Assessment of the Regional and Sectoral Economic Impacts of Heat-Related Changes in Labor Productivity Under Climate Change in China

Yuan Liu, Zhengtao Zhang, Xi Chen, Chengfang Huang, Feng Han, and Ning Li

Abstract
Climate change leads to heat-related changes in labor productivity, which have additional economic impacts. Based on a framework that considers the impacts evolving from climate change to labor productivity to economic impact, we estimate the changes in labor productivity for indoor and outdoor activities and different work intensities at the grid level in China under a wide range of climatic and socioeconomic conditions and then evaluate the economic impacts in seven regions and eight sectors. The results show that (a) the negative impacts of labor productivity are concentrated in outdoor sectors, and the labor productivity of indoor sectors will decrease slightly or even increase due to high air-conditioning device penetration rates under relatively optimistic scenarios. (b) The national results show that total economic impacts increase by 0.28%–0.61% of the GDP for each 1°C rise in the temperature, and the total economic impacts of labor productivity reductions in the most pessimistic scenario reach 1.15%–2.67% of the GDP in 2100. (c) The regional results indicate that the regions with lower labor productivity impacts (Northwest and Northeast China) still suffer large economic impacts, highlighting the importance of economic impact assessments across the regions. (b) The sectors in the seven regions of China that are most sensitive to climate change are agriculture and construction. The economic impacts in the manufacturing and service sectors, which contribute 22%–35% and 11%–15% of regional GDP losses, respectively, cannot be ignored, and should receive more attention in climate mitigation policies.

Plain Language Summary
Climate change will increase the heat stress in working environment, which limits the labor productivity of workers. Reductions in labor productivity will also lead to economic impacts. The consequences of this impact chain within China have been evaluated for the first time. Outdoor workers will be seriously affected by heat stress, while indoor workers’ productivity may benefit from the popularity of air-conditioning devices. However, all regions of China will face the negative economic impacts of increased heat stress under climate change. Even if the heat-related labor productivity of a region is not severely affected, the economic impacts cannot be ignored due to the economic links between regions and sectors. The agriculture and construction suffer from the most serious economic impact. Although labor productivity in the indoor sectors will benefit from the popularity of air-conditioning devices, the economic impact of the manufacturing and service sectors cannot be underestimated.

1. Introduction

Heat stress in hot working environments both indoors and outdoors may adversely affect the occupational safety and health of workers (Parsons, 2014). Heat stress may damage muscle performance (Rowell, 1993), reduce brain function and cause a series of occupational diseases (NIOSH National Institute for Occupational Safety & Health, 2016). The International Organization for Standardization (ISO) and several governments have proposed intervention measures (e.g., increasing rest time during work) based on the work intensity and heat stress in working environments (ISO, 2017) (NIOSH National Institute for Occupational Safety & Health, 2016; GB/T 33658-2017). Both the adverse effects of heat stress on physical functions and intervention measures focused on reducing working hours lead to labor productivity reductions, according to previous studies. Heat stress reduced the labor productivity of Indian farmers (Sahu et al., 2013),...
and surveys of Chinese construction workers showed reductions in the labor productivity of rebar workers laboring in extreme heat (Li et al., 2016; Yi & Chan, 2017). Indeed, at present, approximately one-third of the world's population is exposed to deadly climate conditions for nearly one month of every year (Mora et al., 2017).

Heat stress is occurring more frequently under climate change (Chen et al., 2020; Luo & Lau, 2018; Sherwood & Huber, 2010), and 2015–2019 were the five hottest years on record (Watts et al., 2020). Since climate change-related indicators show a trend of accelerating deterioration (Perkins-Kirkpatrick & Lewis, 2020), most researchers use the wet bulb globe temperature (WBGT), which has a wide range of applications in occupational safety and health (Epstein & Moran, 2006; Lemke & Kjellstrom, 2012), as an indicator of heat stress to estimate future labor productivity by quantifying its relationship with WBGTs (Dunne et al., 2013; Flouris et al., 2018; Kjellstrom et al., 2009). The Intergovernmental Panel on Climate Change's (IPCC's) Fifth Assessment Report pointed out that projected climate change will exacerbate existing health problems, especially in developing countries (Pachauri et al., 2014).

On this basis, several pioneering studies are beginning to focus on the macroeconomic consequences of changes in labor productivity (Aaheim et al., 2012; Ma et al., 2019; Roson & Sartori, 2016). The methodology employed by early studies is idealistic, but these studies confirm the dominant position of changes in labor productivity in economic impact assessments considering climate change (DARA, 2012; Roson & Sartori, 2016). Researchers continue to improve the methodology used in these assessments by distinguishing work intensity (Kjellstrom et al., 2016), including the socioeconomic conditions (Takakura et al., 2017) and considering climate change adaptations (Morabito et al., 2020; Orlov et al., 2020; Takakura et al., 2018) into the estimates. However, economic impact assessments of heat-related changes in labor productivity under climate change are still in the early stage. First, most previous studies focus on the direct economic costs but ignore the indirect economic impacts between regions and sectors (e.g., cross-border economic impacts), which cannot be ignored in assessments of the macroeconomic consequences of climate change (Knittel et al., 2020; Orlov et al., 2020; Zhang et al., 2018). In addition, existing studies analyze global economic impacts and consider the differences between countries (Matsumoto, 2019). However, the unequal distribution of economic impacts within countries has not been characterized, especially for China. On the one hand, China has the largest population in the world, most of which is exposed to high temperature risks (Cai et al., 2021; Liu et al., 2017). On the other hand, China is a vast country with regional variations in climate conditions, natural resources and economic development (Mi et al., 2017). Thus, it is important to assess the unequal distribution of the economic consequences among the different regions in China.

We consider an impact chain from climate change to labor productivity to economic impacts. According to the future climatic and socioeconomic conditions predicted by representative concentration pathways (RCPs) and shared socioeconomic pathways (SSPs), we estimate heat-related changes in labor productivity for different work intensities at the grid level in China from 2020 to 2100. To estimate the macroeconomic impacts in China, an adaptive multiregional input-output (AMRIO) model is used to quantify the regional and sectoral economic impacts of changes in labor productivity. The results of the AMRIO model, which are presented as a percentage of the GDP, are defined as the total economic impacts (GDP loss), and the changes in labor productivity weighted by the proportion of labor income in the GDP are defined as direct economic costs.

## 2. Method

To quantitatively assess the impact of heat stress under climate change on China's labor productivity and the resulting economic impact, we adopt an interdisciplinary theoretical framework (Figure 1) (Orlov et al., 2020; Takakura et al., 2018): Projections of climate variables are used to calculate the WBGT of each grid (0.5° × 0.5°) in China (Section 2.2). Then, WBGTs are introduced into expose-response functions to quantify the impact of heat stress on labor productivity (Section 2.3). RCPs and SSPs are combined to estimate the trend of the air-conditioning penetration rate (Section 2.4). Finally, the changes in labor productivity are employed as shocks and input into the economic model to calculate the economic impact of climate change under different RCP-SSP combinations (Section 2.5).
Climate Projections and Scenario Settings

The climate variables are derived from the simulation results for the daily temperature and near-surface relative humidity obtained from 12 global climate models (GCMs) provided in the Coupled Model Intercomparison Project 5 (CMIP5) (Table S1 in Supporting Information). We use four climate conditions: RCP2.6 (corresponding to the 2.0°C target), RCP4.5 (intermediate emission path), RCP8.5 (continuous increase in greenhouse gases) and no climate change (climate conditions were fixed in 2012, which is consistent with our previous study). In addition, ERA5 reanalysis data sets are used to evaluate the simulation capabilities of the GCMs. Both GCM data sets and reanalysis data sets are interpolated to 0.5° × 0.5° grids using bilinear interpolation. The detailed information is described elsewhere (Chen et al., 2020).

The estimations of the future population and economy are obtained from the downscaling data of SSPs provided by Murakami and Yamagata (Murakami & Yamagata, 2019). This data captures the difference in urban and nonurban areas in a more reasonable manner and has a better simulation effect on grid-level GDP per capita. We use SSP1 (sustainable development path), SSP2 (intermediate path) and SSP3 (regional competitive path). The scale of the population and economy under different SSPs are provided in the supporting information (Figures S1 to S3 in Supporting Information). The combination of different RCPs and SSPs represents completely different climate and socioeconomic conditions. We considered three different scenario settings: RCP2.6-SSP1 represents the most optimistic estimate, the effects of climate change using this combination are small, and the regional development is balanced; RCP4.5-SSP2 represents the middle path, the effects of climate change using this combination are moderate, and the world develops according to the typical trend in recent decades; RCP8.5-SSP3 represents the most pessimistic estimate, although the probability that this scenario will occur is low (Fujimori et al., 2017), this combination is adopted by most studies and represents the lower limit of economic impact assessments (Dong et al., 2015; Liu et al., 2017).
2.2. Calculation of the WBGT

We use the WBGT to measure heat stress in the environment (ISO, 2017); this measurement is widely used in occupational safety and health assessments considering heat exposure (Parsons, 2014). The measurement of heat stress in the work environment considers the temperature, humidity, radiation and wind. We do not consider individual differences such as gender, age, health status, and clothing. We distinguish between indoor and outdoor workers. The calculation of indoor WBGT follows the methods proposed by Epstein and Moran (2006) and Stull (2011): the WBGT is calculated based on the linear relationship between the wet bulb temperature (WBT) and WBGT. Due to the difficulty of obtaining the black bulb temperature, the calculation of the outdoor WBGT uses a “simplified WBGT” that considers the temperature and humidity (ABOM, 2010), which reflect heat stress for average outdoor conditions and ignores the effects of wind and radiation (Lee & Min, 2018; Willett & Sherwood, 2012). See the supporting information for detailed processing information.

The WBGT calculated above is based on daily data obtained for each grid. To better characterize the change in labor productivity that occurs within a day, we use the “44+4” method (Kjellstrom et al., 2018) and consider the legal working time (8h) in China, assuming that WBGT is close to WBGTmean (calculated by the daily average temperature) from 8:00 to 10:00 and 16:00 to 18:00, is close to WBGTmax (calculated by the daily maximum temperature) from 11:00 to 12:00 and 13:00 to 14:00 and is close to the average of the WBGTmean and WBGTmax for the remaining working hours. Then, we estimate the daily average impact on labor productivity based on the WBGTmean, WBGTmax, and the average of WBGTmean and WBGTmax.

2.3. Air-Conditioning Devices

An air-conditioning device can reduce the heat stress of indoor workers and is an effective adaptation measure for workplaces with high temperatures. According to Isaac and van Vuuren (Isaac & van Vuuren, 2009), the air-conditioning device penetration rate is constrained by climate conditions and economic development. The former links the maximum climate saturation of air-conditioning devices with cooling degree days (CDDs) (A degree day is defined as the difference between mean daily temperature and a given reference temperature. For metrics designed to reflect the refrigeration demand, the reference temperature is considered to be a human comfort temperature, which is 26°C following the “Design code for heating ventilation and air conditioning of civil buildings” (GB50736-2012)), and the latter links the availability of air-conditioning devices with GDP per capita. Most prior studies are based on the exponential function and logistic function developed by Sailor and Pavlova (2003) and corrected by McNeil and Letschert (2008), which represent the climate maximum saturation and availability of air-conditioning devices, respectively. However, existing functions cannot reflect the explosive growth of air-conditioning devices in China (McNeil & Letschert, 2008). Therefore, we use the observed air-conditioning device penetration rates, CDD and per capita GDP in China from 1978 to 2018 to calibrate the above two functions (Figure S4 in Supporting Information).

Based on the CDD and per capita GDP obtained for different RCP-SSP combinations, we can calculate the annual air-conditioning device penetration rates for each grid in China from 2020 to 2100 (Figure 2). The introduction of air-conditioning device penetration rates is based on three key assumptions: (a) If air-conditioning devices are available, then the productivities of indoor workers are not reduced, regardless of the thermal environment. (b) Due to the lack of reliable air-conditioning device penetration data, we assume that the trends of air-conditioning device penetration rates in various economic sectors are the same as those of the household sector. (c) The additional energy consumption and related economic costs caused by air-conditioning devices are not considered in the present study.

2.4. Labor Productivity

The relationship between the WBGT and labor productivity is based on the exposure response function used for the “High Occupational Temperature Health and Productivity Suppression” program (Hothaps program) (Kjellstrom et al., 2009), which was calibrated by Sahu et al. (2013) through epidemiological studies and has been widely used in the study of heat stress affecting labor productivity (Brode et al., 2018; Orlov et al., 2020). The Hothaps program assesses the relationship between the WBGT and labor productivity.
through a two-parameter logistic function, where different parameter combinations represent high, moderate and low work intensity (Figure S5 in Supporting Information). In this study, labor productivity is defined as the percentage of a working hour that a worker can perform his/her intended work. If no rest time is needed, because of heat, during a working hour, then the work capacity is 100%. If 75% rest time is needed, the work capacity is 25%, etc.

Work intensity is quantified by the thermal metabolism rate, which measures the energy cost of a task and is the main factor in the balance of heat exchange between the human body and the environment (unit: Watt) (NIOSH National Institute for Occupational Safety & Health, 2016). The thermal metabolism rate under low work intensity is less than 233 W, the moderate work intensity is approximately 234–349 W, and the high work intensity is greater than 350 W (NIOSH National Institute for Occupational Safety & Health, 2016).

To measure the change in labor productivity in each economic sector, we refer to classifications proposed in prior research (Kjellstrom et al., 2009; Hsiang et al., 2017) and the status of occupational safety and health in China (Li et al., 2014; Su et al., 2020): agriculture and construction are outdoor high-intensity tasks; the mining, manufacturing, energy supply, transport and storage, and hotel and restaurant industries involve indoor moderate-intensity tasks; and the other service industries involve indoor low-intensity tasks (Table S2).

We can use the exposure response function to calculate the daily labor productivity of each sector and each grid under three RCP-SSP combinations and the NoCC condition. The estimation of the change in labor productivity involves three steps: (a) Labor productivity is recalculated using the estimation of the air-conditioning device penetration rate calculated in Section 2.3. (b) The daily labor productivity change is calculated from the labor productivity under three RCP-SSP combinations minus the value under the NoCC condition in the corresponding year. (c) According to the projection of population scale under the three SSPs and the sectoral distribution of employed population in each region in 2012 (Table S3 in Supporting Information), the changes in labor productivity at the grid level are aggregated to the regional level and finally input into the economic model (Section 2.5). The results of the present study do not consider the flow of the labor force across regions and sectors.
2.5. Economic Model

In the present study, the AMRIO model is used to estimate the economic impacts of heat-related changes in labor productivity in hot working environments under climate change. The AMRIO model is based on the Leontief production function and uses an iterative model framework to simulate the macroeconomic impact of external shocks and the economic ripple effects between regions and sectors (Liu et al., 2020). The AMRIO model originated from a traditional input-output (IO) model and was initially used to evaluate the macroeconomic impact of natural disasters (Hallegatte, 2008; Li et al., 2013). IO models have been widely developed and applied in climate change studies to assess aspects, such as agriculture (Huang et al., 2020), sea level rise (Hallegatte et al., 2011), and economic ripple effects (Zhang et al., 2018), due to low data requirements and clear reflections of economic links that exist between sectors and regions (Rose, 2004). The AMRIO model used in this study is based on the Chinese multiregional IO table (Mi et al., 2017), which divides China into seven regions, covering eight sectors in each region. A detailed description of the model is provided in (Hallegatte, 2008) and (Liu et al., 2020).

Each sector in the economy can be regarded as a producer, where labor is one of the main inputs for production. Each sector is also a consumer who needs intermediate products from other sectors. It is assumed that the total output meets the intermediate demand and the final demand of consumers under the NoCC condition. However, this economic balance is adversely affected by a reduction in labor productivity caused by heat stress under climate change and subsequently, adversely affects the supply chain. Thus, a reduction in labor input reduces output from the perspective of the producer. We input the percentage of the change in labor productivity (Section 2.4) as the percentage of the change in the output in each sector into the AMRIO model year by year for iterative calculations. Importantly, for clarify, we assume that the economic structure is fixed in 2012 and the economic scale of the corresponding year refers to the SSPs.

It should be noted that the result, which is reported as a percentage of the GDP, is regarded as the total economic impact (GDP loss) in the corresponding year, which considers the indirect impacts related to the connection between regions and sectors. In addition, referring to the calculations of the “first-order effect” (Roson & Sartori, 2016), we estimate the direct economic costs based on the changes in labor productivity, which are weighted by the proportion of labor income in the GDP.

2.6. Uncertainties

The uncertainty in this study can be decomposed into uncertainty regarding labor productivity and uncertainty inherent in the AMRIO model. The uncertainty regarding labor productivity is driven by climate and socioeconomic conditions, the exposure response function, and the interactions among these factors (Hsiang et al., 2017). Monte Carlo sampling is used to determine the uncertainty related to the climate variables (12 GCMs) and exposure response function (1,000 resamplings) for each RCP-SSP combination. Figure 3 shows the uncertainty related to changes in labor productivity. In addition, in order to determine which factors contributed to the difference in the GDP change rates, we conducted an analysis of variance (ANOVA) for China’s total GDP change rates.

The results of an AMRIO model are usually sensitive to the shocks introduced (i.e., changes in labor productivity) and model parameters. The range of changes in labor productivity was determined, and we input different percentiles (10th, 25th, median, 75th and 90th) into the AMRIO model to determine the uncertainty of the results. In addition, we set the interval of the model parameters (up and down 30% based on the standard values) to determine the sensitivity of the AMRIO model to parameters (Mendoza-Tinoco et al., 2017). The uncertainties in the AMRIO model are shown in the shaded areas in Figure 5 and Figure 6.

3. Results

3.1. Labor Productivity

We obtained the impact of climate change on labor productivity of different work intensities (Figure 3) by employing the calculations presented in Section 2.1–2.4. The changes in labor productivity need to be explained by differences in work intensities, RCP-SSP combinations and regions.
Indoor workers laboring under low and moderate intensity are almost immune to heat stress under climate change. Labor productivity shows an upward trend (since the 2030s) under RCP2.6-SSP1 and RCP4.5-SSP2 relative to the NoCC condition in SC, CC, and EC, which is mainly due to the high air-conditioning penetration rate in these regions (Figure 2). Under RCP8.5-SSP3, labor productivity shows a downward trend due to a high WBGT and low air-conditioning penetration rate. SSP3 represents a path of stagnant economic development but a large population (Figures S1 and S2 in Supporting Information), so the availability of air-conditioning devices is low and cannot meet the cooling demands of indoor workers. However, overall, indoor workers will be less affected by heat stress in the future (the impact on labor productivity is within 1%).

In contrast, the productivity of outdoor workers is severely affected by heat stress. It should be noted that the ordinate axes in Figure 3 are not the same. The productivity of outdoor workers in various regions initially shows downward trends and stabilizes after the 2050s and 2080s under RCP2.6-SSP1 and RCP4.5-SSP2, respectively; under RCP8.5-SSP3, the productivity of outdoor workers continues to decline from 2020 to 2100. The productivity of outdoor high-intensity workers falls by more than 10% by the late 21st century in most regions. The reduction in labor productivity is the largest in Southern China (SC), reaching 15%–26% in 2100, followed by Eastern China (EC) and Central China (CC), where labor productivity reductions reach 10%–19% and 9%–19%, respectively. Even in the northernmost part of China, the labor productivity of Northeastern China (NEC) will fall by 4%–16% in 2100 relative to the NoCC condition.

Figure 4 shows the spatial distribution of the expected changes in labor productivity in China by the late 21st century (2090–2100). The red area shows the increase in labor productivity for indoor low and moderate work intensity in SC under RCP2.6-SSP1 and RCP4.5-SSP2 relative to the NoCC condition, which is consistent with Figure 3. Under RCP8.5-SSP3, the productivity of indoor low- and moderate-intensity workers decreases from north to south, but there are some scattered light-colored areas (areas with less reduction), which correspond to the provincial capitals of China. This occurs because the provincial capitals
are richer than the surrounding areas, and the use of air conditioning reduces labor productivity losses in the provincial capitals.

### 3.2. National Economic Impact

The macroeconomic impacts at the national level are shown in Figure 5a, which are calculated based on the percentage change in the GDP under the NoCC condition. Under the most pessimistic scenario (RCP8.5-SSP3), the GDP losses in China reached 1.03%–2.51%, and the trend of increasing economic impacts will not stop in this century. The GDP losses under RCP2.6-SSP1 and RCP4.5-SSP2 will stabilize after the 2050s and 2080s, reaching 0.14%–0.75% of the GDP and 0.37%–1.29% of the GDP, respectively. Therefore, GDP losses can be limited to 1% of the GDP in the most optimistic scenario. In addition, we estimate the relationship between the temperature increase and GDP loss (Figure 5b), where the temperature increases are calculated relative to the preindustrial values. The fitted results show a significant linear relationship ($R^2 = 0.987$). For each 1°C increase in the temperature, the GDP loss will increase by 0.28%–0.61%, which also means that if the 1.5°C target is achieved, China’s GDP loss will be reduced by 0.14%–0.30% relative to the 2.0°C target.

The results from an ANOVA analysis (Figure S6 in Supporting Information) reveal that until the middle of the 21st century, the difference in GCMs is the primary contributor to the variance of the results of China’s total GDP loss rates. However, in the second half of the 21st century, the difference between RCP-SSP combinations is the primary contributor to the variance. For example, by 2100, approximately 79% of the variance in the results is explained by the difference between RCP-SSP combinations.
3.3. Regional Economic Impacts

Figure 6 shows the economic impacts of changes in labor productivity in the regions of China. These impacts are calculated based on the percentage change in the regional GDP from the NoCC condition. The trends for regional GDP losses are similar to the results at the national level. Except for the continuous increase in GDP losses under RCP8.5-SSP3, the GDP loss of each region under the other two RCP-SSP combinations reaches a peak. Under RCP2.6-SSP1, the GDP loss in several regions of China has a decreasing trend. For example, the average GDP loss in CC in the 2080s is approximately 0.57%, while that in the 2090s is approximately 0.51%. Similar trends are also obvious in EC and SC, where the average GDP loss decreased by approximately 0.11% and 0.08% from the peak value, respectively. The reduction in GDP losses under RCP2.6-SSP1 is attributed to the popularization of air-conditioning devices and stringent emission reductions (van Vuuren et al., 2011).

Climate change has increased inequality between regions, causing regional impacts to exceed the expected national averages (Hsiang et al., 2017). Under RCP8.5-SSP3, the median GDP loss of each region is approximately 2% in 2100 relative to the NoCC. However, this does not mean that the economic impact is equal in all regions of China. The average GDP loss is approximately 2.23% in NWC in the 2090s (RCP8.5-SSP3), but workers in this region are rarely exposed to heat stress (Figure 3). The economic impacts in NWC can be explained by (a) a large proportion of workers in outdoor high-intensity sectors (agriculture and construction) and (b) ripple effects outside this region, which spread through the economic connections between regions. In contrast to NWC, workers in SC will be severely affected by heat stress in the future, but this is not fully reflected in the macroeconomic results. Since reductions in labor productivity of outdoor workers will be much greater than that of indoor workers, the smaller proportion of the employed population of outdoor sectors in SC may prevent it from more GDP losses.

Figure 7 shows the relationship between direct economic costs and regional GDP losses. The direct economic costs are calculated as the variation in labor productivity in each sector and region multiplied by the share of labor income in the GDP. The direct economic costs due to changes in labor productivity are
Figure 7. Relationship between regional GDP losses and direct economic costs under three representative concentration pathway (RCP)-shared socioeconomic pathway (SSP) combinations. Table in the left panel shows the regression coefficients of regional GDP losses responses to direct economic costs in seven regions of China, and the p-values of all coefficients are less than 0.001 (see Supporting Information for detailed regression results, Tables S4 to S6).
Figure 8. Average sectoral economic impacts (% of value added) of the various regions from 2090 to 2100. Abbreviations: CC, Central China; EC, East China; NC, North China; NEC, Northeast China; NWC, Northwest China; SC, South China; SWC, Southwest China.

0.03%–0.24%, 0.02%–0.42%, and 0.02%–0.88% of GDP during the 21st century under RCP2.6-SSP1, RCP4.5-SSP2 and RCP8.5-SSP3, respectively, which are all lower than the regional GDP losses. When combining the results of seven regions, there is a significant linear relationship between the direct economic costs and regional GDP losses under three RCP-SSP combinations. The regression results for NWC and SC under RCP8.5-SSP3 indicate that each 1% increase in the direct economic cost leads to an increase of 9.21% in the regional GDP loss in NWC and an increase of 2.61% in SC. The regression coefficients may reflect labor dependency in different regions (described as the number of workers used to produce one unit of GDP, Figure S7 in Supporting Information). Regions with high labor dependence are more susceptible to the impact of reductions in labor productivity. This result explains part of the reason for the higher regional GDP losses in NWC shown in Figure 6.

3.4. Sectoral Impacts

Economic connections between sectors may alter the valuation of economic impacts in different sectors. Figure 8 shows the economic impacts of changes in labor productivity for each sector and region at the end of the 21st century. The economic impacts are shown as percentages of the sector’s value added. As a high-intensity outdoor sector, agriculture suffers from the most serious economic impact, followed by the construction industry. Such characteristics are obvious in different regions and for different combinations. It should be noted that there are no gains in the results under RCP2.6-SSP1 and RCP4.5-SSP2, which seems to be inconsistent with the results presented in Figure 3. This can be explained by (a) the reduction in labor productivity in outdoor sectors is much larger than the labor productivity gains of the indoor sectors and (b) the indirect economic impacts; that is, the indoor sectors are affected by economic ripples from the outdoor sectors.

Although labor productivity in the indoor sectors will benefit from the popularity of air-conditioning devices, the economic impact of the manufacturing and service industries cannot be underestimated. At the end of the 21st century, the loss of manufacturing contributed to 22%–35% of the regional GDP losses in various regions, with EC and SC having the largest proportions (Figure S8 in Supporting Information). The large economic impacts in manufacturing can be explained by the large proportion of China’s manufacturing employment population, especially in EC and SC, which accounted for more than one-quarter of employment.
In addition, the service industries contribute to 11%–15% of the regional GDP losses (Figure S8), but due to the low work intensity of the service industries, the value-added losses in this sector are not obvious in various regions.

The characteristics of the sectoral economic impacts in NWC are different from those of other regions, especially under RCP8.5-SSP3. In addition to agriculture and construction, the economic impacts of indoor sectors such as mining, manufacturing, energy supply, and service industries in NWC are also evident and almost the same as the value-added losses of the outdoor sectors.

4. Discussion

We assessed heat-related changes in labor productivity in China from top to bottom and the resulting economic impacts under various climatic and socioeconomic conditions using a quantitative method for estimating the economic impacts due to interregional and intersectoral linkages.

Heat-related changes in labor productivity vary with climate and socioeconomic conditions, geographic locations and work intensity. The results are basically consistent with those of previous studies (Kjellstrom et al., 2018; Orlov et al., 2020), but the estimations of indoor labor productivity reductions are smaller. The estimations of indoor labor productivity are related to air-conditioning device penetration rates because current studies assume that indoor workers benefitting from air-conditioning devices are not exposed to heat stress. The penetration rate is generally predicted by linking the CDD and income. We calibrate the original functions based on the penetration rates of air-conditioning devices in the past 40 years in China. The corrected functions reflect the rapid electrification process and avoid underestimating the air-conditioning device penetration rate in China. The results of the present study show that indoor workers in China will rarely be affected by heat stress in the future. The difference between the changes in labor productivity and economic impacts in indoor and outdoor conditions illustrates the importance of considering air-conditioning devices. However, we do not consider the economic impacts of using air conditioners (e.g., energy demand). Changes in energy demand will lead to high economic losses under climate change (Hasegawa et al., 2016). Therefore, all costs related to air-conditioning devices should be included in future economic impact assessments, and reducing the costs is an adaptation measure that needs to be considered as a response to climate change.

Another possible adaptation for responding to climate change is the reallocation of resources in the economy (Hsiang et al., 2017). We use the AMRIO model to estimate the extent to which this adaptation has changed the direct economic cost of reductions in labor productivity. Considering different RCP-SSP combinations, we input changes in labor productivity into the AMRIO model and run multiple iterations to calculate the total economic impacts. The total economic impacts for each RCP-SSP combination obtained in this study are larger than the direct economic costs (Figure 7). However, the results of Takakura et al. (2017) show that only the total economic impacts under SSP3 are larger than the direct economic costs, and the ratio of total economic impacts to direct economic costs estimated by Hsiang et al. (2017) is approximately 0.94 (2.61–9.21 in this study). The larger total economic impacts found in this study may be explained by the following: (a) China has the largest labor force in the world, and the proportion of the labor force working in outdoor high work intensity sectors is large; (b) China is a developing country, and its underdeveloped economy may be more sensitive to reductions in labor productivity; and (c) the AMRIO model is subject to rigid economic connections and lacks elastic substitution, which will make it overestimate the economic impacts (Koks et al., 2016). The possibility of substitution or flexibility of trade share under the IO framework should be considered in future studies to increase the flexibility of IO modeling (Guan et al., 2020; Oosterhaven & Többen, 2017). The computable general equilibrium (CGE) model has a detailed description of the behavioral mechanism of economic entities and is a classic analysis tool in climate change research. The comparison between a CGE model and an IO model is also one of the focus of the next research. In short, these simulations are rough approximations of the complex national economy and do not capture the effects of international trade, but they indicate that the propagation effects through the inter-regional and inter-sectoral linkage will expand or exacerbate the economic impacts of heat stress.

Researchers have reached a broad consensus that climate change will increase global income inequality (Burke et al., 2015), and poor countries will suffer most of the damage from climate change (Mendelsohn et al., 2006). The primary reason why poor countries are so vulnerable is their geographic locations. Cli-
Climate change is supposed to exacerbate the already severe heat-related effects in low-latitude countries. In contrast, the economy and population in China are concentrated in the east and south (e.g., EC and SC) (Figures S1 to S3 in Supporting Information). The direct impacts of climate change in poor regions are less than those in rich regions (Figure 3), but the former will suffer extensive economic damage from climate change (Figure 6). Most of these losses come from indirect economic impacts outside poor regions, which ultimately result in total economic impacts that are several times the direct economic costs (Figure 7). The results indicate that the economic impacts of climate change in the poor regions of China are not due to their geographical locations but the propagation effects through the supply chain.

The following limitations of this study should be considered when discussing these results. First, the annual heat-related labor productivity reduction is simulated as a separate event in this study, and the interactions between different years should be considered (Zeng & Guan, 2020). Second, the results of the present study do not consider the flow of the labor force across regions and sectors, and this assumption is clearly unrealistic. The migration of the labor force away from regions and sectors adversely affected by climatic factors (Aaheim et al., 2012) should also be considered in economic impact assessments and adaptation measures employed to address climate change. Third, differences in the air-conditioning device penetration rates in different sectors was not considered but rather unified as the air-conditioning device penetration rate in the household sector. It is necessary to conduct extensive empirical studies in the future to verify the penetration rates of air conditioners in different sectors. In addition, the large reductions in the labor productivity of outdoor workers are impressive, but the results do not consider workers’ adaptation measures. For example, outdoor workers can choose flexible working hours to avoid heat stress (e.g., working in the early morning or evening); workers in the agriculture and construction sectors can replace high-intensity manual labor with mechanized devices. However, it is crucial to quantify the economic impacts for the most pessimistic scenario (i.e., without considering adaptation measures) to clarify how much of the economic losses can be avoided by mitigating heat stress under climate change. A cost-benefit evaluation of the adaptation measures would be helpful for formulating an optimal climate adaptation plan.

5. Conclusion

In this study, we explore each step of the “climate change-labor productivity-economy” impact chain in China and calculate the total economic impact. If climate change mitigation fails (RCP8.5-SSP3), GDP losses caused by heat-related reductions in labor productivity will reach 1.03%–2.51% of GDP in 2100, and this downward trend will not stop in the 21st century. GDP losses can be limited to 1% of the GDP in the most optimistic scenario (RCP2.6-SSP1). The regional results show the unequal distribution of economic impacts in China. Regions where labor productivity is rarely affected by heat stress (NWC and NEC) still suffer large economic impacts. Especially under RCP8.5-SSP3, the total economic impacts in NWC and NEC reach 1.14%–5.28% and 0.76%–3.35% of the regional GDP in 2100, respectively, indicating that even if the direct impacts of climate change are small, the indirect economic impacts cannot be ignored due to the economic links between regions and sectors. The sectors most sensitive to climate change in the seven regions of China are agriculture and construction, which are outdoor high work intensity sectors. More attention should be paid to the manufacturing and service sectors, which contribute to 22%–35% and 11%–15% of the regional GDP losses, respectively. The present study provides a new perspective: The economic impact of climate change is assessed within a single country. This study also provides support for the formulation of differentiated climate change mitigation policies. In future studies, more comprehensive worker-related impacts and adaptation measures should be considered.

Data Availability Statement

The CMIP5 multimodel data sets are publicly available and can be downloaded in the Data Distribution Center of Intergovernmental Panel on Climate Change (https://www.ipcc-data.org/index.html). The European Center for Medium-Range Weather Forecasts reanalysis data are available online (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5). The downscaled GDP and population data (0.5° × 0.5°) from the SSPs are available online (https://www.cger.nies.go.jp/gcp/population-and-gdp.html). The Chinese MRIO table is included in (Mi et al., 2017), and is available at (https://doi.org/10.1038/s41467-017-01820-w).
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