{q_g}{\boldsymbol{q}_h} \frac{\mathrm{d}\boldsymbol{q}_h}{\mathrm{d}w} \right),$$

where, for product g, η_{gg} and η_{hg} are own-price and cross-price elasticities, respectively.

For any sector, the partial effect of w on the aggregate output value would go through two potential channels. The primary channel is a direct physical effect on the quantity of the product g and $h \neq g$ (represented by $\frac{\mathrm{d}q_g}{\mathrm{d}w}$ and $\frac{\mathrm{d}\boldsymbol{q}_h}{\mathrm{d}w}$). As noted above, agriculture includes four main sectors in our context, namely cropping, livestock, forestry, and fisheries. In China's cropping sector, the top six planted crops are corn, wheat, rice, vegetables, soybeans, and oil crops, which are all annual crops. The direct physical impact of high temperatures on the outputs of a crop is likely to stem primarily from the adverse impact of high temperatures on crop productivity (e.g., yield impacts). In a similar manner, high temperatures may also reduce the outputs of the other three sectors through their physical impacts. For instance, elevated temperatures are expected to reduce the total production of meat products (e.g., pork, poultry, beef), milk, and egg in the livestock sector, by imposing heat stress on livestock animals (Slimen et al., 2016). Several studies find that a warming climate has reduced global fishery output (e.g., fish and mollusk) and forest outputs (e.g., timber) (Cohen et al., 2016, Tian et al., 2016).

In addition to direct physical impacts, w generates indirect effects by influencing product prices and the relative share of different products (represented by $\frac{q_g}{\boldsymbol{q}_h}$). The potential impact mechanism due to price changes includes both the effects transmitted through product g's own price (i.e., $\frac{1}{\eta_{gg}}$) and those through another product h's price (i.e., $\frac{1}{\eta_{hg}} \frac{q_g}{q_h}$ for any $h \neq g$).

Therefore, the extent to which *w* indirectly affects output value of a sector depends on (i) how *w* physically affects each product's output, (ii) the own-price and cross-price elasticities of product *g*, and (iii) the relative share of product *g* with respect to the other products in the same sector. In sum, the impact of temperature on the aggregate output value of a sector is a price-weighted average of product-specific impacts that contain both direct physical impacts and indirect price impacts. However, we note that, with relatively stable demand, the indirect price effects would be salient only if a product is traded in a very thin market and the shock in *w* is excessive and spatially far-reaching.

Illustrated by this conceptual model, the empirical estimates in our framework differ in a few ways from previous estimates in the literature. First, our estimates will provide information on climatic responsiveness beyond those measured only through direct physical impacts (e.g., yield impacts). Moreover, by embedding potential price mechanisms and the relative importance across products, our estimates not only reflect temperature's overall impact on a sector, but also have internalized potential short-run adjustments induced by general-equilibrium price effects within a sector.

We note that it would also be appealing to follow the Ricardian framework and focus on climatic impacts on farm profits (e.g., Deschênes and Greenstone, 2007). We do not take this approach since our data have no sectoral measures of profits, nor do we have detailed information on the prices and quantities of specific inputs (e.g., labor, fertilizer, chemicals). However, our focus on the output values has the advantage of excusing us from the potential confounding effects of input adjustments. To put in another way, our focus on the partial effect of *w* on output values would be equivalent to examining the partial effect on profits had the partial effect of *w* on inputs been muted.

4. Data

4.1 Agricultural Datasets

The National Bureau of Statistics (NBS) provided county-level administrative data on agricultural outputs in mainland China for 2,415 counties over the period 1995-2015. The data measure the real value of each county's total agricultural outputs (in 1990's billion Chinese *yuan*, CNY), which is the sum of the deflated total value of outputs from cropping, livestock, forestry, and fisheries. The definition of these four agricultural sectors is based on the sectoral delineation publicized by the NBS. We focus on the period of 1995-2015 because data prior to 1995 do not report sector specific values, and data after 2015 are not available.

The data also provide additional product-level information for cropping, livestock, and fisheries. On cropping, the data set contains county-specific total crop production (in metric tons) and planted acreage (in hectares) for major food/feed crops. We use these measures to calculate county-level yields of different crops. Major crop categories include rice, wheat, corn, soybeans, cotton, oil crops, and vegetables. For oil crops and vegetables, the data do not detail the specific types of oil seeds or vegetables. For each crop category in each year, we calculate county-average crop yields as the total county-level production divided by their respective planted acreage.

On livestock, the data set reports detailed information on county-level livestock production, including total meat production, total production of pork, mutton, and beef combined, total production of poultry meat, milk and egg (all measured in metric tons), and the total number of pigs slaughtered (measured in heads). On fishery, the county-level statistics report total fish production from freshwater and seawater, and the measures of freshwater aquaculture and seawater catches (all in metric tons).

Lacking county-level forest products statistics, we compile available firm-level statistics covering over 100 state-owned forestry enterprises and wood farms from *China Forestry Statistical Yearbook* over the period of 1998-2010. The firm-level data set reports annual production of five major categories of forestry products, including raw log, saw log, chipboard, plywood, and non-timber forestry products. The first four timber products are measured in cubic meters, and the last category is measured in metric tons. Firm-level forestry production data are aggregated to county-level data, with county-year as the unit of observations.

The regional division we adopt follows the official definition of agricultural zones in *Sustainable Development Plan for China's Agriculture*, a technical document jointly enacted by multiple governmental agencies (see the zones in Figure 1). We exclude the Tibetan conservation zone from our empirical analysis because it covers most of the Qinghai-Tibet plateau where agricultural production is highly fragmented. It is also restricted by conservation policies for both geographical and environmental reasons. Elsewhere, we consider the northern region as the zones of Northeast, Northwest, and Huang-Huai-Hai combined; the southern region is the combined remainder. With the Tibetan zone excluded, this north-south division is almost exactly aligned with the Huai River - Qin Mountains line.

4.2 Climatological Dataset

The National Meteorological Information Center (NMIC), an ancillary institution to the China Meteorological Administration, provided daily weather data from 820 weather stations. These weather stations are widely distributed across mainland China (see Supplementary Figure S1). The data included daily weather measures including minimum, maximum, and average temperatures, total precipitation and sunshine duration, average air pressure, relative humidity, and wind speed. Our main analysis relies on air temperature data to construct temperature variables for all regressions so that the estimates are readily comparable across regions and sectors. We supplement measures of web-bulb temperature following Stull (2011) and Gisbert-Queral et al. (2021) for the livestock sector, and measures of sea surface temperature for fisheries using Merchant et al. (2019).

4.3 Data Linking

The climatological data are spatially linked with the agricultural data. We use the inverse-distance weighting (IDW) method to impute finer-scale weather data for each of the counties included in our county-level agricultural data. Specifically, we use a radius of 200 km surrounding the centroid of a sample county, and compute the weighted averages of weather variables recorded by all weather stations within the circle, weighted by the station's distance to the centroid of the county. This IDW strategy follows previous contextually similar studies (Zhang et al., 2017; Chen and Gong, 2021). It has the advantage of preserving fine-scale variation in weather that enable empirical analysis at a county-level resolution.

The final sample used in our analyses of output values is an unbalanced panel of roughly 40,000 observations over the years 1995-2015. The sample mean of the total agricultural output for a Chinese county is approximately 1.01 billion CNY at 1990's price. In most Chinese counties, cropping and livestock are the two major sectors contributing to the value of agricultural output.

We report summary statistics of the agricultural and climatic variables by region in Supplementary Table S2, and the last column presents the formally tested statistical difference in each variable between the north and the south. It is evident that most agricultural and climatic variables exhibit considerable and statistically significant differences between northern and southern China, consistent with the rationale of historical north-south divide we introduced in Section 2. Supplementary Figure S2, by focusing on the key variables of temperatures, further depicts that the temperature distribution in southern China is considerably higher above that in northern China, with much more days with temperatures above 30 ℃.

5. Estimation and Results

5.1. Differentiated Temperature Sensitivities across Regions and Sectors

We use a bin model under a panel fixed effect framework to flexibly characterize temperature effects on aggregate output values.

$$\log(R_{i,t}) = \sum_{k=1}^{K} \beta_k Tbin_{k,i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \alpha_i + \lambda_t + h_p(t) + u_{i,t} \quad (1)$$

where $R_{i,t}$ represents the aggregate values of agricultural products in county i in year t. $Tbin_{k,i,t}$ is a set of temperature variables that measure the number of days with daily temperature falling into a specific bin. To maintain useful information on diurnal variation in daily temperature, we conduct a sinusoidal interpolation between daily maximum and minimum temperatures before forming the temperature bins.[7] We would have lost very meaningful information, especially on the impacts of higher temperatures on agriculture, had we used daily average temperatures instead. With this interpolation, our estimated marginal effect essentially reflects the impact of changing a 24-hour's temperature. For convenience, we use "one day" to represent the 24 hours in the following discussions.

In our baseline specification, we set up 5 ℃ bins with the first and last knots being 0 ℃ and 35 ℃. The first bin therefore corresponds to temperatures below 0 ℃ and the last bin accounts for temperatures above 35 ℃. This choice of bin size accommodates both our demand for flexibility and our concern that multicollinearities might arise from using narrow bins.[8] In estimation, we omit the bin for 10-15 ℃ to set it as the reference. We choose 10-15 ℃ since all counties in our sample have experienced temperature within this range in all years.

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[7] The sinusoidal interpolation essentially allows for a portion of a day to be counted toward a certain temperature bin.

[8] Carter et al. (2018) point out the potential issue of regressor multicollinearity when using narrow bins to identify nonlinear temperature effects, especially when the bins are formed based on within-day temperature interpolation. See section 4.1 in Carter et al. (2018).

We acknowledge that degree days, which accumulate heat over certain temperature ranges within a certain time window, have been a commonly adopted measure of temperature in previous studies estimating climate-crop yield relationships. However, in our setting, temperature bins formed over the whole year are preferred, and this modelling choice is rooted in our objective. Here we are not quantifying the climatic response of a single product, and our use of the value-based measure incorporates the value of outputs that can be produced over different time periods during a year.[9] Besides, using flexible bins does not require imposing pre-determined crop-specific temperature thresholds that are necessary for defining degree days. It also allows us to capture the full temperature distribution within a year; lower temperature bins mostly reflecting cold periods like winter, and the higher temperature bins mostly reflecting hot periods like summer. Any β_k identified through estimation represents the percentage change in the output value induced by exposure to one more day of temperature within the kth temperature bin, relative to the exposure to the reference bin of 10-15 ℃.

The vector $\mathbf{X}_{i,t}$ holds a set of control variables including total precipitation and sunshine duration, as well as average relative humidity, air pressure and wind speed, all at annual level. We include linear and quadratic terms of these variables to allow for potential nonlinear effects. For the rest of the terms, α_i is a county fixed effect that absorbs time-invariant county characteristics; and λ_t is year fixed effect that captures location-invariant time shocks. In addition, we control for regional trends by specifying provincial-level linear and quadratic time trends in $h_p(t)$, following the convention in the climate-agriculture literature (e.g., Schlenker and Roberts, 2009; Chen et al., 2016). $u_{i,t}$ is the error term.

With the control variables and regional trends under this county fixed-effect framework, the identification of temperature effects exploits exogenous, location-specific year-to-year variations

[9] For instance, the growing seasons of winter wheat and soybeans cover different periods in a year, and livestock production takes place throughout the whole year.

in a county's intra-annual temperature distribution. Since both spatial and serial correlation and heteroscedasticity exist in the error structure, our inference is based on a two-way clustering strategy (Cameron et al., 2011). Specifically, we cluster our standard errors by counties and by province-by-year pairs.

We first conduct regressions on data from all counties without distinguishing northern and southern regions. Using the flexible bin estimation, we find that temperature has no significant impact on the aggregate output value if Chinese agriculture is considered as a whole. In the first plot of panel A in Figure 3, we show that most of the bin estimates are very close to zero. Although one more day in the 30-35 ℃ bin is associated with a 0.60% reduction in the aggregate output value, this impact is statistically insignificant even at the 90% confidence level.[10]

[Figure 3 is inserted here]

The non-response of the aggregated value to temperature is partially masked by the response heterogeneity across specific sectors in agriculture. As we show in the other four plots of panel A in Figure 3, high temperatures significantly decrease the output values in cropping and livestock sectors, while their impacts are rather muted in forestry and fishery sectors. Specifically, one more day in the 30-35 ℃ bin reduces the output values in cropping and livestock sectors by 0.62% and 0.61%, respectively. The marginal effect is even larger on the livestock sector when temperature is above 35 ℃ compared to the impact with a day in the 30-35 ℃ bin (-0.76% versus -0.61%).

The differentiated impacts of temperature shown in panel A of Figure 3 illustrate strong heterogeneity across specific sectors in response to increasing temperatures. Had we not disaggregated the total output values of all agricultural products, we could have been misinformed

[10] Using county-level data in China, Chen and Gong (2021) show that high temperatures significantly reduce agricultural yields (measured in per-acre output values) for the entire China. We reconcile their results with ours through a set of replications. See details in Appendix G.

by the non-response of the aggregated value and neglected the important distributional impacts across specific sectors in agriculture.

Still, recognizing sector-specific sensitivity does not diminish need to explore region-specific sensitivity to temperature fluctuations, especially since China's vast territory features a substantial north-south divide in both climatic endowment and agricultural development. Therefore, in panels B and C of Figure 3, we report region-specific estimates obtained from bin regressions on the northern and southern samples, respectively.

In panel B of Figure 3, we show that temperatures higher than 35 ℃ have strong negative impacts on the aggregate agricultural output value in the north. Our point estimate indicates that one more day with temperatures over 35 ℃ reduces the total output value by about 4.95%. This large negative impact of extremely high temperatures is constituted of the impacts on cropping, livestock, and fishery sectors. Specifically, one more day with temperature over 35 ℃ is associated with output value losses of 2.58%, 2.61%, and 2.11% for these three sectors, respectively.[11] Moreover, although not reflected in the estimates of the aggregate impacts, temperatures above 25 ℃ start to have significant negative impacts on both cropping and livestock sectors. Specifically, one more day within 25-30 ℃ decreases the output values in cropping and livestock sectors by 1.05% and 0.91%, respectively. The negative impacts become larger, at 1.44% and 1.31% for a day with temperature in 30-35 ℃ for these two sectors.

The responsiveness of agricultural output values in the south sharply contrasts with that in the north. Panel C in Figure 3 depicts that none of the bin estimates is statistically significant when the outputs are either aggregated or measured for a specific sector. We also formally test the north-

[11] Our point estimate of the highest temperature bin on aggregate output value indicates that one more day with temperatures over 35°C reduces the total output value by about 4.95%. But we note that this estimate is less precisely estimated with a wide 95% confidence interval, and it does not statistically differ from the corresponding point estimates on cropping, livestock, and fishery sectors.

south contrast in their agricultural value responses to high temperatures. We conduct our tests using two different interactive specifications: (i) interacting all temperature bins with a regional dummy, i.e.,

$$\log(R_{i,t}) = \sum_{k=1}^{K} \beta_k Tbin_{k,i,t} + \sum_{k=1}^{K} \theta_k North_i \times Tbin_{k,i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \alpha_i + \lambda_t + h_p(t) + u_{i,t}$$

and (ii) interacting all weather variables with a regional dummy, i.e.,

$$\log(R_{i,t}) = \sum_{k=1}^{K} \beta_k Tbin_{k,i,t} + \sum_{k=1}^{K} \theta_k North_i \times Tbin_{k,i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + North_i \times \mathbf{X}_{i,t}\boldsymbol{\varphi} + \alpha_i + \lambda_t + h_p(t) + u_{i,t} \ .$$

In these equations, $North_i$ represents the northern indicator. The identified θ_k and $\boldsymbol{\varphi}$ capture the north-south disparity in responses of agricultural output values to temperatures and other weather variables, respectively. Our results in Table 1 show consistent evidence that rising temperatures indeed affect agricultural values differently between northern and southern China, with high temperatures above 35 ℃ causing a significant damage to agricultural output values in the north.

Taken together, the results in Figure 3 reflect that the negative impacts of high temperatures on agriculture in China are mostly driven by their impacts in the northern areas, and in particular by their impacts on the cropping and livestock sectors.[12] We also conduct a series of sensitivity checks on these results. In Appendix A.1, we show that these findings are robust to different widths of the temperature bins. In Appendix A.2, we show that the patterns of the estimates remain even if we alter the specifications of weather controls and regional time trends. In Appendix A.3, we further evaluate the appropriateness of our two-way clustered inference by discussing results using one-way or alternative two-way clustering strategies. Our baseline findings remain robust to these variations in temperature bin widths, weather controls, specifications, and clustering strategies.

[12] Previous discussions on agricultural adaptability in southern China point to the abundant water resources of this region, pre-existing adaptations of cropping systems (e.g., double cropping), technology adoption (e.g., heat-tolerant seed varieties), and productive efforts (e.g., farm management). See, for example, discussions in Huang et al. (2015). We support these north-south differentiation with a rich set of product-level estimates in the next section.

5.2 Product-specific Estimates and Within-sector Heterogeneity

The estimates of the temperature impacts on total output values we have shown represent the overall responses of all value-based gross products of a sector in agriculture to rising temperatures. As we illustrated with the conceptual model, these estimates integrate both direct and indirect temperature effects on different agricultural products in the same sector. Estimating the indirect effects of temperature on output values through product price changes is infeasible due to the lack of county-level product-specific price data. In this section we focus our attention on examining the direct physical impacts of temperature on major agricultural products, which is also the first-order effect of temperature on the aggregate agricultural output values.

Utilizing available information on specific agricultural products, we assess how different major products in a sector respond to temperature fluctuations. This analysis serves for two purposes. First, the product-specific estimates should provide supportive evidence on regional and sectoral responses we identified in the baseline estimation. Second, the potential response heterogeneity across different products within the same sector would shed lights on understanding the driving forces of temperature impacts on a given sector.

For consistency in interpreting the results, we use the same right-hand-side specification as in our baseline estimation for the product-level analysis, and we replace the dependent variable with the product-specific metric in logarithm. Given the substantial differences between the north and the south, we conduct product-level regressions for the two regions separately.

Cropping. For the northern region, we focus on the five most widely planted crops: corn, wheat, rice, vegetables, and soybeans.[13] For these crops, we use logarithmic yields as the dependent variable, constructed by dividing the crop-specific total outputs (in weight) by its total planted

[13] In the north, the mean acreage share of corn, wheat, rice, vegetables, and soybeans in total planted acreage was 24.6%, 22.8%, 7.9%, 7.2% and 7.3%, respectively, over the 1995-2015 period.

acreage in a county in a year. In panel A of Figure 4, our bin estimates suggest that, in northern China, 30 ℃ is a critical temperature threshold for crop growth, and higher temperatures above 30 ℃ have significant negative impacts on the yields of corn, wheat, and soybeans, but its impacts on rice and vegetables are insignificant.

[Figure 4 is inserted here]

The yield reduction associated with one more day with temperature in 30-35 ℃ is about 1.03% for corn and 1.73% for soybeans. On these two crops, the estimates of the last bin are negative but statistically insignificant, likely due to the lack of statistical power as temperatures above 35 ℃ are relatively rare for most of the corn and soybean growing areas in the north (i.e., Northeast; see Supplementary Table S3).

Wheat in the north also displays its sensitivity to high temperatures. On one hand, warming starts to reduce wheat yields when temperature reaches 25 ℃, and the marginal effect of the 25-30 ℃ bin amounts to -0.50%. On the other hand, the magnitude of the temperature impact on wheat is also larger when temperature is above 35 ℃. For one more day with temperature above 35 ℃, wheat yields decline by about 1.31%, reflecting the detrimental impacts of extremely high temperatures that have frequently occurred in the major wheat-producing region (i.e., Huang-Huai-Hai Plain; see Supplementary Table S3).

Among the top-five crops in the north, rice and vegetables are relatively insensitive to high temperatures, as their estimates associated with the high-temperature bins are statistically insignificant.[14] Comparing with corn, wheat, and soybeans, these crops are better shielded from the damages of high temperatures in northern China by facilities like irrigation. Research shows

[14] We note that the highest-bin estimate on rice is negative and large in magnitude, but it is statistically insignificant. Some evidence has shown that rice yields are damaged under excessively high temperatures, even with irrigation buffering the heat impact (for example, see Wassmann et al., 2009). But, statistically speaking, we cannot confirm this in our empirical context.

that the irrigation ratios for rice and vegetables are around 90%, while those for corn, wheat, and soybeans are below 45% (Huang et al., 2006).

Although response heterogeneity exists across the five major crops, the crop-specific estimates in general support the value-based responses identified on the cropping sector as a whole. Specifically, our estimates suggest that the economic losses in cropping associated with high temperatures above 30 ℃ in the north is largely driven by the yield reductions in corn, wheat, and soybeans. The critical temperature threshold (30 ℃) identified here is broadly consistent with previous findings on yield-temperature relationships in China (Chen et al., 2016; Liu et al., 2014) and in the US (Schlenker and Roberts, 2009). Chen et al. (2016) find that corn and soybean yields in China increased with temperatures up to 29 ℃ and 28 ℃, respectively, and temperatures above these thresholds have large detrimental impacts on yields. Liu et al. (2021) show that each additional day with daily maximum temperatures above 30 ℃, can reduce winter wheat yields by 2.0-4.0% in major wheat producing regions of northern China, while the corresponding temperature impact is negligible in southern China.

As shown in panel B of Figure 4, we do not find significant temperature impacts on major crop yields in southern China. For the five most widely planted crops in the south: rice, vegetables, oil crops, wheat, and corn, [15] almost all the high-temperature bin estimates are statistically insignificant, and their point estimates are also closer to zero when comparing with their counterparts of the northern estimates. These results are consistent with the null response of cropping output values to high temperatures in the south.

We note that our estimations of temperature effects on crop yields are based on temperature bins formed over the entire year. This would be problematic and invites substantial measurement errors

[15] In the south, the mean acreage share of rice, vegetables, oil crops, wheat, and corn in total planted acreage was 33.5%, 11.3%, 2.5%, 8.4% and 8.1%, respectively, over the 1995-2015 period.

had we estimated the effects with annual average temperatures. But our use of the flexible bins assuages this concern. By focusing mostly on high temperatures, our bins are able to characterize the proportion of extreme heat for bins constructed over the entire year, the majority of which is accumulated in summer during which most crops still grow. Thus, our bin specifications can effectively capture the effects of high temperatures on crop yields. Nevertheless, in Appendix B, we estimate a set of bin regressions using bins constructed over a more narrowly defined period of growing season. Because most crops accumulate heat for crop development from spring to fall. We therefore form an encompassing and generalized growing season covering March-October and reconstruct our temperature bins over this growing season. Indeed, these additional results, on both values and crops, are highly consistent with our baseline estimates.

Livestock. We collect several quantity measures of livestock production, including total meat production, total production of pork, mutton, and beef combined, total poultry meat production, total number of slaughtered pigs, and the production of milk and egg. We implement the baseline bin estimation using the log-transformed quantity measure of each available product variable. Measured in physical units, the temperature sensitivities of major livestock products are generally consistent with the value-based sensitivities. This is despite the within-sector heterogeneity in northern China.

[Figure 5 is inserted here]

We do not find that high temperatures significantly affect the total meat production in the north. The first plot of panel A in Figure 5 shows that the bin estimates are close to zero and statistically insignificant. This null effect remains when we narrow down the measurement of meat production to the portfolio that consists of pork, mutton, and beef and to pig slaughters. However, when focusing on poultry meat, temperatures above 35 ℃ do have large negative impacts, but these are imprecisely estimated.

Among the products with available quantity measures, milk production is the one for which there is clear evidence of a negative impact of high temperatures in northern China. One more day with temperatures above 35 ℃ lowers total milk production by 2.11% and this estimated effect is statistically significant at the 5% level. Dairy cattle exhibits strong sensitivity to heat stress due to their high metabolic rate during lactation (Das et al., 2016). The heat-induced reduction is thus likely caused by the impact of heat stress on the behavioral and biological functioning of dairy cattle (Polsky and Keyserlingk, 2007). Our finding of a strong negative impact of high temperatures on milk production is in line with the results summarized in a meta-analysis by Henry et al. (2018). A recent study by Ranjitkar et al. (2020) also documents a negative correlation between heat stress and milk production in major milk production regions in China. This large negative impact in the north is especially meaningful since northern China contributes approximately 90% of China's domestic milk production (National Bureau of Statistics, 2021).

The temperature effects on the livestock sector in the north, reflected in the sector-level value-based estimates in panel B of Figure 3, are generally supported by the product-level estimates we show in panel A of Figure 5. Similarly, the null effect on the total output value in the livestock sector in the south (panel C of Figure 3) is largely consistent with the product-level estimates (panel B of Figure 5).

Our baseline estimates reflect the partial effects of air temperature on livestock values and products, controlling for confounding effects of other weather variables. This modelling choice is made to facilitate comparisons of the temperature effects more effectively across different sectors. However, particular interests have been developed in understanding the combined effects of temperature and humidity in the research community (e.g., Gisbert-Queral et al., 2021). We therefore supplement a set of regressions using bins constructed based on web-bulb temperatures in Appendix C. It is worth noting that the web-bulb temperature bin estimates would not be directly comparable with our baseline bin estimates since they carry different information on the sources of the impacts. While our baseline estimates reflect the partial effect of temperature, the estimated effects of web-bulb temperatures reflect the combined effects of temperature and humidity. Nevertheless, our web-bulb temperature estimates still suggest that the northern livestock sector is more sensitive to rising temperatures than the south. We provide more detailed discussions on the web-bulb temperature results in Appendix C.

Forestry. The county-level statistics do not report detailed information on forestry products. To provide supporting evidence based on the product-level estimates, we turn to another data source that compiles firm-level statistics for more than 100 state-owned forestry enterprises and wood farms in China. The data set includes annual records of selected forestry products at the firm level over the period of 1998-2010. We spatially match the locations of these firms with weather information in their residing counties and aggregate the firm-level data to the county-level. Following our baseline estimation strategy, we estimate nonlinear responses of several major products, again using the log-transformed quantity as the dependent variables, to temperature fluctuations using the 5 ℃ bin regressions.

Our estimates provide suggestive evidence that high temperatures above 35 ℃ tend to reduce the outputs of raw forestry products such as raw and saw logs, while their impacts on more processed products and non-timber products are mixed. The negative responses of raw forestry products to high temperatures may reflect temperature-related fire and insect damages (Kirilenko and Sedjo, 2007) and labor productivity losses (Zhang et al., 2018). This finding is also in agreement with the results summarized in a report released by FAO that documents that a warming climate contributes to reduced productivity and dieback of trees in many regions around the world (FAO, 2015). We acknowledge a caveat that, due to the small sample size, these firm-level results are relatively noisy and they could be sensitive to potential outliers. We therefore present these results and provide more detailed discussions in Appendix D.

There is limited firm-level data on forestry enterprises and wood farms located in southern China. This has prevented us from implementing the same regression analyses on forestry production in the south. But an additional analysis based on provincial aggregates of wood production suggests that temperature fluctuations do not significantly affect forestry output in the south (see Supplementary Table S4).

***Fisheries*.** We put together available county-level statistics and provide more specific estimates within the fishery sector. Our data have separate quantity measures on total fish products from freshwater and seawater, respectively. In addition, the data record the tonnages of freshwater aquaculture (fish farming) and seawater catches. It is worth noting that the seawater products are concentrated in the coastal counties, and the total number of observations of seawater variables are much smaller than those of the freshwater variables. Using log-transformed quantity measures as the dependent variables, we conduct our baseline bin estimations on the four separate measures. Because exposures to the highest temperature bin are very sparse, especially in the case of seawater observations, we set the last temperature bin as temperatures above 30 ℃ when implementing these regressions.[16]

[Figure 6 is inserted here]

We present the bin estimates in Figure 6. Like the sectoral value-based estimates, the results in panel A of Figure 6 show that fishery production exhibits temperature sensitivities only in northern China. Within the northern fishery sector, seawater products are more sensitive than freshwater products to high temperatures. Both seawater catches and total seawater fish production display

[16] We also provide additional results with the highest bin included, shown in Supplementary Figure S3. The estimates of the highest bins are very imprecise for seawater regressions.

negative associations with increasing temperatures. Specifically, one more day with temperatures above 30 ℃ is associated with a 2.57% reduction in the quantity of seawater catches, and the associated reduction is quantitatively similar on seawater fish production. Freshwater aquaculture (fish farming) and total freshwater fish production receive minimal impacts from changing temperatures in northern China.

These findings are consistent with the large literature linking temperature with aquaculture production, which finds that, in comparison to freshwater species, production of marine species is more likely to be adversely affected by rising temperatures (Frost et al., 2012). That is because higher temperatures can lower dissolved oxygen concentrations in seawater and reduce seawater salinity, both of which are essential for the growth performance of marine species. In contrast, freshwater products are found to be more vulnerable to water pollution than higher water temperatures (Mugwanya et al., 2022). Unlike the northern estimates, the southern estimates suggest that both freshwater and seawater products are rather insensitive to temperature changes (see results in panel B of Figure 6). This north-south contrast is again consistent with our earlier value-based sector-level estimates.

These baseline estimates of the fishery sector characterize the marginal effects of rising air temperatures on fishery production. These estimates reflect a general relationship between the level of hotness and its local fishery outcomes that can facilitate comparisons across regions and sectors. However, it is worth examining the effects based on temperature measures that are more directly linked to fishery products, especially for seawater products. Thus, we further evaluate the robustness of our seawater product results by using sea surface temperatures to construct bins. Specifically, we extract 0.05 °×0.05 ° grid-level daily sea surface temperature data from Merchant et al. (2019) and spatially match them with coastal counties in our agricultural dataset. Our additional results based on sea surface temperature bins support the north-south contrast in our main findings on fishery products. We provide detailed discussions on the data processing as well as interpretation of the results in Appendix E.

5.3 Intermediate-run Impacts on Agricultural Output Values

In this section, we complement our value-based contemporaneous temperature estimates with a set of intermediate-run estimates on the regional and sectoral values. In particular, we focus on the north since our earlier results indicate that the northern agriculture is more affected by contemporaneous temperature changes relative to the south, while we report and discuss the counterpart results on the southern agriculture in Appendix F.1.

Conceptually, past experiences of high temperatures may affect current year's agricultural output values in two ways. On the one hand, certain agricultural products require a growth period longer than a year and past temperature realizations may be capitalized into final product values through affecting the development process. On the other hand, having experienced shocks in the past may induce adaptive behaviors that lead to discernible implications on future agricultural values.

We employ three different estimation strategies to obtain intermediate-run value estimates that potentially incorporate the effects accumulated through both channels beyond the short run. Our first approach is a moving-average specification that includes both contemporaneous temperature bins and their historical moving averages.

$$\log(R_{i,t}) = \sum_{k=1}^{K} \beta_k Tbin_{k,i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \sum_{k=1}^{K} \delta_k \overline{Tbin_{k,i,t}} + \overline{\mathbf{X}_{i,t}}\boldsymbol{\eta} + \alpha_i + \lambda_t + h_p(t) + u_{i,t} \quad (2)$$

Building on equation (1), we further include intermediate-run counterparts of $Tbin_{k,i,t}$ in $\overline{Tbin}_{k,i,t}$ as moving averages of $Tbin_{k,i,t}$ over the five years preceding year t in equation (2). The estimates of δ_k characterize the induced changes in the value of a sector's output following intermediate-run changes in local temperature distribution. Consistent with this moving average design of the temperature variables, we also include the five-year moving averages of other weather controls in $\overline{\mathbf{X}}_{i,t}$. The other terms are defined in the same way as in equation (1), and the inference is based on the same two-way clustering strategy.

Panel A of Figure 7 presents the intermediate-run temperature effects estimated from equation (2) on northern agriculture.[17] The estimates show that heterogeneities exist across sectors in their responsiveness to intermediate-run temperature changes.

In the cropping sector, although high temperatures above 30 ℃ decrease the sectoral value in the short run, their intermediate-run impacts are economically small and statistically insignificant. On the one hand, it can be rationalized since temperature impacts are in theory contemporaneous on most row crops as their growth period is limited within a year. On the other hand, it reflects that past experience of high temperatures does not negatively capitalize into current values.

In contrast, the negative short-run impacts of high temperatures on the livestock sector likely persist in the intermediate run. Specifically, an intermediate-run increase of a higher-than-35 ℃ day reduces the output value in the livestock sector by 4.1% at a borderline-significant level. Considering that the development of various livestock products requires multiple years, this result is not surprising as heat stress over the past few years accumulates to form lasting impacts on current values.

In the forestry sector, the estimates suggest that exposure to more higher-range temperatures in the intermediate-run has positive effects on forestry values. This result is consistent with some of the prior evidence suggesting that forestry productivity benefits from extended growing season induced by warmer climate conditions (Kirilenko and Sedjo, 2007). These effects are likely

[17] We present the contemporaneous temperature effects estimated from equation (2) in Supplementary Figure S4. These contemporaneous estimates are highly consistent with the baseline short-run estimates reported in Panel B of Figure 3.

cumulative and persistent given that tree growth typically requires much longer time periods than a year. Besides, the intermediate-run response of the output value in the fishery sector is fairly silent, even for very high temperatures.

Paring with this moving-average specification, we adopt a distributed-lag model that more flexibly accounts for lagged temperature effects over time. Specifically, the regression equation is as follows.

$$\log(R_{i,t}) = \sum_{k=1}^{K} \beta_k Tbin_{k,i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \sum_{s=1}^{S}\sum_{k=1}^{K} \delta_{k,s}\, Tbin_{k,i,t-s} + \sum_{s=1}^{S} \mathbf{X}_{i,t-s}\boldsymbol{\eta}_s + \alpha_i + \lambda_t + h_p(t) + u_{i,t} \quad (3)$$

We set *S* equal to 5 to make the intermediate-run estimates from equation (3) comparable with those from the moving-average specification of equation (2). The key difference between this distributed-lag model and the moving-average specification is that the distributed-lag model does not impose homogeneity on the estimated effects of past weather realizations. To put it in another way, equation (2) can be viewed as a special case of equation (3), which requires that all the lagged coefficients of a particular weather variable are the same.

To facilitate interpretation of the intermediate-run effects, we follow the convention and accumulate lagged coefficients over time. Specifically, the intermediate-run effect associated with the *k*th temperature bin is equal to $\sum_{s=1}^{S} \widehat{\delta_{k,s}}$, and we obtain its associated confidence intervals by applying the delta's method. Panel B of Figure 7 illustrates the intermediate-run effects derived from the distributed-lag model, and these results are highly consistent with those from the moving-average specification.[18]

In addition to the two approaches reported above, we conduct the third set of estimations based on the long-difference approach proposed in Burke and Emerick (2016). Burke and Emerick (2016) show that the long-difference estimates "will embody any adaptations that farmers have

[18] We illustrate the cumulative impulse response functions of the highest temperature bin in Supplementary Figure S5.

undertaken to recent trends." This approach would rely on temporal variations in the averages of different episodes over a long time-span to establish temperature-agriculture relationship beyond the short run. As we discuss later, the long-difference estimates, comparing with the moving-average and distributed-lag estimates, provide a slightly different perspective for understanding the intermediate-run effects.

Tailoring the long-difference approach to our empirical context, we consider four episodes within our observed time-span: 1996-2000, 2001-2005, 2006-2010, and 2011-2015. For each episode, we construct the 5-year averages of county-level agricultural values and weather. The regression equation takes the following form:

$$\log\left(\overline{R_{i,t-4\sim t}}\right) = \sum_{k=1}^{K} \delta_k \overline{Tbin_{k,i,t-4\sim t}} + \overline{\mathbf{X}_{i,t-4\sim t}}\boldsymbol{\eta} + \alpha_i + \lambda_t + h_p(t) + u_{i,t} \qquad (4)$$

In equation (4), for any variable $z_{i,t} \in \left\{R_{i,t}, Tbin_{k,i,t}, \mathbf{X}_{i,t}\right\}$, we define $\overline{z_{i,t-4\sim t}} = \frac{1}{5}\sum_{s=0}^{4} z_{i,t-s}$. This long-difference estimation, although utilizes five-year averages, differs in a few aspects from our moving-average specification in equation (2). First, the long-difference estimation contains no contemporaneous weather. Second, the outcome variable is also a moving average, similar to the weather variables. Third, the effective observable periods become much less frequent. In practice, we implement the four-episode long-difference estimation with a fixed effect model since, in this long-difference context, both first-difference and fixed effects estimations would be consistent under the correct specification (Wooldridge, 2005).[19]

It is important to note that, although both the long-difference and the two earlier approaches yield estimates of intermediate-run effects, nuances exist between their interpretations. The moving-

[19] In a two-episodes case, estimating equation (3) with first-differenced and fixed effects models would yield identical results, since the demeaned and first-differenced transformations are mathematically equivalent. For more than two episodes, although exact point estimates differ across fixed-effect and first-difference estimations, both would be consistent under correct specification. The first-differenced expression would collapse to a pooled OLS in the form of $\Delta\log\left(\overline{R_{i,t-4\sim t}}\right) = \sum_{k=1}^{K} \delta_k \Delta\overline{Tbin_{k,i,t-4\sim t}} + \Delta\overline{\mathbf{X}_{it-4\sim t}}\eta + \theta_t + \mu_p t + \Delta u_{it}$, in which Δ is the first-difference operator.

average and distributed-lag models are more transparent in separately estimating the contemporaneous and lagged effects, and the estimated intermediate-run effects from these approaches arguably reflect more information on how the past weather realizations materialize into the development process of forming the current agricultural values. In contrast, the long-difference estimates weigh less on distinguishing contemporaneous and past effects but implicitly incorporate more information related to existing intermediate-run adaptations.

In panel C of Figure 7, we present the long-difference estimates of δ_k from equation (4). Although the general patterns are consistent with those moving-average and distributed-lag estimates shown in panels A and B of Figure 7, the point estimates in panel C display stronger positive responses around 30 ℃ and stronger negative responses above 35 ℃ for cropping and forestry sectors. To better contextualize the implications of these estimated intermediate-run effects and understand potential adaptations, in the next section, we turn to a set of simulation analysis based on these reduced-form estimates.

5.4 Simulations under Uniform Warming Scenarios

Building on our reduced-form estimates obtained from equations (2)-(4), we simulate both short-run and intermediate-run impacts of hypothetical temperature changes on the entire northern Chinese agriculture, preserving the uncertainties of the estimates. Specifically, for each sector, we separately calculate the aggregate impacts on the northern output values manifested in the short run and in the intermediate run, assuming uniform warming of 0.5 ℃, 1.0 ℃, 1.5 ℃, and 2.0 ℃, respectively. We first implement the simulations based on our moving-average and distributed-lag estimates, respectively.[20]

[20] We provide similar simulations for the southern agriculture in Appendix F.2.

Using the estimates from our moving-average specification, the calculations are conducted as follows:

$$\Delta R^{SR}=\sum_{i,t}\sum_{k=1}^{K}\widehat{\beta_k}\times\Delta Tbin_{k,it}\times\frac{\overline{R_{\iota t}}}{\sum_i^I\overline{R_{\iota t}}},\ \text{and}\ \Delta R^{IR}=\sum_{i,t}\sum_{k=1}^{K}\widehat{\delta_k}\times\Delta\overline{Tbin_{k,\iota t}}\times\frac{\overline{R_{\iota t}}}{\sum_i^I\overline{R_{\iota t}}}\ .$$

In these expressions, ΔR^{SR} and ΔR^{IR} are the impacts of a hypothetical temperature change on the value of output in a particular sector aggregated across the entirety of northern China, in the short run (SR) and in the intermediate run (IR), respectively. $\widehat{\beta_k}$ and $\widehat{\delta_k}$ are SR and IR estimates of temperature bins in a sector estimated from equation (2). $\Delta Tbin_{k,it}$ and $\Delta\overline{Tbin_{k,\iota t}}$ are changes in contemporaneous and moving-average temperature bins realized under a specific warming scenario in county i. $\overline{R_{\iota t}}/\sum_i^I\overline{R_{\iota t}}$ represents county i's weight based on the county's output values in a particular sector.

Similarly, we calculate the simulated impacts based on our distributed-lag estimates as follows:

$$\Delta R^{SR}=\sum_{i,t}\sum_{k=1}^{K}\widehat{\beta_k}\times\Delta Tbin_{k,it}\times\frac{\overline{R_{\iota t}}}{\sum_i^I\overline{R_{\iota t}}},\ \text{and}\ \Delta R^{IR}=\sum_{i,t}\sum_{k=1}^{K}\sum_{s=1}^{S}\widehat{\delta_{k,s}}\times\Delta Tbin_{k,it-s}\times\frac{\overline{R_{\iota t-s}}}{\sum_i^I\overline{R_{\iota t-s}}}\ .$$

All terms in these expressions are obtained from the distributed-lag specification of equation (3). Besides, we also construct ΔR based on the long-difference estimates such that $\Delta R=\sum_{i,t}\sum_{k=1}^{K}\widehat{\delta_k}\times\Delta\overline{Tbin_{k,i,t-4\sim t}}\times\frac{\overline{R_{\iota t}}}{\sum_i^I\overline{R_{\iota t}}}$, where the terms correspond to those in equation (4). When calculating the aggregated impacts, based on each set of estimates, we preserve uncertainties in the county-level estimates by applying the delta method on the two-way clustered standard errors for generating confidence intervals.

We report the simulated impacts of different warming scenarios on values of output by sector in Figures 8 and 9. We start with the results based on the moving-average estimates. The short-run estimated impacts are illustrated in red in panel A of Figure 8. They suggest that, if only contemporaneous impacts are considered for northern agriculture, warming is expected to depress the total values of cropping and livestock production, enhance the forestry output value, and have little impact on the fishery sector. Specifically, given 1.0 ℃ of warming, the associated reductions in the total values of northern cropping and livestock sectors would be close to 10%.[21]

The intermediate-run impacts estimated from the moving-average specification are illustrated in blue in panel A of Figure 8. Whilst there are greater levels of uncertainty in these estimates, they indicate contrasting patterns across sectors. Though the intermediate-run impacts tend to reverse the short-run impacts on cropping, they are more aligned with the short-run impacts in the livestock sector. With 1.0 ℃ warming, the point estimates of the simulated intermediate-run impacts on the northern cropping and livestock values are +5.9% and -20.9%, respectively. In the forestry sector, the positive short-run impacts of warming seem likely to be magnified in the longer run given 1.0 ℃ warming, where an additional impact of +25.4% is predicted.[22] These simulated impacts become even larger under a greater level of future warming.

[Figure 8 is inserted here]

In Panel B of Figure 8, we illustrate the simulated short-run and intermediate-run impacts calculated from the distributed-lag model estimates. These results are highly similar to those in Panel A. This consistency is unsurprising given that the intermediate-run effects obtained from the moving-average and distributed-lag specifications are almost identical quantitatively.

In panel A of Table 2, we formally test the statistical differences between the simulated short-run and intermediate-run impacts.[23] For all the sectors except for fisheries, under each warming

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[21] We note that the forestry's output value is predicted to increase by 4.7% under a 1.0°C warming, but this estimate is only marginally significant at the 90% confidence level. There is no meaningful change in the fishery output value under a 1.0°C warming.

[22] The estimated log-differences are 0.058, -0.235, and 0.226 for cropping, livestock, and forestry sectors, respectively. We calculate the percent changes using the exponential transformation, i.e., $\Delta y \cong \exp(\Delta \log(y))-1$.

[23] We implement the tests based on the simulated outcomes originated from the moving-average specification. We obtain indistinguishable testing results when using the simulated outcomes from the distributed-lag specification.

scenario, the estimated intermediate-run impact is statistically different from the estimated short-run impact at the 90% confidence level. These statistical differences have different implications in different sectors. For the cropping sector, since the short-run and intermediate-run impacts are of opposite signs, their statistical difference illustrates a strong reversal in the intermediate run. However, for the livestock (forestry) sector, the statistical difference implies that the short-run negative (positive) impact is likely magnified in the intermediate run.

In panel B of Table 2, aggregating short-run and intermediate-run impacts for each sector under each warming scenario shows that, in general, rising temperatures depress the livestock sector but benefit the forestry sector. The cropping sector, although dampened in the short run, shows strong resilience with its intermediate-run response being large enough to offset its short-run losses. The fishery sector is relatively insensitive in both the short run and the intermediate run.

[Table 2 is inserted here]

In Figure 9, we provide simulation results that build on the long-difference estimates in blue, and we overlay simulation results obtained with the baseline estimates in red. These contrasting results serve as a direct comparison between long-difference and fixed-effects estimates that renders an intuitive understanding of the extent of intermediate-run adaptation. As the results suggest, in the north, the cropping sector is shown to be very resilient as the predicted value changes are all positive. This inferred strong adaptability in cropping is in line with existing research that explicitly documents cropping sector's existing adaptations, including adjusting crop compositions and adopting improved planting technologies in Northeast China (Yang et al., 2007), changing crop planting dates (Cui and Xie, 2022), and expanding the irrigated areas for crops (Sloat et al., 2020).

[Figure 9 is inserted here]

Adaptations may also exist in the livestock sector, but only to a very limited extent. The simulated impacts based on the long-difference estimates are still negative and their magnitudes are non-trivial, despite that the confidence intervals are wide enough to contain zero. China's livestock sector has experienced rapid transition over years, with facilities expanding in size, upgrading in control technologies (e.g., ventilation and cooling), and improving in animal management (e.g., adjustments in stocking density, diet and resting patterns) (Yang, 2013; Bai et al. 2018; Sammad et al., 2020; Schauberger et al. 2019). Although these developments may have contributed to better adaptation to heat, our result suggests that the sector is still far from fully mitigating the physical damages caused by high temperatures.

The forestry sector is shown to be benefited, quantitatively to a slightly larger extent, when adaptation potentials are further incorporated. This finding is also consistent with the results reported in a review article (Wang et al., 2013), finding that regional warming over the past several decades has significantly expanded the forest edge northward and westward, and increased the net primary productivity of forest in Northeast China, which is home to the nation's largest forest area.

We find that, with adaptation accounted for, the fishery sector's responses to future warming are not statistically significant with an almost precisely zero effect. Although exposure to high temperatures raises the metabolic rates of aquaculture species and thus increases the additional demand for energy, Dawood et al. (2021) point out that altering feed quantity and feed quality are some of the effective strategies that have been actively utilized in adapting aquatic animals to rising water temperatures. A large literature has documented that several feed supplements (i.e., probiotics, prebiotics, symbiotics, and medicinal plants) have positive impacts on the growth, immunity, and survival of aquaculture species (for a review, see Mugwanya et al., 2022). The simulation results in Figure 9 suggest that these adaptive strategies may have been undertaken widely by China's fishery sector to cope with high temperatures.

6. Concluding Remarks

This paper provides a holistic evaluation on warming impacts on all the sectors in agriculture in China using both sectoral level value-based and product level quantity-based measures. We find that the differentiated impacts of increasing temperature on China's agriculture are markedly heterogeneous across regions and sectors. Had we not disaggregated the total output values of all agricultural products, we could have been misinformed by the non-responsiveness of the aggregated value, and might have neglected important distributional impacts. The identified regional and sectoral sensitivities and adaptabilities to rising temperatures also have direct policy implications and inform the prioritization of investments on agricultural adaptation to climate change.

First, northern China calls for more effort than southern China. The vulnerability in the north reflects a lack of preparedness of agriculture in confronting rising temperatures. It illustrates an important point: cooler places are not necessarily less threatened by warming. This observation also echoes some recent findings on the relationship between rising temperatures and mortality (e.g., Heutel et al., 2021). Second, although similarly hurt in the short run, the cropping sector is much more resilient than the livestock sector in the intermediate run. This finding calls for immediate action to devise policies and tools to enhance the adaptability of the livestock sector in northern China, especially since the livestock sector in the north contributes to more than half of the country's domestic livestock values, and the most affected sub-sector, dairy production, is strongly concentrated in the north. The urgency of the issue is amplified by the lack of studies on climate change's impacts on livestock farming and the sector's adaptation to them.

We finish with a caveat: the limited time span of our data has prevented us from directly measuring long-run impacts. This can be particularly relevant for improving our estimated results on the forestry sector, given that tree growth takes longer time. Further research is still needed to provide an understanding of regional and sectoral adaptabilities beyond the intermediate run. Still, our approach is readily applicable to investigating possible sectoral and regional heterogeneity in the impacts of warming on agriculture in other countries and regions.

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Figures and Tables

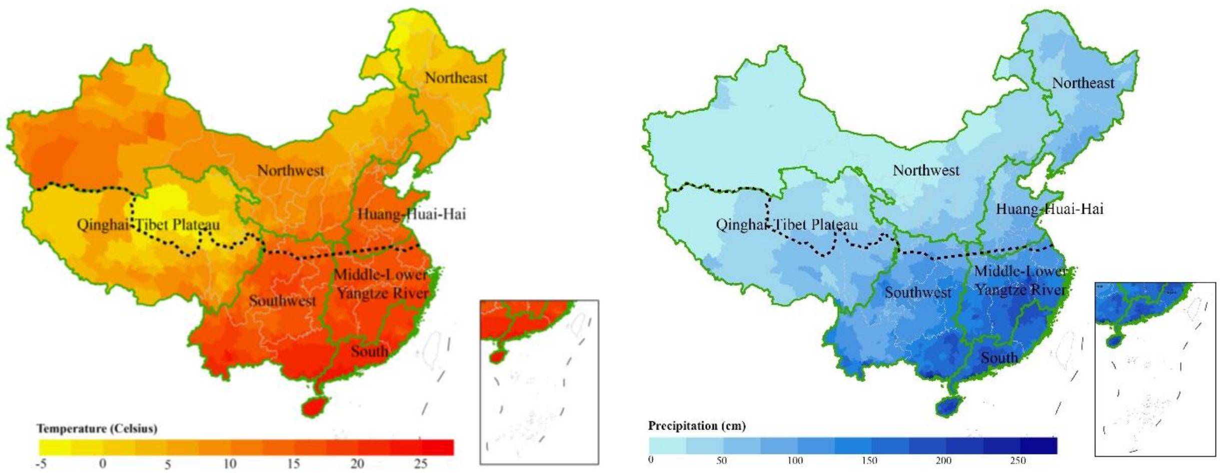


Figure 1. Spatial Distribution of Temperature and Precipitation in Different Agricultural Zones

*Notes***:** This figure shows county-level annual average temperature in ℃ and total precipitation in cm in China over the period 1995-2015. The county-level values are obtained based on spatially interpolating station-based values using the inverse distance weighting method (with a radius of 200 km). The maps are overlaid with the officially enacted agricultural zones in *Sustainable Development Plan for China's Agriculture.* The black dotted line represents the Huai River-Qin Mountains line.

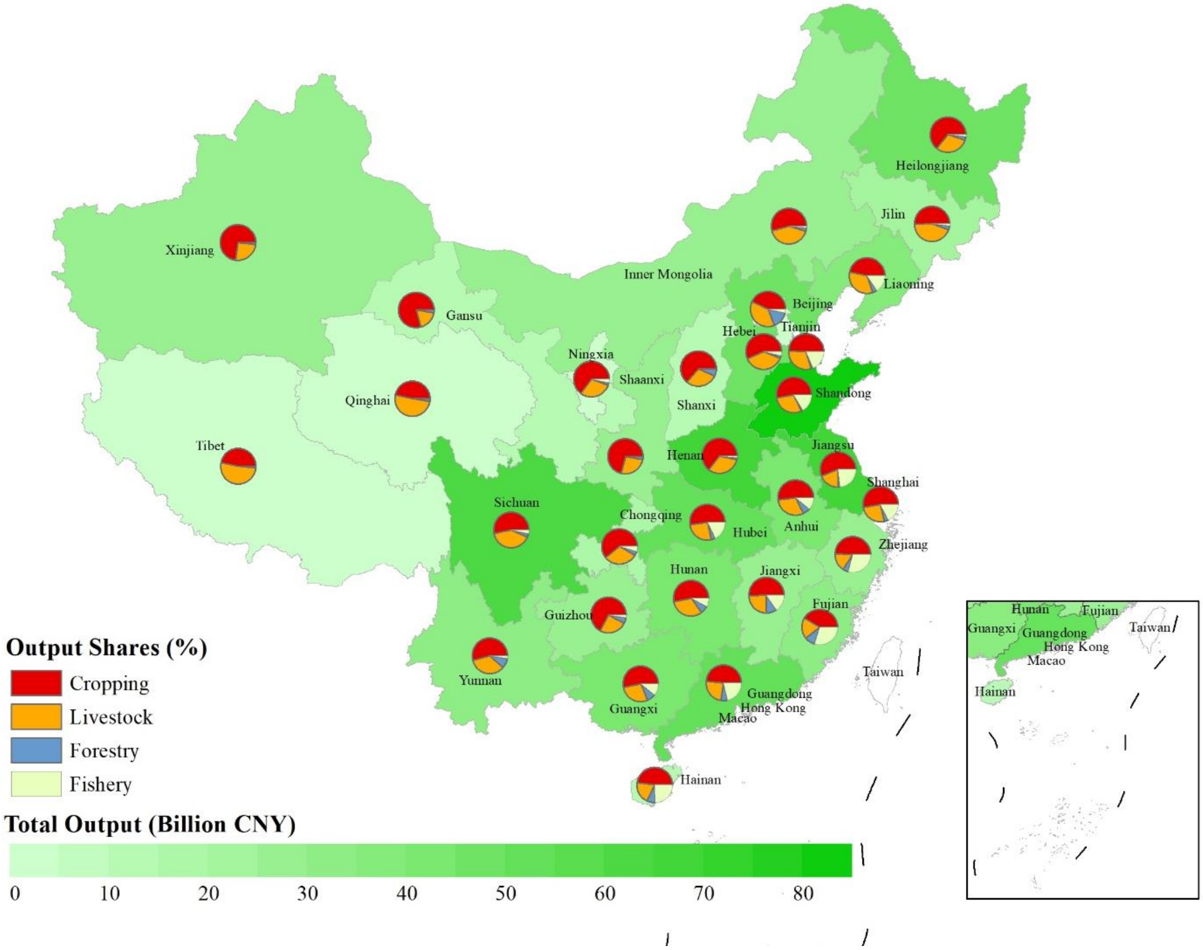


Figure 2. Provincial Statistics of Agricultural Output Values and Compositions

Notes: This figure shows province-level total agricultural output value in China in 2015. Darker green indicates a higher value of agricultural output. The pie chart on top of each province displays the percentage shares of four agricultural sectors (cropping, livestock, forestry and fishery) in that province's total agricultural output value.

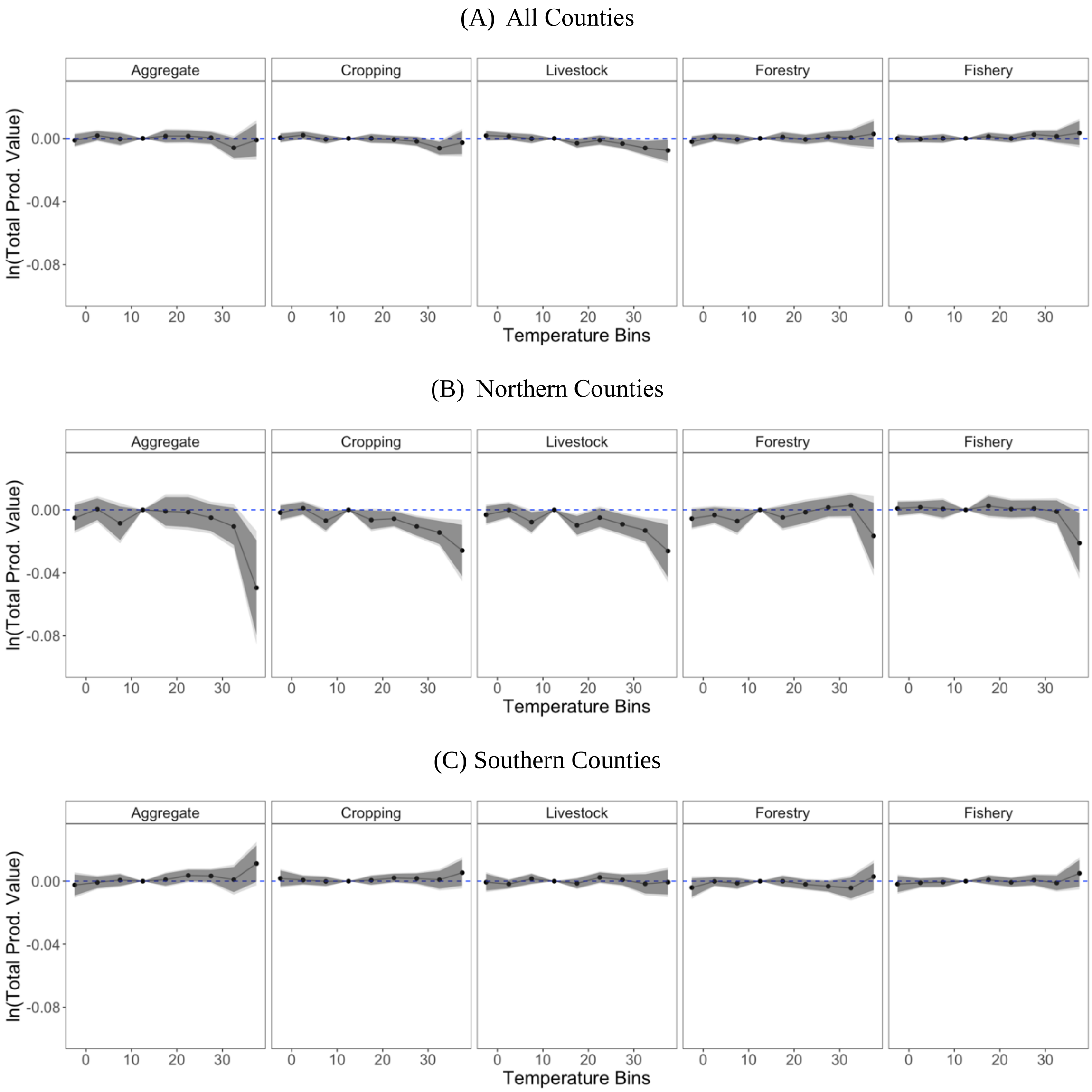
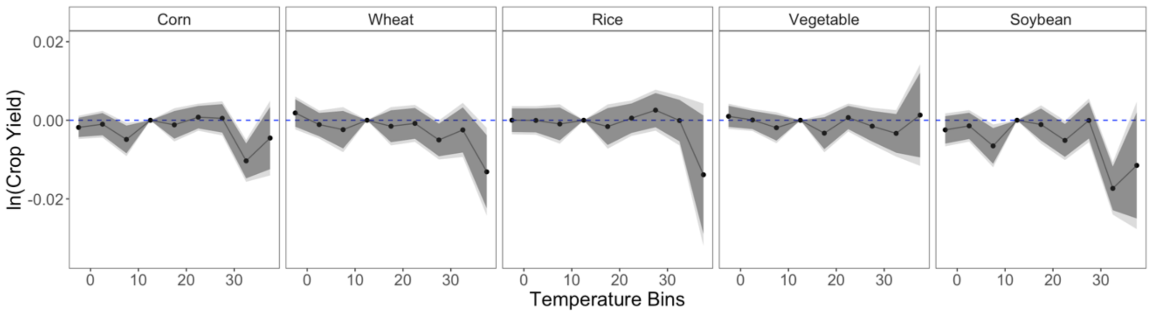


Figure 3. Temperature Effects on Agricultural Output Values

*Notes***:** Each dot represents the point estimate of the corresponding 5 ℃ bin, connected by solid lines. The shallow (dark) bands are 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. All regressions include other weather controls (in linear and quadratic terms), county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. Coefficient estimates are reported in Supplementary Tables S5-S7.

(A) Top-five Crops in the North



(B) Top-five Crops in the South

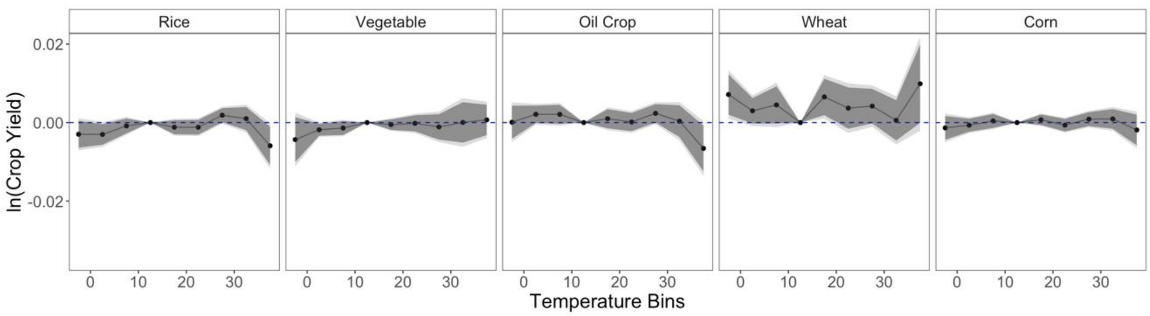
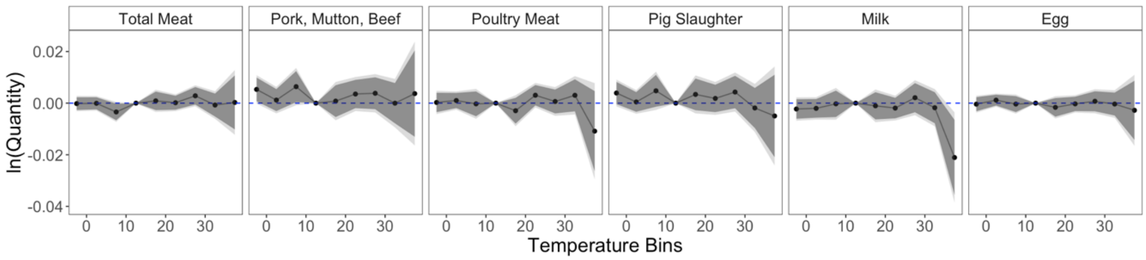


Figure 4. Temperature Effects on Crop Yields

Notes: Each dot represents the point estimate of the corresponding 5 ℃ bin, connected by solid lines. The shallow (dark) bands are 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. All regressions include other weather controls (in linear and quadratic terms), county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. Estimates on the top-five (from left to right, acreage-based) crops are presented for northern regions in panel A and southern regions in panel B. Crop yields are measured in metric tons per ha. Coefficient estimates are reported in Supplementary Tables S9-S10.

(A) Selected Products of the Livestock Sector in the North



(B) Selected Products of the Livestock Sector in the South

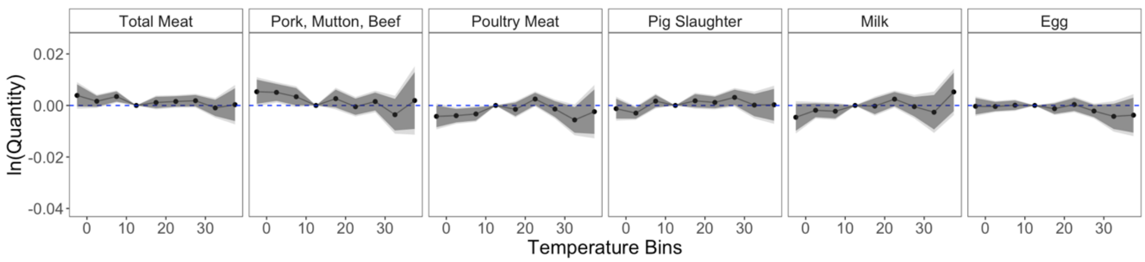
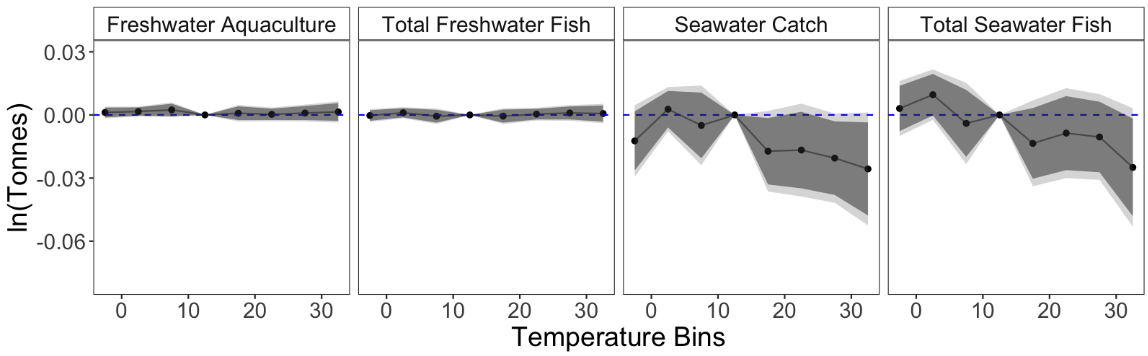


Figure 5. Temperature Effects on Livestock Production

*Notes***:** Each dot represents the point estimate of the corresponding 5 ℃ bin, connected by solid lines. The shallow (dark) bands are 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. All regressions include other weather controls (in linear and quadratic terms), county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. All products are measured in metric tons except for pig slaughter (in heads). Coefficient estimates are reported in Supplementary Tables S11-S12.

(A) Selected Products of the Fishery Sector in the North



(B) Selected Products of the Fishery Sector in the South

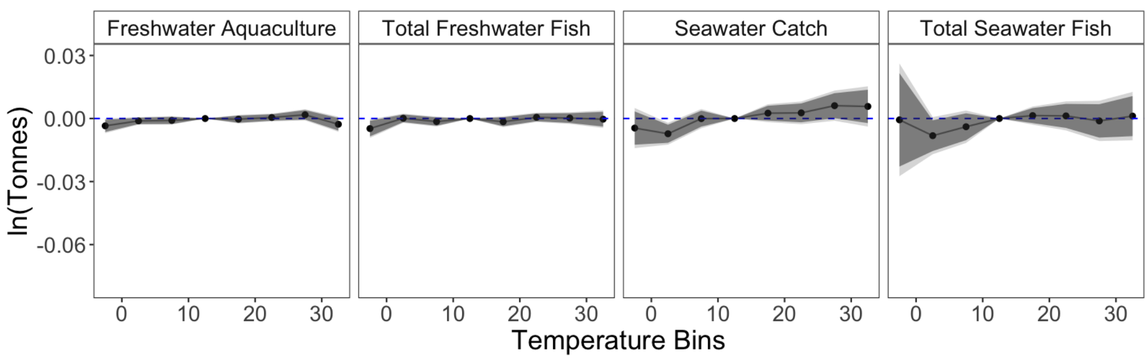


Figure 6. Temperature Effects on Fishery Production

*Notes***:** Each dot represents the point estimate of the corresponding 5 ℃ bin, connected by solid lines. Bins above 30 ℃ are combined. The shallow (dark) bands are 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. All regressions include other weather controls (in linear and quadratic terms), county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. All products are measured in metric tons. Coefficient estimates are reported in Supplementary Tables S14-S15.

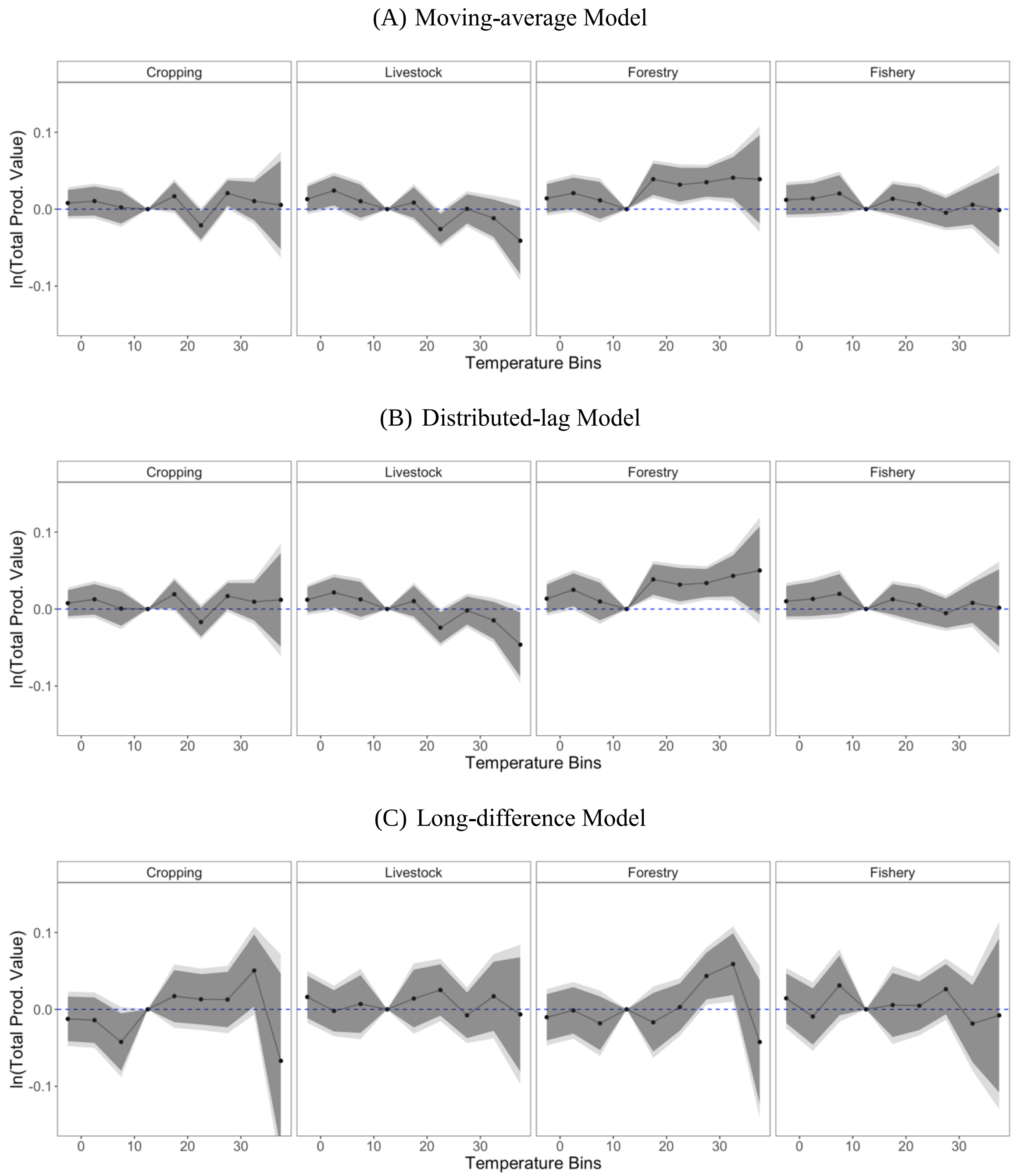
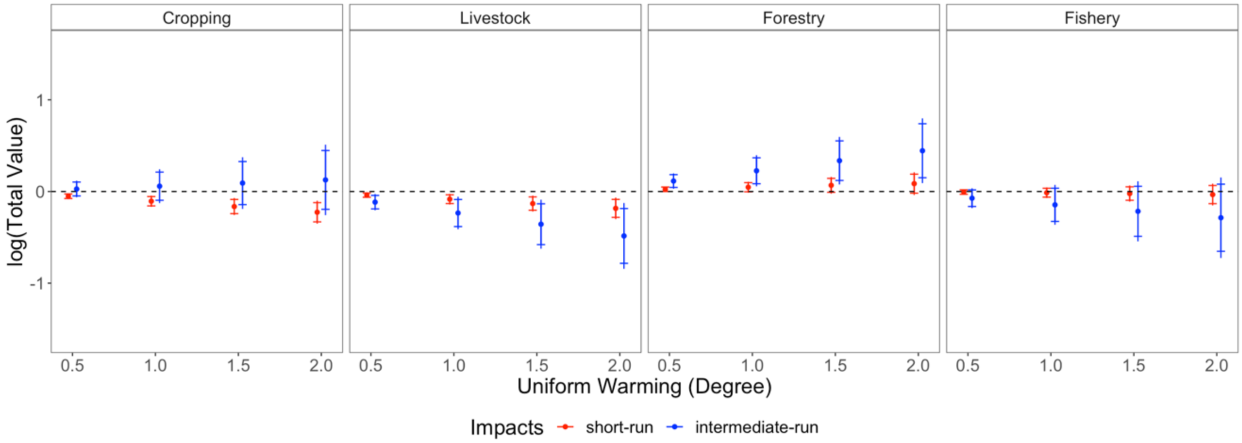


Figure 7. Intermediate-run Temperature Effects on Northern Sectoral Values

Notes: Each dot represents the point estimate of the intermediate-run effects of the corresponding 5 ℃ bin, connected by solid lines. The shallow (dark) bands are 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. All regressions include counterpart variables of other weather controls (in linear and quadratic terms), county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. Coefficient estimates are reported in Supplementary Tables S16-S18.

(A) Simulations Based on the Moving-average Estimates



(B) Simulations Based on the Distributed-lag Estimates

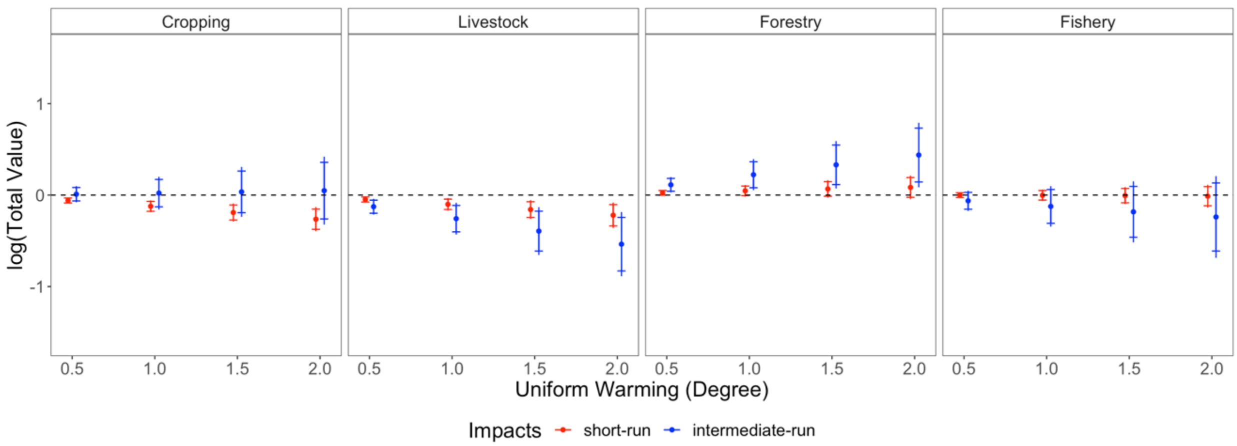


Figure 8. Simulated Warming Impacts on Northern Sectoral Values: Moving-average and Distributed-lag Models

Notes: Each dot represents the point estimate of a simulated impact on the total sectoral value in northern China, under a specific uniform warming scenario (0.5 ℃, 1.0 ℃, 1.5 ℃, and 2.0 ℃, respectively). The whiskers (bars) govern 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. The short-run (intermediate-run) impacts are simulated based on the current year (5-year average/lagged) estimates. Simulated warming impacts are reported in Supplementary Tables S19-S20.

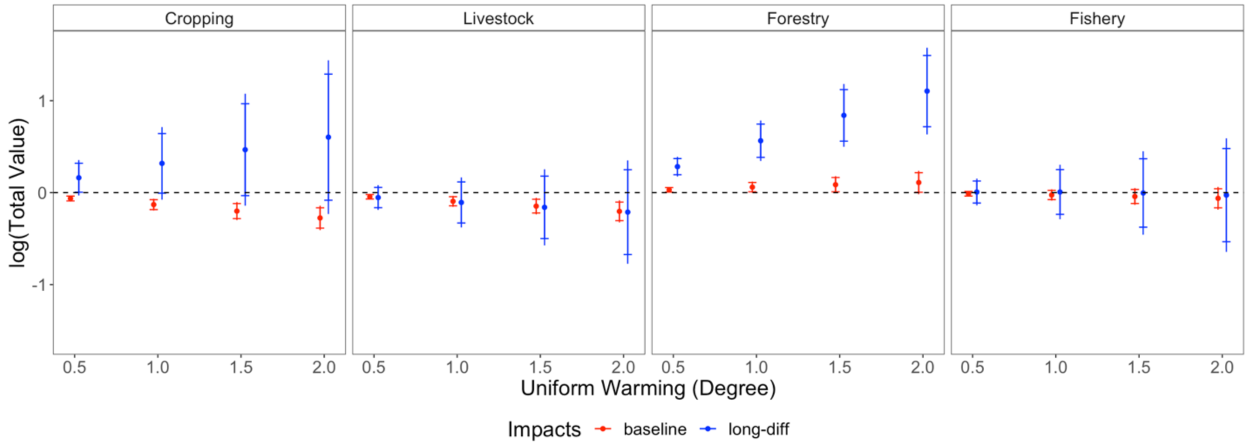


Figure 9. Simulated Warming Impacts on Northern Sectoral Values: Long-difference

Notes: Each dot represents the point estimate of a simulated impact on the total sectoral value in northern China, under a specific uniform warming scenario (0.5 ℃, 1.0 ℃, 1.5 ℃, and 2.0 ℃, respectively). The whiskers (bars) govern 95% (90%) confidence intervals based on two-way clustered standard errors that account for spatial and temporal heteroskedasticity and autocorrelation in the residuals. The short-run (intermediate-run) impacts are simulated based on the panel fixed effects (long-difference) estimates. Simulated warming impacts are reported in Supplementary Table S21.

Table 1. Formal Test of Response Heterogeneity Between Northern and Southern Values

	(1)	(2)
North × bin (<0 ℃)	-0.0039	-0.0044
	(0.0054)	(0.0054)
North × bin (0-5 ℃)	0.0015	0.0004
	(0.0044)	(0.0043)
North × bin (5-10 ℃)	-0.0062	-0.0078
	(0.0066)	(0.0065)
North × bin (15-20 ℃)	-0.0014	-0.0016
	(0.0062)	(0.0061)
North × bin (20-25 ℃)	-0.0014	-0.0019
	(0.0061)	(0.0059)
North × bin (25-30 ℃)	0.0005	-0.0014
	(0.0055)	(0.0052)
North × bin (30-35 ℃)	-0.0044	-0.0045
	(0.0077)	(0.0074)
North × bin (>35 ℃)	-0.0429**	-0.0414**
	(0.0197)	(0.0194)
Interactive Specification	All bins	All variables
Obs	39,266	39,266

Notes: Columns (1) and (2) correspond to the specification where the northern dummy is interacted with (i) all temperature bins, and (ii) all weather variables, respectively. The dependent variable is the logarithmic aggregate value. All regressions include temperature bins and other weather variables (in linear and quadratic terms) that are not interacted, as well as county fixed effects, year fixed effects, and province-level linear and quadratic time trends. The bin for 10-15 ℃ is set as the reference. Only interacted bins are reported in this table. The full results are reported in Supplementary Table S8. Standard errors (in parentheses) are two-way clustered by counties and by province-by-year pairs. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Differences between Short-run and Intermediate-run Temperature Impacts on Northern Agricultural Output Values

	Cropping	Livestock	Forestry	Fishery
Panel A. *Differences between SR & IR impacts*				
SR-IR Diff (0.5 ℃+)	-0.08	0.08	-0.09	0.07
St. Err.	(0.04)	(0.04)	(0.04)	(0.05)
p-value	0.08	0.08	0.03	0.18
SR-IR Diff (1.0 ℃+)	-0.16	0.15	-0.18	0.13
St. Err.	(0.09)	(0.09)	(0.08)	(0.10)
p-value	0.07	0.09	0.04	0.19
SR-IR Diff (1.5 ℃+)	-0.26	0.23	-0.27	0.19
St. Err.	(0.14)	(0.13)	(0.13)	(0.15)
p-value	0.06	0.09	0.04	0.20
SR-IR Diff (2.0 ℃+)	-0.35	0.30	-0.36	0.25
St. Err.	(0.18)	(0.18)	(0.18)	(0.20)
p-value	0.06	0.09	0.04	0.21
Panel B. *Aggregated SR & IR impacts*				
SR+IR Combined (0.5 ℃+)	-0.02	-0.16	0.14	-0.08
St. Err.	(0.05)	(0.05)	(0.05)	(0.06)
p-value	0.64	0.002	0.004	0.21
SR+IR Combined (1.0 ℃+)	-0.05	-0.32	0.27	-0.16
St. Err.	(0.11)	(0.10)	(0.10)	(0.13)
p-value	0.65	0.002	0.01	0.21
SR+IR Combined (1.5 ℃+)	-0.07	-0.49	0.40	-0.24
St. Err.	(0.16)	(0.15)	(0.15)	(0.19)
p-value	0.66	0.002	0.01	0.21
SR+IR Combined (2.0 ℃+)	-0.10	-0.67	0.53	-0.32
St. Err.	(0.22)	(0.20)	(0.20)	(0.26)
p-value	0.66	0.001	0.01	0.22

Notes: The impacts are calculated based on the estimates from the moving-average model. Panel A shows the differences in the short-run (SR) and intermediate-run (IR) simulated impacts on the four sectors of northern agriculture. Panel B shows the linearly combined SR and IR impacts on the four sectors of northern agriculture. The standard errors and the calculation of *p*-values are based on two-way clustering inference by counties and by province-by-year pairs.