Climate Change Effects on Agricultural Production: The Regional and Sectoral Economic Consequences in China

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Abstract Climate is an essential element in agricultural production, and climate change inevitably have an impact on agriculture. Assessing the economic consequences of climate change requires comprehensive assessments of the impact chain from climate to crops and the economy. In our previous study, we derived a dose-response function to estimate the response of crop yields to climate variables through a systematic review. In this paper, a dynamic multiregional input-output model is established to assess the economic consequences of changes in agricultural production on China’s regional and sectoral levels. The results show that (1) the direct economic damage is equivalent to 1% of gross domestic product (GDP) which implies the resulting economic cascade effect (ECE) that amounts to 17.8% of China’s GDP. At the end of 21st century, the ECE is −0.1% to 13.6% of GDP (negative values indicate economic gains) without considering CO2 fertilization effect, of which the ECE in the most pessimistic pathway are equivalent to the total agricultural output in China today. (2) Regional-level results show an uneven distribution of economic impact in China, which is related to the regional economic development. The least developed region in China experiences 2.8 to 8.5 times more ECE caused by climate change than the most developed region. (3) Sector-level results show that agriculture is still the main affected sector, but in developed regions, manufacturing and services also bear part of the ECE.

Plain Language Summary Evidence from numerous studies has confirmed the impact of climate change on agriculture. This paper assesses the economic consequences of changes in agricultural production under climate change in China. We find that the direct economic damage is equivalent to 1% of gross domestic product which implies the resulting economic cascade effect that amounts to 17.8% of total gross domestic product. The most pessimistic estimate of the economic impacts in the 2090s is equivalent to China’s total agricultural output today without considering CO2 fertilization effect of climate change. The economic impacts suffered by different regions of China are related to regional economic development. The least developed region in China experiences more economic damage from climate change than the most developed region. In addition to the agricultural sector, manufacturing and services are expected to experience part of the impacts, especially in developed regions. This paper hopes to provide data support for a comprehensive understanding of climate change impacts in different regions of China by assessing the economic consequences.

1. Introduction

Agricultural production is closely related to climate and thus bears the brunt of climate change. With evidence from numerous studies confirming the impact of climate change on crop yields (Challinor et al., 2014; Knox et al., 2012), a growing number of researchers have focused on the resulting economic impacts (Burke et al., 2015; Costinot et al., 2016; Robinson et al., 2015; Takakura et al., 2019). The negative effects of climate change on Chinese agriculture have been confirmed, and future increases are expected (Liu et al., 2020). Agricultural production accounts for a large proportion of the national economy in China, so the resulting economic consequences cannot be ignored. Meanwhile, debate continues
regarding regional differences in the economic consequences of warming in currently temperate climates, such as that in China.

Recent advances in assessing the impact chain from climate to crops and then to the economy have been rapid (Nelson et al., 2014) and driven by advances in computing power, data, and methodology (Carleton & Hsiang, 2016). As more flexible relationships between climate elements and biophysical responses are identified (Auffhammer & Schlenker, 2014), we can assess the ultimate economic consequences of climate change. The current assessments have been carried out at the global and national levels, showing a substantial probability of large declines in global welfare (Moore, Baldos, & Hertel, 2017) and a potential gross domestic product (GDP) loss of more than 2% in the Middle East and North Africa for warming of 2°C to 3°C (Roson & van der Mensbrugghe, 2012). By the late 21st century, the United States is expected to suffer from an important reduction in GDP due to the impact of warming on agricultural production, and it is notable that the poorest third of counties are projected to experience more damage than the wealthiest third (Hsiang et al., 2017). A global assessment also predict that poor countries are expected to suffer most of the damage from climate change (Mendelsohn et al., 2006).

Most assessments of the economic impacts of climate change are at the national level and ignore regional differences, which are evident in the assessment at the county level in the United States (Hsiang et al., 2017). Moreover, China is usually viewed as a homogenous entity in climate change research; it is a broad country with great regional variations in economic development, agricultural production, and climate change (Mi et al., 2017), which will also lead to different economic consequences of climate change. The country-level impacts of warming on global economic production (Burke et al., 2015) show that China will suffer moderate negative impacts at the end of the 21st century (representative concentration pathway [RCP] 8.5). However, the economic consequences of climate change differ in countries at the same latitude as China: The low latitudes (e.g., India) will suffer severe negative economic impacts, while the high latitudes (e.g., Russia) will benefit from climate change. In addition, the reallocation of production and consumption through interregional and intersectoral trade networks (Schlenker & Roberts, 2009), as well as regional variations in economic development, further alters the economic consequences of climate change in China.

This paper is an extension of our previous study—the time series of crop yield changes in seven regions of China from 2020 to 2099 are obtained based on a systematic review of 49 studies (Liu et al., 2020). In this paper, a dynamic multiregional input-output (AMRIO) model is developed to assess the economic consequences of crop yield changes. The economic consequences in this paper are divided into direct economic damage (DED) and economic cascading effect (ECE). For clarity, the DED indicates changes in agricultural output caused by climate change, and the ECE indicates the interregional/intersectoral economic consequence of climate change. The effect of CO₂ fertilization is not considered in this paper because of its widespread debate.
2. Methods and Data

2.1. Methodology

In this study, an integrated modeling approach was adopted to assess each step in the impact chain from climate-crops-economic impact (Figure 1). The predictions of the future climate of 19 global circulation models (GCMs) under four RCPs were used to produce climate variables from 2020 to 2099 in seven regions of China (see supporting information for details). Crop models link climate change to economic impacts. However, a single crop model remains relatively limited in yield projections, and the results from different crop models show considerable spread (Challinor et al., 2014). Thus, a systematic review methodology was adopted to synthesize a large number of studies to derive dose-response functions estimating the effects of climate variables on agricultural production (see supporting information for details). Then, the climate results were used as input to simulate the time series of yield change, which in turn became inputs into economic models as changes in agricultural output (i.e., DED). Finally, an AMRIO model was developed based on the multiregional input-output (MRIO) table to calculate the responses of the economic system (i.e., ECE) to changes in agricultural output. After the introduction of DED (changes in crop yields) into the model, it affected the output of different economic sectors in different regions through trade networks (characterized by MRIO table), which will eventually be reflected as change in the value added of each sector in each region. We measured the size of ECE by the amount of change in value added relative to the baseline, expressed as a percentage change in GDP.

2.2. Model Construction

The computable general equilibrium (CGE) model and input-output (IO) model are considered to capture interregional and intersectoral trade networks and are therefore often used to assess the impact of climate change on macroeconomic systems (Rosenzweig et al., 2017), but neither model is considered to be superior to the other (Table S4). For example, the nonlinear structure of the CGE model simulates the market elasticity and overall substitution tendencies well, but it seems to be overly optimistic (Li et al., 2013). The construction of Social Accounting Matrix for CGE model also requires a large number of exogenous variables (Xia et al., 2016). The traditional IO model is linear and neglects the interdependence between price and output (Rose, 2004) but reduces data requirements through assumptions and parameter substitution. Despite the limitations of the traditional IO model, it has been widely used and developed thanks to the lower data requirements, especially in disaster and climate change research. The representative models are the MRIO model, the adaptive regional input-output (ARIO) model (Hallegatte, 2008), and the ARIO model with inventory and labor (Zhang et al., 2018).

2.2.1. AMRIO Model

Here, we proposed an AMRIO model based on the MRIO model and the ARIO model. The MRIO model can capture both forward and backward propagations of the decline in agricultural productivity caused by climate change as well as the multiregional economic impacts through interregional trade networks. However, the current MRIO model (Jiang & Guan, 2017) cannot consider both the supply-side and demand-side effects and can only reflect the static response of the overall economy to climate change without considering adaptation of the economic system (see supporting information for details). The ARIO model introduces an adaptive strategy (Hallegatte, 2008), which can consider the limitation of production capacity. It can consider the adaptation of the sector production capacities and production bottlenecks caused by production chain disruptions. But it is based on a local IO table and only considers the economic system of a single region, so it is unable to identify the interaction between various economic sectors of different regions.

Thus, we combined the advantages of the MRIO and ARIO models to develop an AMRIO model. The basic framework of the AMRIO model is similar to the ARIO model. The IO table, the supply side, and the demand side are linked through the following equation, taking region $r$ sector $i$ as an example:

$$Y^r(i) = \sum_{s=1}^{n} \sum_{j=1}^{m} A^{rs}(i, j) Y^s(j) + \sum_{s=1}^{n} F^{rs}(i) + \sum_{s=1}^{n} \sum_{j=1}^{m} D^{rs}(i, j),$$

where $i, j = 1, ..., m$ for all economic sectors and $r, s = 1, ..., n$ for all regions in this study; $Y$ is the total output vector; $A$ is the MRIO table; $F$ is the final demand matrices; and $D$ is the DED caused by climate change, that is, the decline in output in the agricultural sector, measured as a percentage change of the value added in
agriculture. Then, we can calculate the production and consumption of each sector in each region, as well as the production bottlenecks caused by climate damage (see supporting information for details).

As discussed above, the ARIO model focuses on the economic impact of a single region and does not adequately consider multiregional economic adaptation. Therefore, we made the following modifications to the adaptation module.

Generally speaking, if sector $i$ in region $r$ decreases $\Delta z$ in supply of the intermediate demand to sector $j$ in region $s$ due to climate damage, then sector $j$ in sector $s$ will shift its demand to the same sector in other regions within time $\tau^1$. Similarly, when the final demand cannot be satisfied (sector $i$ in region $r$ decreases $\Delta f$ in supply of the final demand to region $s$), it can also be transferred to other regions:

$$Z_{ri}^{\tau}(i, j) = \frac{\Delta t}{\tau^1} \Delta z_{ri}^{\tau}(i, j) \sum_{q \neq r} Z_{rq}^{\tau}(i, j)$$  \hspace{1cm} (2)

$$F_{ri}^{\tau}(i) = \frac{\Delta t}{\tau^1} \Delta f_{ri}^{\tau}(i) \sum_{q \neq r} F_{rq}^{\tau}(i)$$  \hspace{1cm} (3)

where $Z_{ri}^{\tau}(i,j)$ is the intermediate demand from sector $j$ in region $s$ to sector $i$ in region $r$, $F_{ri}^{\tau}(i)$ is the final demand from sector $i$ in region $s$ to region $r$, $\tau^1$ describes how fast is the substitution, and $\Delta t$ is the time step. For sector $i$ in other regions (e.g., region $q$), if their production meets all current demands, then these sectors will increase the supply to sector $i$ in region $r$ in proportion:

$$Z_{ri}^{\tau}(i, j) = \frac{\Delta t}{\tau^1} \Delta z_{ri}^{\tau}(i, j) \sum_{q \neq r} Z_{rq}^{\tau}(i, j) Z_{ri}^{\tau}(i, j)$$  \hspace{1cm} (4)

$$F_{ri}^{\tau}(i) = \frac{\Delta t}{\tau^1} \Delta f_{ri}^{\tau}(i) \sum_{q \neq r} F_{rq}^{\tau}(i)$$  \hspace{1cm} (5)

Eventually, the substitution of intermediate products and final products will disappear, that is, after the recovery of production in sector $i$ in region, the original consumer demand for this sector will also return:

$$Z_{ri}^{\tau}(i, j) = \frac{\Delta t}{\tau^1} \Delta z_{ri}^{\tau}(i, j) Z_{ri}^{\tau}(i, j)$$  \hspace{1cm} (6)

$$Z_{ri}^{\tau}(i, j) = \frac{\Delta t}{\tau^1} \Delta z_{ri}^{\tau}(i, j) Z_{ri}^{\tau}(i, j)$$  \hspace{1cm} (7)

$$F_{ri}^{\tau}(i) = \frac{\Delta t}{\tau^1} \Delta f_{ri}^{\tau}(i) F_{ri}^{\tau}(i)$$  \hspace{1cm} (8)

$$F_{ri}^{\tau}(i) = \frac{\Delta t}{\tau^1} \Delta f_{ri}^{\tau}(i) F_{ri}^{\tau}(i)$$  \hspace{1cm} (9)

where $\tau^1$ describes how fast the substitution disappears, $T_{ri}^{\alpha}(i,j)$ is the substitution of intermediate product $Z_{ri}^{\tau}(i,j)$ to $Z_{ri}^{\alpha}(i,j)$, and $F_{ri}^{\alpha}(i)$ is the substitution of final product $F_{ri}^{\tau}(i)$ to $F_{ri}^{\alpha}(i)$.

2.2.2. Assumptions

1. Importantly, the scale and structure of China’s economy and population are fixed at the 2012 level, that is, we estimate the impact on agriculture and the resulting economic consequences if the future climate change scenarios (i.e., RCPs) occur in 2012. This assumption can eliminate the large uncertainty included in the socioeconomic development estimates, and it is easier to understand the comparison of the results with the values observed in 2012.

2. To reduce the uncertainty caused by introducing exogenous variables into the model, there are three assumptions for AMRIO model: (i) The size and distribution of cultivated area of different crops in different regions are fixed at the 2012 level. (ii) After introducing the impact of climate change on agricultural production (i.e., DED) into the model, the balance of supply and demand in the final economic system is still based on 2012. (iii) Products and services are exchanged between different sectors in different regions, and each sector produces only a specific product or service. Also, products or services produced by the same sector in different regions are substitutable, and the cross-region substitutions are costless.
2.3. Data Set

2.3.1. Time Series of Yield Change

Time series of yield change at the regional level in China are constructed following a four-step process (Liu et al., 2020): (i) Regional-level projections of average annual temperature and precipitation are constructed based on 19 GCMs and 4 RCPs. (ii) Then, a systematic review methodology was adopted to synthesize the projected yield changes in three major crops (wheat, rice, and maize; cash crops are not included due to lack of data) based on a data set of 667 projections from 49 peer reviewed studies. (iii) Subsequently, a dose-response function of each region is derived to estimate the effects of climate variables on agricultural production. (iv) Finally, input the time series of climate variables under each RCP in each region to obtain the corresponding time series of yield change (see supporting information for details).

Figure 2 displays the crop yield changes in seven regions of China under RCP8.5. Except for South China (SC), crop yields in the other regions of China show significant downward trends, especially in Northeast China (NEC) and Northwest China (NWC). In addition, yield changes show positive values in the 2020s to 2060s, indicating that climate change may have positive effects on agriculture, which is discussed in section 3.

Therefore, we use the percent changes in crop yields from the previous study as input to the AMRIO model for changes in agricultural output, based on the assumption in section 2.2.2 that the cultivated area in different regions remains unchanged.

2.3.2. Economic Data

The Chinese MRIO table, excluding Hongkong, Macao, Tibet, and Taiwan, compiled by Mi et al. (2017) is adopted in this study. Then, we divide the provinces in the MRIO table into seven regions: Northeast, North, Central, East, South, Northwest, and Southwest, which is consistent with our previous study (Liu et al., 2020). In addition, we merged the 30 economic sectors from the original MRIO table into 11 because of data unavailability and to avoid redundant calculations. Detailed descriptions of regional divisions and sectoral mergers are provided in the supporting information.

The exogenous variables of the AMRIO model include characteristic times and overproduction parameters. The overproduction parameters are calculated based on the agricultural investment in the China Agricultural Yearbook (MOA, 2013). The characteristic times parameters are measured based on freight traffic and freight ton kilometers in the China Statistical Yearbook (NBSC, 2013).

2.4. Uncertainty

We decompose the uncertainty in ECE into contributions from yield change projections and the AMRIO model. Uncertainty in yield change projections is driven by climate uncertainty (e.g., temperature and precipitation) and sampling used to derive dose-response functions, as well as uncertainty generated by the...
interactions among these factors (Hsiang et al., 2017). In each RCP scenario, Monte Carlo sampling is used to account for uncertainty in climate variables (RCP2.6, RCP4.5, and RCP8.5 = 19 GCMs and RCP6.0 = 13 GCMs) and dose-response functions (1,000 permutations). Figure 2 displays regional-level uncertainty in the yield change projections under RCP8.5. Notably, the samples used to derive the dose-response functions between yield changes and climate variables contain uncertainty, which remains uncharacterized due to missing data. The uncertainties in yield change projections are shown in the dark shaded area in Figures 3a and 4.

Uncertainty in the AMRIO model is driven by introduced exogenous variables, including characteristic times and overproduction parameters. We set the interval of exogenous variables (up and down by 30% based on standard values), defined as different verification groups, and the values of each group of parameters were taken at 5% intervals (Mendoza-Tinoco et al., 2017). Simultaneously, this method is also used to verify the robustness of the AMRIO model (see supporting information for details). The uncertainties in the AMRIO model are shown in the light shaded area and error bars in Figures 3a, 4, and 5.

Figure 3. Estimates of ECE caused by crop failure under climate change in China. (a) Time series of ECE from 2020 to 2099 under four RCPs, the mean (line), the uncertainty ranges of 19 GCMs (dark shaded area), and the uncertainty ranges of model (light shaded area) are shown. (b) ECE as a function of DED. Dots = median; whiskers = range. The black line is the regression curve for all medians ($\Delta ECE = 16.176 \Delta DED^2 + 1.524 \Delta DED + 0.144$), and the shaded region is bounded by the regression curve for upper and lower limits of each distribution.

Figure 4. Time series of the ECE in regions of China under four RCPs, the mean (line), the uncertainty ranges of 19 GCMs (dark shaded area), and the uncertainty ranges of model (light shaded area) are shown. SWC = Southwest China; NWC = Northwest China; CC = Central China; SC = South China; NEC = Northeast China; NC = North China; EC = East China.
3. Results and Discussion

3.1. National ECE Caused by Climate Change

With numerous studies confirming the impact of climate change on agricultural production, we estimate the ECE of the impact on China’s economy (Figure 3a). The results show that limiting the increase in global mean temperature to 2°C (RCP2.6) can minimize the economic consequences of climate change.

Meanwhile, the economic feedback on climate change may be positive. However, under RCP4.5, RCP6.0, and RCP8.5, if the climate from 2090 to 2099 occurred in 2012, crop failure caused by climate change would result in ECE of 0.3% to 3.8% GDP, 1.3% to 5.7% GDP, and 5.3% to 14.8% GDP, respectively. Notably, the ECE of the 2090s under RCP8.5 may exceed the current total output of agriculture in China.

The ECE trends show that the impact of crop failure on China’s economy due to climate change begins to increase rapidly after the 2040s and varies under different RCPs. Combining the impacts under different scenarios, we estimate the nonlinear relationship between ECE and DED (Figure 3b) and find expected ECE increases of 7.4% to 15.6% GDP for every 1% increase in DED (Table S6). This response is well approximated by a quadratic function, which proves that the overall economic decline caused by climate change cannot be ignored. The ECE caused by impacts in a single sector should be considered, as the impact on GDP is much greater than that of DED.

The economic impacts of climate change have been assessed around the world. The impact of climate change on agricultural production in the 2080s will cause the EU economy to lose −0.7% to 1.0% of GDP, and Northern Europe will benefit from this change (Ciscar et al., 2011). The ECE of climate change to the U.S. economy is estimated to be 0.9% to 1.5% GDP in 2080 to 2099 under RCP2.6, RCP4.5, and RCP8.5 (Hsiang et al., 2017). Moore, Baldos, Hertel, and Diaz (2017) pointed out that China is estimated to suffer from 0% to 5% welfare losses (normalized by the value of crop production) due to the impact of the agricultural sector at 3°C warming. Dellink et al. (2019) presented a global quantitative assessment of the economic

![Figure 5](image-url)
consequences of climate change through 2060 and found that the negative impact of agriculture on the national economy under climate change is approximately 2.5% to 2.9% GDP in India and 0.8% to 1.8% GDP in Africa. Comparing the above studies with the impact of crop failure on China’s economy during the same period in this study, it can be found that the ECE in China is higher than those of the EU and the United States and is roughly equivalent to those in India and Africa. Less developed economies are considered to bear the most of losses caused by climate change partly due to higher climate-induced crop yield losses (O’Neill et al., 2017) and due to economic structure, in which agriculture accounts for a large share of the national economy (Cui et al., 2018).

3.2. Inequality of ECE Between Regions and Sectors

3.2.1. Spatiotemporal Distributions of ECE in Regions

The regional-level ECE (Figure 4) shows benefits for the NWC under RCP2.6 due to the positive effects of climate change on agricultural production in this region. However, as the temperature rises, the positive impact of climate change on China’s economy is limited, and the ECE in each region shows important uncertainties, especially in NEC and SC. The considerable decline in future crop yields in NEC (Figure 2) also seriously affects the region’s economy. The median ECE is estimated to be 14.9% to 66.0% of regional GDP from 2080 to 2099 in NEC (RCP4.5, RCP6.0, and RCP8.5). It can be found that if the projected climate (RCP8.5) at the end of the 21st century occurred today, the economic impact of crop failure in the NEC is exceeded half of regional GDP. The sharp increase in ECE in SC occurs after the 2060s, especially under RCP8.5. However, agricultural production in SC shows no significant decline after the 2060s (Figure 2). Consequently, the abnormal increase in ECE in SC can be attributed to interregional trade networks. Even if the agricultural production in SC is free from climate change, changes in supply and demand in other regions will be reflected in various economic sectors, thereby impacting the overall economy (OECD, 2015).

Regional differences in the economic consequences of climate change are also reflected in the effects on developed and less developed regions. Panels for different regions in Figure 4 are shown in ascending order from left to right of regional GDP per capita (statistics in 2012; see supporting information for details). The regions represented by the left panels have higher ECE than the right, except for NEC and SC (RCP8.5). The least developed regions in China (SWC) experiences 2.8 to 8.5 times more ECE caused by climate change than the most developed regions (EC) during 2080 to 2099. Similar patterns of inequality in regional economic impacts are also identified at the county level in the United States. On the one hand, crop failure in underdeveloped regions is worse (Figure 2), which directly leads to greater economic impacts. On the other hand, agricultural production in developed regions is less affected by warming and therefore gain more access to market, while less developed regions face more severe competition and suffer losses (FAO, 2018).

3.2.2. Inequality of ECE Between Sectors

Inequality in ECE across sectors can help us better understand the distribution of ECE across regions. We consider 11 economic sectors in the AMRIO model; however, the results show vast differences between sectors, with agricultural ECE being much higher than those in other sectors (Figure S4). To avoid a tedious analysis, we aggregate the economic sectors into four sectors (agriculture, manufacturing, energy supply, and services) in section 3.2.2 (Table S8). Figure 5 displays the distribution of ECE across regions and sectors. It can be found that limiting climate change impact to only agriculture sector significantly underestimates this impact. Other sectors also suffer important impacts through intersectoral trade networks, and this impact varies in the distribution of sectors between different regions.

The ECE of agriculture is still the worst, especially in SWC, NWC, and CC. From 2020 to 2099 (RCP8.5), the ECE of agriculture in these regions accounts for 64.6% to 92.2%, 71.0% to 76.6%, and 67.6% to 81.4% of the total regional ECE, respectively. Crop failure in these regions is severely affected by climate change, combined with the fact that agricultural production accounts for a large share of regional GDP (NWC = 8.4% and CC and SWC = 8.2%), so the agricultural market is severely affected, but the impact on other sectors is not obvious.

Figure 5 shows that the sharp increase in ECE in SC under RCP8.5 (Figure 4) mainly comes from agriculture. According to the interregional and intersectoral trade networks in the Chinese MIRIO table, agricultural production in SC relies on products of agriculture and manufacturing in CC, NEC, and SWC, which suffer from severe climate damage. While there is no obvious DED in SC, it is not immune to the cascading effects of climate change.
The impact of warming on agriculture in NEC has two phases, which are positive and negative. Crop yields experience a slight increase under climate change from 2020 to 2039, similar to NC and EC (Figure 2). We also capture this positive feedback from the economy in the AMRIO model, which is mainly reflected in the agriculture in NEC and NC. However, manufacturing in NEC, NC, and EC all suffers from the cascading effects of crop failure, resulting in approximately 1.3% (±0.5%) manufacturing value added. As the temperature rises, the economic impacts on agriculture in these three regions are no longer positive after the 2040s. Notably, it cannot be ignored that the ECE suffered due to manufacturing and services in these three regions. By the end of the century, the ECE of agriculture, manufacturing, and services in EC are 8.2% to 12.7%, 4.2% to 6.7%, and 3.1% to 4.4% of value added by sectors, respectively. The ECE of manufacturing in NC is particularly obvious, except for 2060 to 2079, which is higher than that in agriculture. The ECE of agriculture still accounts for a large proportion of NEC on account of severe crop failure during 2080 to 2099, but the ECE of manufacturing and services also reach 3.4% to 4.1% and 3.3% to 3.9% of value added by sectors, respectively.

4. Conclusions

In this study, an AMRIO model is used to evaluate the interregional and intersectoral ECE caused by the impact of warming on Chinese agricultural production, and the results are as follows:

1. Crop failure caused by climate change is estimated to have a serious impact on China’s economy. The cascading effect is crucial in assessing the economic consequences of climate change, and the ECE caused by climate change is approximately 18 times that of DED. Specifically, the ECE (5.9% to 13.6%) caused by the decline in agricultural production in the 2090s (RCP8.5) is equivalent to the total output of China’s present agriculture (7.2% to 9.6%). However, the GDP loss during the same period under RCP2.6 can be limited to −0.1% to 0.7% (negative values indicate economic gains). Therefore, we cannot ignore the potentially large benefits of limiting warming in a low emission scenario (Burke et al., 2018).

2. Our results are “bottom-up” estimates (Hsiang et al., 2017) of ECE, with the aim to understand the underlying mechanisms and describe the inequality of the economic consequences of climate change across regions and sectors. NEC suffers the bulk of ECE due to severe crop failure, with agriculture and manufacturing being the most affected. The ECE in SC is also very serious after 2060s, while there is no obvious downward trend in agricultural production during the same period. It can be found that the serious economic consequences are not necessarily caused by local agricultural losses, and out-of-region cascading effects should also be emphasized in climate change impact assessments. Results in EC and NC show that in addition to the agricultural sector, manufacturing and services in developed regions are expected to bear part of the ECE.

3. We also find that the economic impacts under climate change are unequal in developed and underdeveloped areas. Such inequalities are widespread around the world (not just in agricultural sector) and seem to be inevitable (FAO, 2018; Mendelsohn et al., 2006; Stevanović et al., 2016). The cause of inequality is that interregional trade may magnify the economic impacts of climate change in underdeveloped regions. However, we do not blame the open market, which is particularly important for large and negative productivity shocks (Baldos et al., 2019), but remind policy makers to pay attention to comprehensive of the economic consequences of climate change, so as to formulate regional climate mitigation policies to reduce the between-region inequality.

Notably, the results of the AMRIO model should be interpreted with caution. IO models probably overestimate the economic consequences of climate impacts due to the linear structure of the price mechanism and the lack of flexible substitutions (Koks et al., 2016). But for China, the government’s macrocontrol reduces the market elasticity, which included in the CGE model could lead to extreme changes in prices and quantity of products, so it is likely to underestimate the economic impact of climate change. In general, we believe that the AMRIO model can be used as a supplement to CGE models. The former can be regarded as the upper limit and the latter as the lower limit, which helps to comprehensively and rigorously understand the scope of the economic consequences of climate change.

Since the impacts of climate change on forest ecosystems, livestock, and labor productivity are not included in our model, this study is not the final estimate of climate change effects on agricultural. Another important
statement is that we have not considered the effect of increased CO$_2$ concentration, which can compensate for the decrease in crop yields caused by warming, but this effect may be overestimated in existing laboratory studies and field experiments (Long et al., 2006). In addition, large uncertainty exists in model evaluation, for example, greenhouse gas concentrations, crop models, and the assumptions for the AMRIO model all put the results at huge risk of uncertainty. Moreover, the AMRIO model only captures the amount of ECE but fails to capture the flow of ECE between regions and sectors. For example, Figure 5 displays a sharp increase in ECE in SC under RCP8.5, but at present, we cannot quantitatively describe the source of the increase. The next step of the research plan consists of improving the AMRIO model by improving the dynamic market simulation and refining the quantitative description of the interregional and intersectoral cascade effects. Considering that the impact of climate change is also multisectoral, we will consider the responses of energy systems, labor, and rising sea levels to climate change in future research. Furthermore, our results will be dynamically adjusted with research advances as the biophysical models (e.g., crop models) and climate models.

In summary, despite the limitations of this study, we focus on interpreting the inequality of economic consequences of climate change across regions and sectors. The results show that the distribution of ECE is not only related to natural conditions but also to socioeconomic conditions.

**Conflict of Interest**

All authors declare no financial conflicts of interest with this research.

**Data Availability Statement**

Yield change data sets for this research are included in Liu et al. (2020) and are provided in supporting information (listed in Tables S2, S3, and S9). The Chinese MRIO table is included in Mi et al. (2017) and is available online (https://doi.org/10.1038/s41467-017-01820-w). The climate data are publicly available and can be downloaded in the Data Distribution Centre of Intergovernmental Panel on Climate Change (https://www.ipcc-data.org/index.html).

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