Earth's Future

RESEARCH ARTICLE
10.1029/2018EF000883

Key Points:
- Increased heat exposure due to climate change will reduce labor capacity
- Efficacy and plausibility of working time shift as an adaptation measure to avoid heat stress is evaluated
- Working time shift is insufficient to offset the impact without stringent climate-change mitigation

Supporting Information:
- Supporting Information S1

Correspondence to:
J. Takakura,
takakura.junya@nies.go.jp

Citation:
Takakura, J., Fujimori, S., Takahashi, K., Hasegawa, T., Honda, Y., Hanasaki, N., et al. (2018). Limited role of working time shift in offsetting the increasing occupational-health cost of heat exposure. *Earth's Future*, *6*, 1588–1602. https://doi.org/10.1029/2018EF000883

Received 29 MAR 2018
Accepted 17 SEP 2018
Accepted article online 19 SEP 2018
Published online 21 NOV 2018

Limited Role of Working Time Shift in Offsetting the Increasing Occupational-Health Cost of Heat Exposure

Jun'ya Takakura[1], Shinichiro Fujimori[2], Kiyoshi Takahashi[1], Tomoko Hasegawa[1], Yasushi Honda[3], Naota Hanasaki[1], Yasuaki Hijioka[1], and Toshihiko Masui[1]

[1]National Institute for Environmental Studies, Ibaraki, Japan, [2]Department of Environmental Engineering, Kyoto University, Kyoto, Japan, [3]Faculty of Health and Sport Sciences, University of Tsukuba, Ibaraki, Japan

Abstract Climate change increases workers' exposure to heat stress. To prevent heat-related illnesses, according to occupational-health recommendations, labor capacity must be reduced. However, this preventive measure is expected to be costly, and the costs are likely to rise as the scale and scope of climate change impacts increase over time. Shifting the start of the working day to earlier in the morning could be an effective adaptation measure for avoiding the impacts of labor capacity reduction. However, the plausibility and efficacy of such an intervention have never been quantitatively assessed. Here we investigate whether working time shifts can offset the economic impacts of labor capacity reduction due to climate change. Incorporating a temporally (1 hr) and spatially (0.5° × 0.5°) high-resolution heat exposure index into an integrated assessment model, we calculated the working time shift necessary to offset labor capacity reduction and economic loss under hypothetical with- and without-realistic-adaptation scenarios. The results of a normative scenario analysis indicated that a global average shift of 5.7 (4.0–6.1) hours is required, assuming extreme climate conditions in the 2090s. Although a realistic ($<$3 hr) shift nearly halves the economic cost, a substantial cost corresponding to 1.6% (1.0–2.4%) of global total gross domestic product is expected to remain. In contrast, if stringent climate-change mitigation is achieved, a realistic shift limits the remaining cost to 0.14% (0.12–0.47%) of global total gross domestic product. Although shifting working time is shown to be effective as an adaptation measure, climate-change mitigation remains indispensable to minimize the impact.

Plain Language Summary Outdoor workers are exposed to excessive heat stress particularly in hot seasons and its impact is expected to increase as a result of climate change. This will reduce the capability of labor and eventually cause economic loss. Shifting working time to earlier morning, when it is cooler than during midday, can be an effective way to reduce the effect of heat stress. In this study, we investigated the effectiveness and plausibility of a working time shift as an adaptation measure to climate change. Although a working time shift was shown to be effective to reduce the effect of heat stress, the required amount of shift was beyond the realistic range unless stringent climate-change mitigation was achieved. If society tries to avoid the economic impacts of climate change on outdoor labor only by working time shifts, outdoor workers in many regions will need to start working well before dawn. Climate-change mitigation and other adaptation measures (e.g., mechanization of work, body cooling, etc.) are also inevitable to minimize the impact of climate change.

1. Introduction

Heat exposure limits the capability of physical activity in working sites considering the risk of heat-related illnesses (International Organization for Standardization, 1989; National Institute for Occupational Safety and Health [NIOSH], 2016). This means that the per-hour time that workers are allowed to engage in labor (labor capacity) must be limited depending on the environmental heat exposure level. Limited labor capacity will result in lower output of economic activities, and thus, economic loss will be evoked. This economic loss can be interpreted as the occupational-health cost for preventing heat-related illnesses by limiting the labor capacity. This situation will be worsened by climate change (Dunne et al., 2013; Kjellstrom et al., 2009; Suzuki-Parker & Kusaka, 2016), and the associated economic loss is expected to be enormous (Kjellstrom, 2016; Roson & Van der Mensbrugghe, 2012; Takakura et al., 2017; Wenz & Levermann, 2016). A recent study (Takakura et al., 2017) projected that the global economic loss associated with labor capacity reduction due to climate change will be 2.6 to 4.0% of global total gross domestic product (GDP) at the end of this century under the worst climate-change case.

The members of the Conference of the Parties countries agreed to keep the temperature change well below the 2 °C goal adopted in the Paris Agreement in 2015 (United Nations Framework Convention on Climate Change, 2015) while the 2 °C target had already existed for approximately two decades. However, whether achieving this goal is possible remains uncertain because of the requirement for long-term continuous mitigation efforts. Moreover, even if the temperature increase remains below 2 °C, a nonnegligible economic loss (nearly 0.5% of global total GDP) is still expected due to labor capacity reduction (Takakura et al., 2017). Thus, in addition to climate-change mitigation, adaptation measures are also needed in order to minimize the impact of climate change.

Air conditioning is an effective adaptation measure for indoor work. Although it can be somewhat costly (Hasegawa et al., 2016) and can increase energy demand (Waite et al., 2017), the labor capacity reduction of indoor work due to climate change is expected to become negligible by the late 21st century due to the spread of the use of air conditioning. In contrast, economic losses associated with outdoor work will make up a large portion of total economic losses (Takakura et al., 2017). Therefore, adaptation measures for outdoor work are needed. One practical way to avoid heat exposure in outdoor work can be working during the early morning or at night. Since the extent of heat exposure is higher during midday and lower in the early morning, the daily average labor capacity would increase if the working time were shifted earlier. Such working time practices (start working from just after sunrise; Crowe et al., 2010) have already been adopted in some workplaces exposed to excessive heat stress and have been suggested to be effective in reducing worker's heat exposure (Occupational Safety and Health Administration, 2014), but its effectiveness has not been assessed on a global scale. In order to efficiently manage the risk of labor capacity reduction, it is necessary to quantitatively evaluate the feasibility and effectiveness of the adaptation measure.

In the present study, we first quantify the working time shift in hours that will be required in the future to offset the labor capacity reduction. Then, using an integrated assessment model (IAM) framework, we evaluate the degree of economic loss that will remain if either climate mitigation or adaptation measures, or both, cannot completely offset the labor capacity reduction. We estimate labor capacity and required working time shift based on the climate data of general circulation models (GCMs) and the recommendation (NIOSH, 2016) of labor capacity limitation. We explore four climatic conditions associated with representative concentration pathways (RCPs; van Vuuren et al., 2011) RCP2.6, RCP4.5, RCP6.0, and RCP8.5 in conjunction with five different GCMs (Hempel et al., 2013). Here labor capacity represents the proportion of time allowed to engage in labor. For example, if the labor capacity is 0.75, workers can work 75% of time, but must rest 25% of the time in order to reduce the risk of heat-related illness. The baseline (without adaptation) working time is assumed to be from 9:00 AM to 5:00 PM. Due to unavailability of worldwide statistics on working time practices, we adopted this simple assumption in the normative scenario analysis and conducted sensitivity analysis for this assumption. The required working time shift (required shift) is calculated as the amount of shift required to keep the yearly labor capacity at approximately the same level (no less than 95%) as that during the base period (2001–2010). For example, if the required shift is 3 hr, then the shifted working time is from 6:00 AM to 2:00 PM. The required shift is determined each year for each country. The economic loss is measured as the percentage change in GDP compared to the level of the no-climate-change (NoCC) condition. We calculate the GDP by the Asia-Pacific integrated model/computable general equilibrium (AIM/CGE) model (Fujimori et al., 2012).

The scenario analysis of the present study is hypothetical and conceptual, and the main purpose of the present study is to provide general insight that can contribute to adaptation and mitigation strategies rather than to accurately estimate the actual economic loss.

2. Materials and Methods

2.1. Hourly WBGT Estimation

In order to quantify the hourly labor capacity, we estimated the hourly wet bulb globe temperature (WBGT), which is an environmental heat exposure index that is widely used for the purpose of preventing heat-related illness (Budd, 2008). The framework for estimating hourly resolution WBGT was developed in a previous study

(Takakura et al., 2017), and a small modification was performed in order to better describe the diurnal variation of the WBGT. Hourly outdoor (nonshaded) and indoor (shaded, without natural wind) WBGT can be calculated if hourly standard meteorological observational variables (air temperature, humidity, solar radiation, wind speed, and air pressure) are available (Bernard & Pourmoghani, 1999; Lemke & Kjellstrom, 2012; Liljegren et al., 2008). As of today, however, future global projections of such meteorological variables are seldom available at hourly intervals. In order to resolve this problem, a two-step procedure is adopted. The first step is to calculate the hourly WBGT from hourly basis terrestrial meteorological observational data. A statistical relationship between daily representative meteorological variables, which are available from GCMs, and the WBGT of each hour is then extracted. For this purpose, we used terrestrial weather station data (Integrated Surface Database of the NOAA) and solar radiation data (SSE Daily Data of the NASA Langley Research Center Atmospheric Science Data Center) corresponding to the weather stations. A total of 292,380 data (collected at 572 terrestrial stations worldwide [Figure S1 in the supporting information] between 1 January 1996 and 30 June 2005) were used. Each data set includes hourly temperature, relative humidity, wind speed, and air pressure. Since the available solar radiation data were daily data, they were disaggregated to hourly data considering the solar zenith angle at each hour. The 572 stations were selected so that their spatial distribution was as uniform as possible and covered all climate zones. The hourly outdoor (Liljegren et al., 2008) and indoor (Bernard & Pourmoghani, 1999; Lemke & Kjellstrom, 2012) WBGT are estimated based on the hourly weather station data and hourly disaggregated solar radiation data, respectively. At the same time, daily representative values (daily mean temperature, daily maximum temperature, daily minimum temperature, daily mean relative humidity, daily mean wind speed, daily mean air pressure, and daily mean solar radiation), which are available from the GCMs, are also calculated. At this stage, we have obtained pairs of daily representative values and hourly WBGT. By applying a statistical machine learning technique to these data pairs, we obtain the regressors, by which we can estimate the hourly WBGT from daily representative values. Formally, the regression formula can be expressed as follows:

$$W\hat{B}GT_{d,hh,io} = f_{hh,io}(\mathbf{x}_{d-1}, \mathbf{x}_d, \mathbf{x}_{d+1}, \mathbf{r}_d) \tag{1}$$

where $\mathbf{x}_d = (x_{d,1}, x_{d,2}, \ldots, x_{d,7})$, $\mathbf{r}_d = (r_{d,00}, r_{d,01}, \ldots, r_{d,23})$, in which $x_{d,1}$ through $x_{d,7}$ are, respectively, the daily mean temperature, daily maximum temperature, daily minimum temperature, daily mean relative humidity, daily mean wind speed, daily mean air pressure, and daily mean solar radiation, and $r_{d,hh} = x_{d,7}\cos\theta_{d,hh}$, with $\theta_{d,hh}$ being the solar zenith angle at time *hh* of day *d* (if $\cos\theta_{d,hh} < 0$, $r_{d,hh} = 0$). The workplace location is indicated as indoor or outdoor by the subscript *io*, respectively. Therefore, we used a total of 48 regressors (24 for indoor and 24 for outdoor) to estimate the hourly WBGT. As the regressors, support vector regression of LIBLINEAR (Fan et al., 2008) is used, considering the performance and computational cost. In the first version of the regressors (Takakura et al., 2017), all of the variables were used to estimate the WBGT. In general, however, selecting a subset of variables can improve the performance of the estimation. We selected variables by a stepwise procedure to minimize root-mean-square errors (RMSEs) of the estimates for each regressor.

The accuracy of estimation was then evaluated by the cross-validation strategy so as to assure the feasibility of spatial generalization. Here spatial generalization refers to the regressors' performance being maintained, even if the regressors are applied to data from locations other than that where the training data was obtained. The data set of the present study consists of 292,380 samples from 572 stations, which are divided into four groups (Figure S1). Three-quarters of the station data are used to train the regressors, and the accuracy of the trained regressors is evaluated by the remaining station data. This procedure is repeated four times by changing the group to be evaluated. Comparisons between the actual hourly WBGT and the estimated hourly WBGT based on the machine learning technique are shown in Figures S2 and S3. Although sudden fluctuations in the actual WBGT were difficult to predict, general tendencies in the diurnal variations could be reproduced. The correlation coefficient, RMSE, and systematic error (bias) for all data are shown in Table S1. We checked whether these errors could affect the result of the subsequent analysis. We calculate labor capacity for each hour based on the estimated WBGT, and values aggregated for a year are used in the subsequent analysis (explained in section 2.2 in detail). The day-to-day errors (RMSEs) in the estimated WBGT may not be negligible and are approximately 2 °C at maximum (Table S1). The maximum ΔCapacity/ΔWBGT(°C) is approximately 0.045 for 400 W of work (Figure S4). Thus, day-to-day hourly labor capacity error is expected to be around 0.09 (9%) on average. However, since the biases are negligible

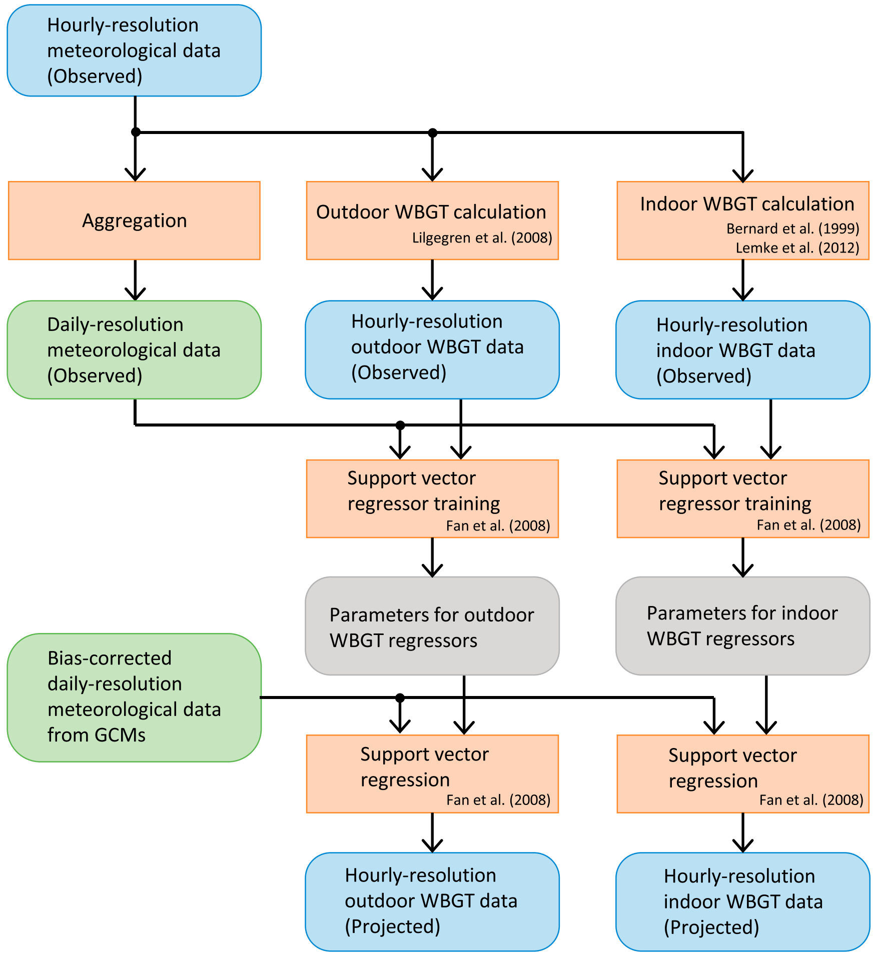

Figure 1. Framework of the hourly WBGT estimation from daily resolution GCM data. Rectangles represent processes and rectangles with rounded corners represent data or parameters. WBGT = wet bulb globe temperature; GCM = general circulation model.

(they are less than the resolution of the WBGT bins (0.1 °C) we used in the present study), as shown in Table S1, aggregation (averaging) can reduce the effect of random error by a factor of $N^{-1/2}$, where N is the number of aggregated data. Thus, expected error is $0.09 \times 365^{-1/2} = 0.0047$ (0.047%), which is substantially smaller than the uncertainty caused by other factors (e.g., uncertainty caused by differences in GCMs). Therefore, it was judged the overall agreement was sufficient to capture the tendencies of diurnal variations and to calculate the yearly aggregated labor capacity used in the present study.

After the cross-validation procedure was completed, all of the data were used to train the regressors. We then applied these regressors to bias-corrected GCM data (Hempel et al., 2013) and obtained the future hourly WBGTs with a spatial resolution of 0.5° × 0.5° globally for both outdoor and indoor workplaces. (The indoor WBGT is used for workplaces without air conditioning.) The framework of the procedure used to estimate the hourly WBGT used in the present study is shown in Figure 1. Note that regressors were trained and validated for station data, not for gridded data. This may produce some biases in the estimation of the WBGT but will not seriously affect the main results of the present study for following reasons: (i) bias correction of the GCM data was conducted so that the statistical characteristics of these data match those of terrestrial observations; (ii) the spatial generalization ability of regressors is high, as demonstrated by the cross validation procedure; and (iii) even if biases exist in the estimated WBGT, the estimated WBGT will produce biases both for current and future labor capacities, which will cancel each other out because we focus primarily on the relative change from current value.

More local-scale phenomena, such as urban heat island effects, are not considered, because our goal is to quantify the effect of global climate change.

2.2. Labor Capacity and Required Shift in Working Time

The proportion of the time allowed to engage in labor (labor capacity) is determined based on the WBGT and the intensity of the work (International Organization for Standardization, 1989; NIOSH, 2016). In general, as the environment becomes hotter or the work intensity increases, workers should rest longer in order to maintain their core body temperatures. The value of labor capacity is determined considering the human heat balance needed to maintain the core body temperature within the safe range. In the present study, we used the recommendation of NIOSH (2016), in which the required break time is indicated discretely. We interpolated the recommendation linearly and obtained a continuous value of labor capacity corresponding to the WBGT and work intensity (Figure S4). Labor capacity is calculated for each grid cell (0.5° × 0.5° resolution) and for every hour. Here the 1-hr labor capacity is represented by $CAP_{g,y,d,hh}$, where g, y, d, and hh denote the grid cell, year, day, and hour of day (local solar time of each grid cell), respectively. The daily and yearly labor capacities are, respectively, calculated as follows:

$$Cap_{g,y,d}^{WT_{c,y}} = \frac{1}{H_d} \sum_{hh \in WT_{c,y}} Cap_{g,y,d,hh} \tag{2}$$

$$Cap_{g,y}^{WT_{c,y}} = \frac{1}{D_y} \sum_{d} Cap_{g,y,d}^{WT_{c,y}} \tag{3}$$

where $WT_{c,y}$ is the working time of country c in year y, H_d is the total number of working hours for a day, and D_y is the total number of working days in year y. The baseline working time is set as being from 9:00 AM to 5:00 PM ($WT_{c,y}$ = {09, 10, …,16}). The calculated yearly labor capacity of each grid cell is averaged for each country weighted by population distribution (Jones & O'Neill, 2016), and we obtain the annual labor capacity for each country as follows:

$$Cap_{c,y}^{WT_{c,y}} = \frac{\sum_{g \in G_c} p_{g,y} Cap_{g,y}^{WT_{c,y}}}{\sum_{g \in G_c} p_{g,y}} \tag{4}$$

where $p_{g,y}$ is the population of grid cell g in year y, and G_c is the set of grid cells belonging to country c. When calculating the effect of working time shift, the assumed starting/closing time for working is shifted earlier while keeping the total number of working hours constant (8 hr). In order to estimate the required shift in working time, the average labor capacity for outdoor heavy (metabolic rate of 400 W) work during the base period (2001–2010) is calculated for each country and is used as the target labor capacity. In general, as the shift increases, the labor capacity increases. The required shift is defined as the minimum shift in working time by which the labor capacity is no less than 95% of the target labor capacity. The resolution of $WT_{c,y}$ is 1 hr, but when calculating the required shift, the result is interpolated and treated as a continuous value. In the present study, $WT_{c,y}$ is assumed to be uniform within each country and each year, whereas the optimal and required working time shift can differ depending on the season of the year, particularly in midlatitude or high-latitude countries. For example, in midlatitude or high-latitude countries, almost all labor capacity reduction occurs during the summer (Figure S5). Thus, the assumption that worktime shift is implemented only during the summer is more realistic (just like daylight saving time). However, when no working time shift is required, the daily labor capacity is 1.0 (or approximately 1.0) regardless of the working time assumption. Therefore, this seasonally uniform assumption would not affect the calculation of the labor capacity or the required shift. The calculated required shift can be interpreted as the amount of shift during the hot season of the year.

For the climatic conditions, RCP2.6, RCP4.5, RCP6.0, and RCP8.5 were considered (van Vuuren et al., 2011). RCP2.6 corresponds to the very stringent climate-change mitigation target, by which the 2 °C goal will be achieved. RCP8.5 corresponds to the case in which greenhouse gas emissions continue to grow. RCP4.5 and RCP6.0 are intermediate conditions. Corresponding values of radiative forcing at the end of the 21st century are 2.6, 4.5, 6.0, and 8.5 W/m^2, respectively. Note that mid-century radiative forcing under RCP4.5 is larger than that under RCP6.0, and thus, expected temperature rises under these two RCPs are similar during the 21st century. Five different bias corrected GCMs (Hempel et al., 2013; input data of ISIMIP), namely, GFDL-ESM 2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M, are used. The distribution of the population and the working-age population of each country is based on the shared socioeconomic pathway (SSP; O'Neill et al., 2013). Among the SSPs, we used SSP2, which is considered to be the "middle of the road" pathway.

2.3. Economic Analysis

We also conduct an economic analysis in order to quantify the reduction in economic impact by implementing the adaptation measure. The AIM/CGE model (Fujimori et al., 2012) was used for this purpose. The AIM/CGE model is a 1-year-step, recursive, general-equilibrium-theory-based economic model that divides the world into 17 regions, each of which includes 44 industrial sectors and one aggregated household sector. (See Table S2 for a list of regions and Table S3 for a list of industrial sectors.) The parameters in the model were calibrated based on the social accounting matrix (Dimaranan, 2006) and energy balance table (International Energy Agency, 2013a, 2013b) in the base year and were updated every year recursively. The AIM/CGE model has been widely applied in global-scale mitigation and impact studies (Fujimori et al., 2017; Hasegawa et al., 2016; Hasegawa, Park, et al., 2016; Masui et al., 2011; Takakura et al., 2017). The production of each industrial sector is represented by a multinested production function, with labor as one of its inputs multiplied by a labor productivity coefficient. The value added $VA_{r,s,y}$ produced by the inputs $QF_{r,f,s,y}$ in year y is represented as

$$VA_{r,s,y} = \alpha_{r,s,y}\left(\sum_{f\in F}\delta_{r,f,s}\left(k_{r,f,s,y}QF_{r,f,s,y}\right)^{-\rho_{r,s}}\right)^{-\frac{1}{\rho_{r,s}}} \tag{5}$$

where $\alpha_{r,s,y}$ is the efficiency parameter, $\delta_{r,f,s}$ is the share parameter, $k_{r,f,s,y}$ is the coefficient of input factors, and $\rho_{r,s}$ is the substitution parameter. The subscript r corresponds to one of 17 regions, s corresponds to one of 44 industrial sectors, and f represents an input factor. Moreover, F is the set of input factors, and F = {labor, capital, land}. Thus, the labor productivity coefficient in region r in year y for industrial sector s is $k_{r,\mathrm{labor},s,y}$. The calculated labor capacity is aggregated for 17 regions weighted by the working-age population (Kc & Lutz, 2017) of each country c and used as the labor productivity coefficient of region r. Different assumptions on the workplace and the work intensity are applied sector by sector, and thus, labor capacities also differ among sectors. The decision to assign the workplace and the work intensity was made based on the classification of industrial sectors in the economic model (Table S3), the characteristics of each industrial sector, and consistency with the previous studies. As pointed out in previous studies, agriculture (primary industry sectors) and construction sectors will suffer from heat exposure because their work mainly involves outdoor labor and air conditioning cannot be used (Kjellstrom et al., 2009). Therefore, the workplaces of primary industrial sectors and the construction sector are assumed to be outdoors, whereas the workplaces of other manufacturing sectors and the service sector are assumed to be indoors. The work intensity represented by the metabolic rate is assumed to be 400 W for the primary industry sector and the construction sector, 300 W for other manufacturing sectors, and 200 W for the service sector, considering the intensity of physical activity of each industry (Ainsworth et al., 2011) and consistency with previous studies (Kjellstrom et al., 2009; Takakura et al., 2017). For a detailed correspondence for the 44 sectors, see Table S3. Although the intensity of the work may be lowered in the future due to mechanization and automation, such a reduction would be quite difficult to predict quantitatively. In the present study, we applied the constant-work-intensity assumption throughout the simulation period, while the increased total factor productivity (TFP) of each industrial sector and labor and capital substitution are assumed to be consistent with the SSP storyline. In order to make the model parameters consistent with the SSP storylines, a two-step procedure was conducted. In the first step, we adjusted the TFPs of the baseline scenarios as an adjustment variable to obtain exactly the same GDP outcomes as assumed in the SSP storyline. The calculated TFPs in the baseline scenarios are then applied to the scenario analyses (Fujimori et al., 2017). For indoor work, the availability of air conditioning devices is also considered. If air conditioning devices are available, the labor capacity will not be affected.

In the analysis for the condition without adaptation, the working time is assumed to be from 9:00 AM to 5:00 PM throughout the simulation periods. For the condition with adaptation, the working time is shifted

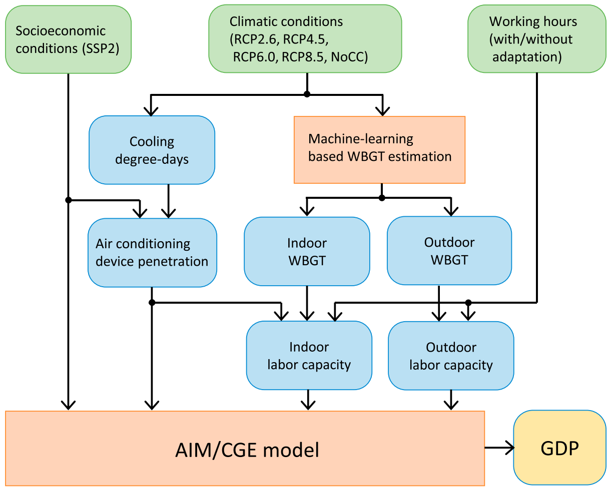

Figure 2. Framework of the economic analysis using the AIM/CGE model. Rectangles represent a model or a process, and rectangles with rounded corners represent data or variables. Variables are aggregated for 17 regions (Table S2) before being fed into the AIM/CGE model. AIM/CGE = Asia-Pacific integrated model/computable general equilibrium; GDP = gross domestic product; RCP = representative concentration pathway.

if the yearly average labor capacity of each region is lower than the base-period level. In calculating the shifted yearly average labor capacity, we assumed the maximum shift to be 3 hr, that is, a start time of working not earlier than 6:00 AM, but overcompensation is not assumed, as follows:

$$Cap_{c,y}(shifted) = \begin{cases} Cap_{c,y}^{WT_{shifted3}} & \left(Cap_{c,y_{base}}^{WT_{normal}} \geq Cap_{c,y}^{WT_{shifted3}}\right) \\ Cap_{c,y_{base}}^{WT_{normal}} & \left(Cap_{c,y_{base}}^{WT_{normal}} < Cap_{c,y}^{WT_{shifted3}}\right) \end{cases} \tag{6}$$

where WT_{normal} = {09, 10, …,16} and $WT_{shifted3}$ = {06, 07, …,13}. A maximum shift of 3 hr is decided considering the sunrise time. In low-latitude countries, labor capacity reduction occurs throughout the year, and the sunrise time is approximately constant (around 6:00 AM) throughout the year. In midlatitude or high-latitude countries, most labor capacity reduction occurs during the summer (between the March equinox and the September equinox in the Northern hemisphere, or between the September equinox and the March equinox in the Southern hemisphere, as shown in Figure S5). Thus, a shift in working time is required only during the summer, when the sunrise time is earlier than 6:00 AM. Therefore, a shift of 3 hr is possible when required globally. The working time shift is applied only for outdoor work.

The penetration rate of air conditioning devices is estimated based on climatic and socioeconomic conditions (Hasegawa, Park, et al., 2016). The maximum potential demand (P) of air conditioning devices is determined by the number of degree-days. The affordability of air conditioning devices (A) is determined by per capita GDP. Then the penetration rate of air conditioning devices is calculated as $P \times A$ (Isaac & van Vuuren, 2009). This calculation is conducted for 17 regions each year. The cost of air conditioning devices is represented in the AIM/CGE model but is excluded from the calculation of economic loss, because air conditioning is regarded as a normal economic activity (autonomous adaptation) in the present study.

The cost of climate-change mitigation can also be estimated using the AIM/CGE model. However, in the present study, we run the economic simulation under the "business as usual" condition, in which no mitigation measures are taken, in order to evaluate the impact of the climate change independent of the cost of the climate-change mitigation.

The economic simulation was conducted from the base year (2005) to the end of this century under four RCPs and five GCMs, as described above. In addition to these four RCP scenarios, we also considered the NoCC condition. In the NoCC condition, the climate is fixed at the 2005 level, which is the base year of the AIM/CGE model. The socioeconomic condition is based on the SSP2 scenario. The economic loss is measured by the percentage change in GDP from the level of the NoCC condition.

Before executing the future economic simulation by the AIM/CGE model, a calibration procedure was conducted so that the output of the model matches the observed economic indicators and the labor productivity coefficients in the base year was set to unity. Because of this procedure, only the relative change (not the absolute value) in the labor productivity coefficient (labor capacity) from the base year can affect the results of the economic simulation. An overview of the economic analysis is shown in Figure 2.

2.4. Sensitivity Analysis for Base-Period Working Time

In the normative scenario analysis, the working time during the base period (2001–2010) is assumed to be from 9:00 AM to 5:00 PM. However, some regions are already affected during the base period, and so it is possible that working time shift may already be adopted as an adaptation measure in these regions. Unfortunately, no reliable statistics on the current working time are available globally. Therefore, in this analysis, we adopted a hypothetical rule-based determination of working time because the purpose of this sensitivity analysis is to investigate the sensitivity of our simulation results to the baseline working time assumption, rather than to improve the accuracy of the simulation. In this analysis, we assumed that if the

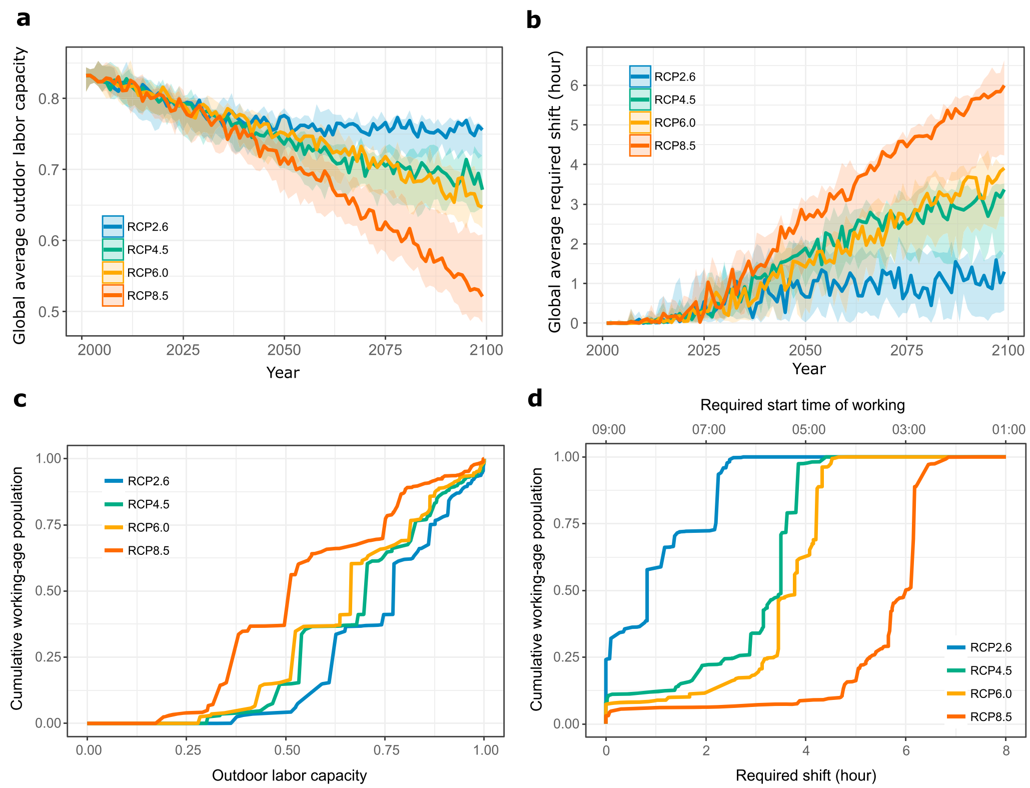

Figure 3. Labor capacity and required shift of working time for outdoor work. (a) Global average outdoor labor capacity (weighted by working-age population). (b) Global average required shift of working time (weighted by working-age population). (c) Cumulative distribution of global working-age population corresponding to the labor capacity during the 2090s. (d) Cumulative distribution of global working-age population corresponding to the required shift during the 2090s. The medians (solid lines) and ranges (shaded areas) of five GCMs are shown in (a) and (b), and the medians of five GCMs are shown in (c) and (d). GCM = general circulation model.

base-period outdoor labor capacity is reduced by more than 15%, then the country has already adopted working time shifting (baseline adaptation). Both during and after the base period, the maximum amount of shift is assumed to be 3 hr (the start time of work is later than 6:00 AM). Therefore, for example, if a shift of 3 hr is implemented during the base period, there will be no additional adaptation capability.

3. Results

3.1. Labor Capacity and Required Shift

The estimated global average outdoor labor capacity during the base period is 0.82 (0.81–0.84; median [minimum − maximum] of five GCMs; Figure 3a). This means that 18% (16–19%) of working hours must be used for breaks in the case of outdoor heavy work. The expected labor capacity declines steadily as global warming progresses without adaptation. Under the highest-emission scenario (RCP8.5), the outdoor labor capacity during the 2090s will be 0.54 (0.50–0.62), which means that 46% (38–50%) of working hours must be used for breaks. The required working time shift also becomes larger as climate change progresses. Under RCP8.5, a global average shift of 5.7 (4.0–6.1) hours is required in order to maintain the base-period level of labor capacity during the 2090s (Figure 3b). In this situation, approximately half of global outdoor workers must start working before 3:00 AM (Figure 3d). Under RCP2.6 (remaining below an increase of 2 °C), the labor capacity will be 0.76 (0.72–0.77) during the 2090s. The corresponding global average required shift is 1.1 (0.21–1.7) hours. This implies that stringent climate-change mitigation can drastically alleviate challenges to adaptation in labor capacity reduction. The labor capacity reduction and the required shift corresponding to RCP4.5 and RCP6.0 are expected to lie between those under RCP2.6 and RCP8.5. The results are spatially heterogeneous (Figures 4 and 5). In most high-latitude countries, the required working time shift is

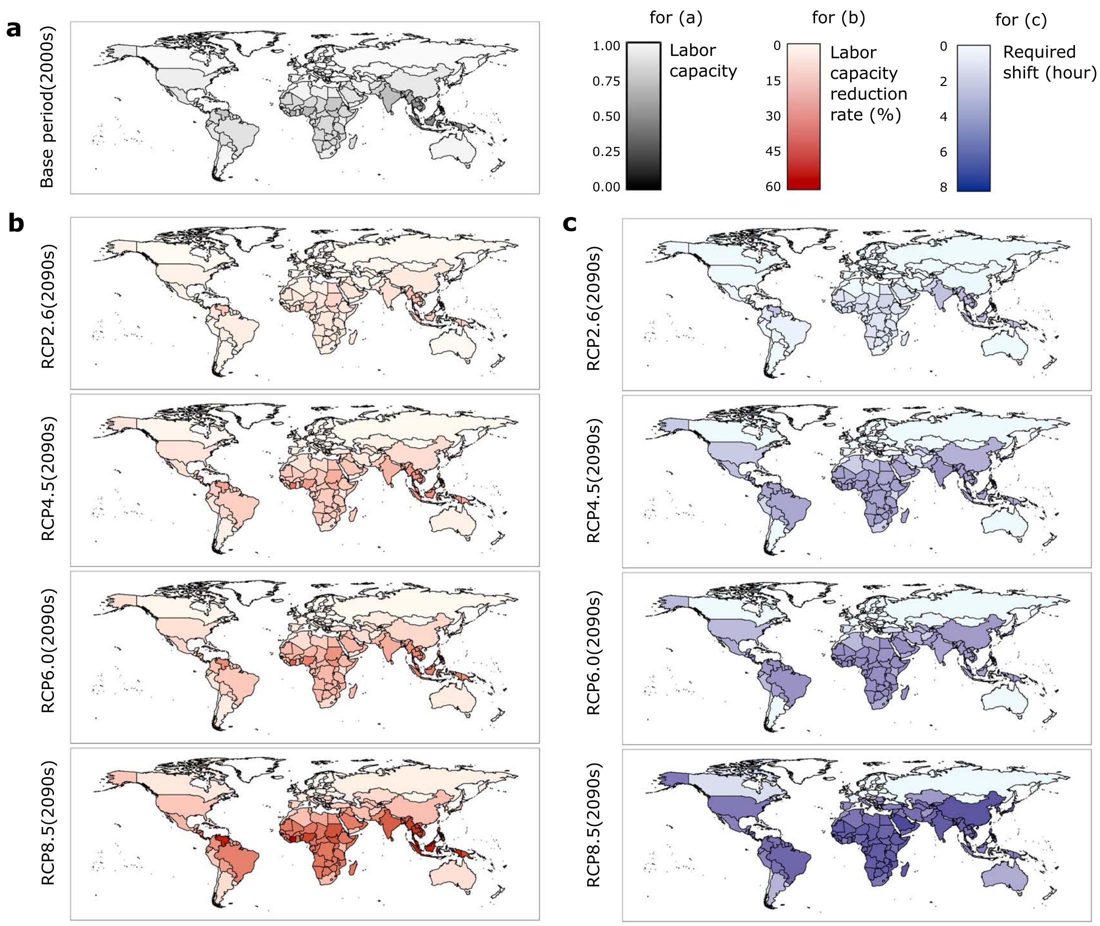

Figure 4. Regional distribution of outdoor labor capacity reduction and required shift. (a) Average outdoor labor capacity during the base period. (b) Average outdoor labor capacity reduction rate in 2090 compared to the base period level. (c) Shift of working time required in order to maintain the base-period level of labor capacity during the 2090s. All plots are medians of five GCMs. GCM = general circulation model.

marginal because the increased temperature remains below the threshold for the labor capacity limitation. In contrast, a large shift is required in low-latitude countries, with a maximum required shift of 7.5 (5.2–9.7) hours under RCP8.5 (Figure 5b).

While we quantified the required shift only from the viewpoint of heat stress, the realistic range of the shift would be restricted by other factors, too. Daylight availability is an important factor because daylight is indispensable for most outdoor work as illuminance. Daylight is also important to entrain a worker's biological rhythm to his/her diurnal activity patterns (Reppert & Weaver, 2002). Other factors, such as noise regulations (Granneman, 2013) and social/family relationships (Strazdins et al., 2006), also inhibit an excessive amount of shift. Thus, while a greater shift might be possible by using lighting equipment in some cases, sunrise time is considered as a reasonable threshold for the realistic range of start time of working. However, Figure 5b indicates that the start time of working is expected to be earlier than sunrise in many low-latitude countries (except under RCP2.6), which suggests that the realistic range (<3 hr) of shift cannot completely offset the labor capacity reduction without stringent climate-change mitigation. Consequently, the economic losses cannot be completely offset by the adaptation measure.

3.2. Macroeconomic Effects

In order to quantify the remaining economic losses, we further conduct an economic analysis using an IAM, the results of which indicate that the adaptation measure (maximum 3-hr shift) significantly reduces the global total economic loss. However, the adaptation measure was unable to completely offset the economic loss under all climate conditions except RCP2.6 (Figure 6a). Without climate-change mitigation (RCP8.5) or under

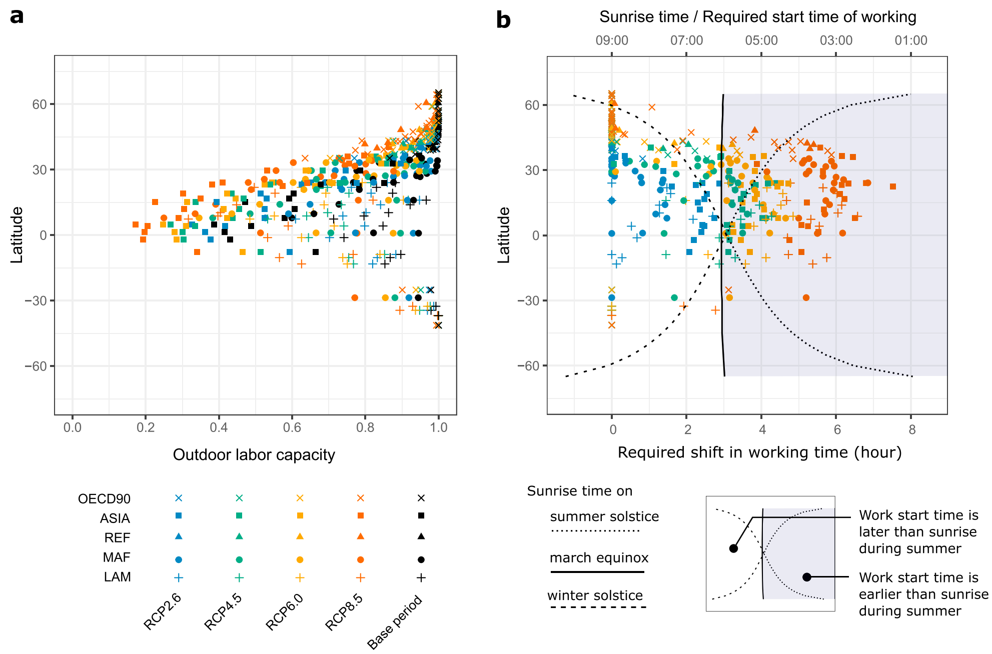

Figure 5. Relationship among latitude, required shift, sunrise time, and labor capacity. (a) Labor capacity during the base period (black dots) and during the 2090s (colored dots). (b) Required shift of working time during the 2090s and corresponding start time of working. The solid line represents the time of sunrise on the March equinox, and the dashed lines represents the times of sunrise on the summer solstice (local solar time). Latitude is represented by the geographical mean of each country (countries with large isolated enclaves are excluded). Each dot represents a country. The medians of five GCMs are shown. OECD90: North America, Western Europa, and Pacific OECD countries. ASIA = Asian countries, excluding OECD90 countries; REF = Eastern Europa and the former Soviet Union; MAF = Middle East and African countries; LAM = Latin America and Caribbean countries; GCM = general circulation model.

less stringent mitigation efforts (RCP6.0 and RCP4.5), even if the adaptation measure is implemented, the global total GDP loss rates during the 2090s are 1.6% (1.0–2.4%), 0.58% (0.40–0.91%), and 0.45% (0.32–1.0%) for RCP8.5, RCP6.0, and RCP4.5, respectively. In contrast, if both the most stringent mitigation and the adaptation measure are implemented (RCP2.6 with adaptation), then the global total GDP loss rate is marginal and is limited to 0.14% (0.12–0.47%). Without the adaptation measure, even under the most stringent mitigation target (RCP2.6), the global total GDP loss rate is 0.44% (0.41–0.92%).

The finding that shifting working time does not cancel out the negative impacts of global warming without the stringent climate-change mitigation is further supported by the nonlinear relationship between the GDP loss rate and global mean temperature rise (Figure 7). The slope of the fitted curve for the with-adaptation results is gentle below +2 °C and becomes increasingly steeper as the temperature increase exceeds 2 °C. This suggests that the 2 °C goal would be reasonable from the viewpoint of preventing the impacts of labor capacity reduction, given that a working time shift of 3 hr is the adaptation limit. The Paris Agreement also mentions the more ambitious target of temperature change of less than 1.5 °C, whereas a change of between 1.5 and 2 °C would be marginal as long as the adaptation measure is effectively implemented.

Although the global total economic loss can be reduced by mitigation and adaptation, the regional GDP loss rates vary substantially among regions (Figure 6). Under RCP2.6 with adaptation, the GDP loss rates during the 2090s are 0.00% (−0.01–0.03%) in North America, Western Europa, and Pacific Organization for Economic Co-operation and Development (OECD) countries (OECD90), 0.36% (0.32–1.4%) in Asian countries, excluding OECD90 (ASIA), −0.02% (−0.02–0.01%) in Eastern Europa and the former Soviet Union (REF), 0.17% (0.09–0.21%) in the Middle East and African countries (MAF), and 0.04% (−0.02–0.07%) in Latin America and Caribbean countries (LAM; where a negative loss rate indicates a GDP gain, which is caused by relative advantages in international economic competition). Larger GDP loss rates are mainly expected in ASIA, MAF, and LAM, most of which are located in lower latitude areas. Among these regions, ASIA is most severely affected due to higher exposure to heat stress and relatively high economic dependence on outdoor work (Figure S6).

10.1029/2018EF000883

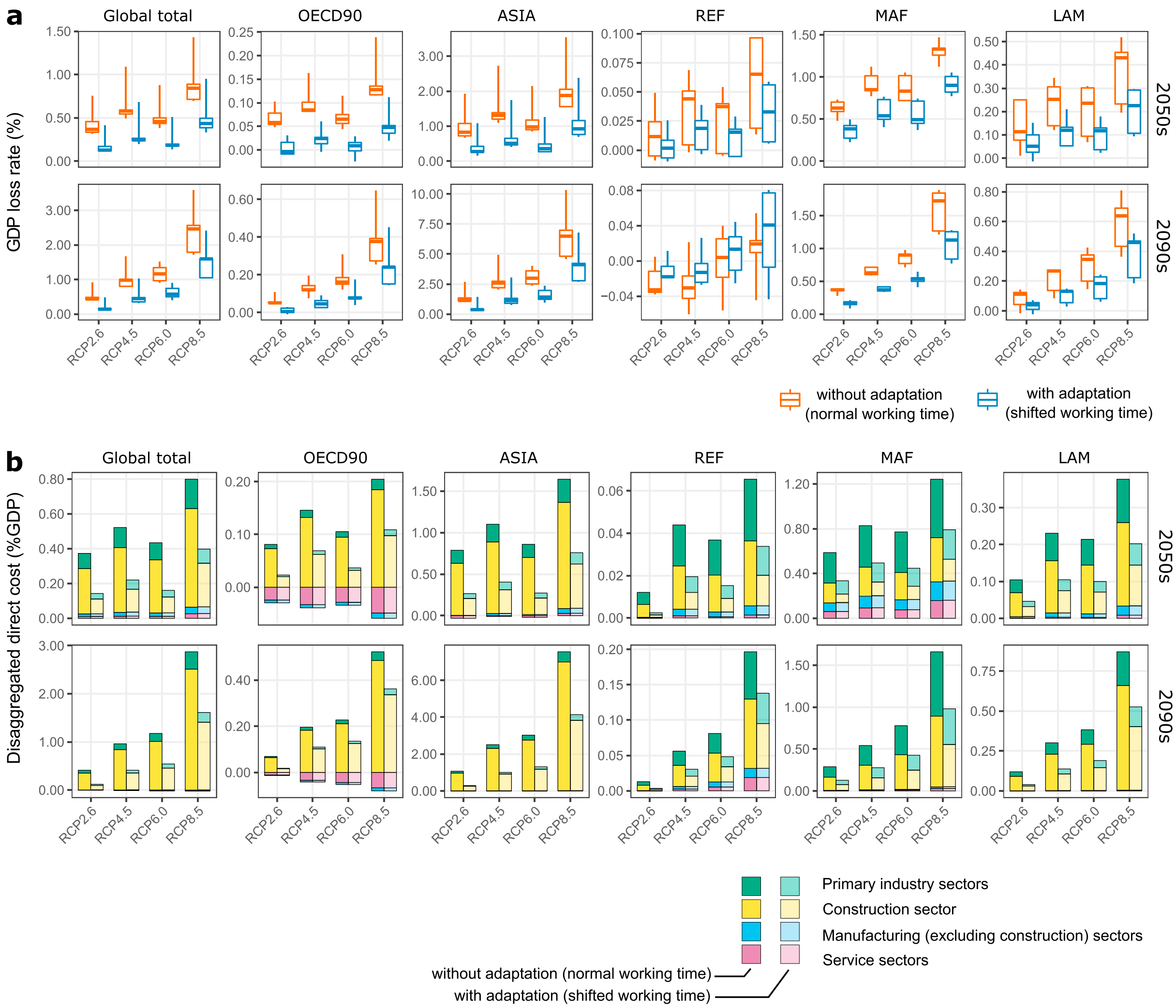

Figure 6. Global total and regional GDP loss rate and direct cost. (a) GDP loss rate and (b) direct cost for each industrial sector. "Without adaptation" means no working time shift, whereas "with adaptation" means a working time shift of up to 3 hr. The GDP loss rates and direct costs are represented as differences from the NoCC level. Direct cost is represented by the additional wage required to compensate for the labor capacity reduction. For the GDP loss rate, the medians and ranges of five GCMs are shown. For direct cost, the medians of five GCMs are shown. Negative direct costs are generated by overcompensation as a result of installing additional air conditioning devices. Primary industry and construction sectors are assumed to involve outdoor work, and the remaining sectors are assumed to involve indoor work. GDP = gross domestic product; GCM = general circulation model.

3.3. Effect of Base-Period Working Time Assumption

In addition to the regional inequalities shown above, these would-be severely affected regions are already being affected during the base period (Figures 4a and 5a). In these regions, shifting working time (working from just after sunrise; Crowe et al., 2010) may already be implemented in order to avoid heat exposure. Therefore, the future additional adaptation margin (the margin between the current work start time and the realistic limit of work start time, e.g., sunrise time) in these regions may be smaller than assumed in the normative scenario (3 hr). If this is the case, the effectiveness of shifting working time is not as high as expected, particularly in low-latitude countries, and regional inequalities may be further amplified. The result of the sensitivity analysis for the base-period working time assumption confirms this idea. If we assume baseline adaptation, future GDP loss rates without additional adaptation are generally smaller (Figure S7a) thanks to the baseline adaptation, but the GDP loss rates with additional adaptation are larger, particularly in ASIA, if we assume baseline adaptation (Figure S7b). This is mainly because of the lower additional adaptation margin in the future due to the baseline adaptation. In addition, maintaining the current-level labor capacity in the future will become more difficult because current level of labor capacity becomes higher if we assume

10.1029/2018EF000883

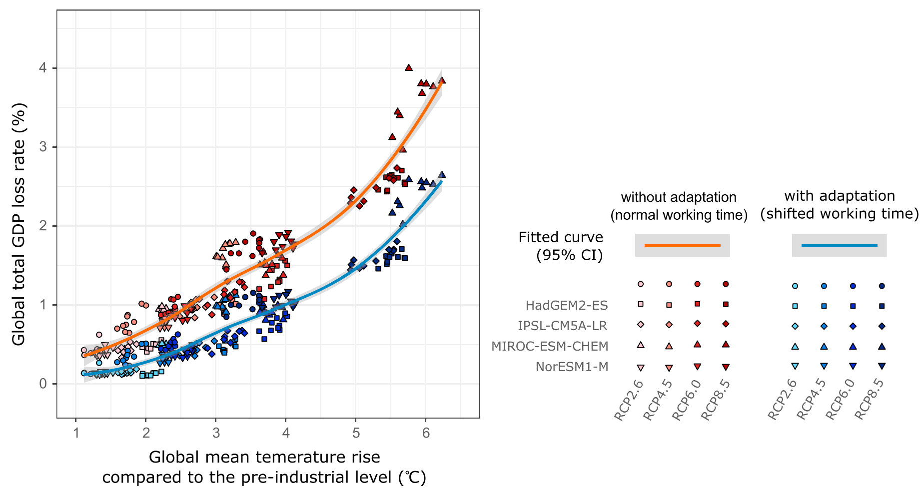

Figure 7. Relationship between GDP loss rate and global mean temperature rise. The results of five GCMs for each year (during the 2090s) are plotted. The fitted curve was calculated by local polynomial regression fitting with the 95% confidence interval of the fitted curve. “Without adaptation” means no working time shift, whereas “with adaptation” means a working time shift of up to 3 hr. The GDP loss rates are represented as differences from the no-climate-change level. The global total GDP loss rates during the 2090s corresponding to 1.5, 2.0, 3.0, and 4.0 °C global mean temperature rises predicted by the fitted curves are 0.48%, 0.68%, 1.2%, and 1.7% without adaptation and 0.17%, 0.28%, 0.65%, and 1.0% with adaptation, respectively. GDP = gross domestic product; GCM = general circulation model.

baseline adaptation. This result also highlights the existence of the limit of the adaptation margin. In such situations, the relative importance of the climate-change mitigation can become larger.

4. Discussion

Our results show not only the effectiveness of the working time shift as an adaptation measure for climate change but also its limitation and the importance of the climate-change mitigation. Without stringent climate-change mitigation, many outdoor workers should start working before sunrise if they want to completely offset the labor capacity reduction, and substantial economic losses will remain if the shift is limited to the realistic range.

In the present study, relatively strong homogeneous assumptions are applied across regions and within industrial sectors. In particular, the assumption on the base-period working time can affect the results. As shown by the sensitivity analysis, if the current society has already adapted to excessive heat exposure by shifting the working time, which is evident in some regions, particularly in the agricultural (primary industry) sector (Table S4), the expected remaining economic impacts can be larger because the future additional adaptation margin is smaller. Split working times, as exemplified by the siesta, would have similar effects. Therefore, the estimated effectiveness of the working time shift as an adaptation measure is biased toward being more effective, and the importance of the mitigation may be underestimated. Therefore, even if we consider these possible biases, we can still conclude that climate-change mitigation is indispensable for minimizing the climate-change impacts, regardless of the implementation of working time shift. Moreover, a larger portion of economic loss is caused by the construction sector (Figure 6b), and the current working time in the construction sector is not as early as that of the agricultural sector (Bates et al., 2010; Bodin et al., 2016; Chan & Yang, 2016; Chan et al., 2017; Crowe et al., 2010, 2013; Delgado Cortez, 2009; Hassan et al., 2017; Inaba & Mirbod, 2007; Ioannou et al., 2017; Maiti, 2008; Meade et al., 2017, 2015; Miller et al., 2011; Sahu et al., 2013; Vatani et al., 2016, summarized in Table S4). In the sensitivity analysis, up to 3 hr of shift was assumed during the base period for the construction sector as well as the agricultural sectors. Therefore, while the working time assumption used in the normative scenario of the present study may not be exact, the associated error in the estimated economic loss (GDP change rate) is expected to be within the range of the result of the sensitivity analysis and not to affect the general conclusion.

In our economic simulation, hypothetically, a working time shift of up to 3 hr is considered to be feasible and is implemented in the model. When implementing the simulation in the real world, however, possible side effects and social situations should also be considered. For example, although the goal is not avoiding heat exposure, night-shift work has been adopted in a number of industries and daylight saving time has been implemented in many countries. Epidemiological studies have indicated that night-shift work can increase the risk of disease (Haus & Smolensky, 2013) and occupational accident rates (Folkard, 2003), which is caused by the dissociation between the human internal biological clock and activity patterns (Haus & Smolensky, 2013). This dissociation cannot be adjusted even if the shift is permanent (Folkard, 2008). Even a shift of only 1 hr due to daylight saving time has detectable side effects (Kantermann et al., 2007; Sipilä et al., 2016), particularly just after the transition. In midlatitude or high-latitude countries, the amount of shift should be adjusted depending on the season, as in daylight saving time, and thus, a shift of 3 hr considered in the present study may have more noticeable negative consequences. Patterns of commuting (Nurul Habib, 2012) and required operating times of social services (Neutens et al., 2010), and so forth, will change if a pervasive working time shift is enacted. In such situations, infrastructure and social customs may have to be reformed. In addition, many people are reluctant to wake up early (Chelminski et al., 1997). In order to consider and resolve such issues, complementary local or individual-level (bottom-up) investigations are also necessary for designing actual adaptation strategies, although these are beyond the scope of the global-scale (top-down) IAM framework adopted in the present study to grasp general situations.

In this modeling framework, we focused on the effect of the working time shift on the economic consequences, but the effect on climate-change mitigation is also important. For indoor work, we assumed air conditioning as an adaptation to climate change, which increases energy demand (Waite et al., 2017) and possibly causes additional CO_2 emissions. Shifted activity patterns can change diurnal energy demand variation (Stowie et al., 2015; Torriti et al., 2015) and eventually energy demand-supply balance. In particular, if large-scale renewable energies, such as photovoltaic generation, which has a diurnal variation in its output, are deployed in the power grid, the diurnal energy demand variation becomes more important. In order to analyze these issues, a more elaborate energy modeling framework is required for both the demand and supply sides, but this is beyond the scope of the present study.

There are several considerations when interpreting the results. First, the labor capacity is calculated based on recommendations intended to prevent occupational heat-related illness. At actual worksites, these recommendations are not always followed (Maiti, 2008; Xiang et al., 2015), and observed worktime reductions associated with increased heat exposure (Yi & Chan, 2017) are generally smaller than those of the recommendations presented herein. Therefore, the changes in GDP calculated in the present study would be greater than that in a real economy. This should be interpreted as an economic cost of heat-related illness prevention by following the recommendation strictly (Takakura et al., 2017), rather than an actual economic loss. Second, while the future increase in the TFP, changes in the industrial structure, and labor and capital substitution are represented in the economic model according to the socioeconomic scenario, the production method (structure of production function) is essentially unchanged and constant work intensity is assumed throughout the simulation period. However, if the production were perfectly automated in the future (Frey & Osborne, 2017), physical labor would no longer be needed and would not be affected by heat stress. Modeling such structural changes is one of the greatest challenges remaining to be met, and the result should be considered to be a status-quo estimation in terms of the means of economic production. Third, there are additional possible adaptation measures other than the working time shift. For example, wearing cooling vests or ingesting ice are not treated in the present study. Their effectiveness is being studied (Kenny et al., 2011; Naito et al., 2017), and combining these measures is another option to reduce the adverse impacts of climate change. The shifting pattern of working time also has alternative options. Only a one-way (toward earlier time) shift with constant total working hours is considered in the present study, but splitting working time, for example, by siesta or simply lengthening the total working hours, may also be effective. Identifying the optimal time schedule for working is an interesting research topic, but such research should be conducted locally considering individual situations.

5. Conclusions

Regardless of above-mentioned considerations, the results of the present study provide valuable insights for adaptation and mitigation strategies to address climate change. Despite the Paris Agreement, considering the considerably high economic cost required to realize the stringent climate-change mitigation target, it might be a reasonable choice to focus mainly on adaptation measures, and reducing or discarding the mitigation target. However, the results of the present study revealed that the adaptation capability is not infinite and adaptation difficulties depend highly on the mitigation level. Without stringent climate-change mitigation, more specifically the 2 °C goal, the expected required shift in working time is beyond the realistic range (>3 hr), and nonnegligible economic losses will remain even if the working time shift is implemented as an adaptation measure. We again emphasize that a single adaptation measure is not a be-all-and-end-all solution to climate change.

Acknowledgments
The authors declare no financial conflict of interests. The present study was supported by the Environment Research and Technology Development Fund (S-14) of the Environmental Restoration and Conservation Agency. The data used in the present study are available at the following: GCM data (https://www.isimip.org/gettingstarted/downloading-input-data/), meteorological observation data (https://www.ncdc.noaa.gov/isd), solar radiation data (https://eosweb.larc.nasa.gov/project/sse/sse_daily_data), sunrise time data (https://www.esrl.noaa.gov/gmd/grad/solcalc/), socioeconomic scenario data (https://tntcat.iiasa.ac.at/SspDb/), and population distribution data (https://www2.cgd.ucar.edu/sections/tss/iam/spatial-population-scenarios).

References

Ainsworth, B. E., Haskell, W. L., Herrmann, S. D., Meckes, N., Bassett, D. R. Jr., Tudor-Locke, C., et al. (2011). 2011 Compendium of physical activities: A second update of codes and MET values. *Medicine and Science in Sports and Exercise*, *43*(8), 1575–1581. https://doi.org/10.1249/MSS.0b013e31821ece12

Bates, G. P., Miller, V. S., & Joubert, D. M. (2010). Hydration status of expatriate manual workers during summer in the Middle East. *The Annals of Occupational Hygiene*, *54*(2), 137–143. https://doi.org/10.1093/annhyg/mep076

Bernard, T. E., & Pourmoghani, M. (1999). Prediction of workplace wet bulb global temperature. *Applied Occupational and Environmental Hygiene*, *14*(2), 126–134. https://doi.org/10.1080/104732299303296

Bodin, T., García-Trabanino, R., Weiss, I., Jarquín, E., Glaser, J., Jakobsson, K., et al. (2016). Intervention to reduce heat stress and improve efficiency among sugarcane workers in El Salvador: Phase 1. *Occupational and Environmental Medicine*, *73*(6), 409.

Budd, G. M. (2008). Wet-bulb globe temperature (WBGT)—Its history and its limitations. *Journal of Science and Medicine in Sport*, *11*(1), 20–32. https://doi.org/10.1016/j.jsams.2007.07.003

Chan, A. P. C., & Yang, Y. (2016). Practical on-site measurement of heat strain with the use of a perceptual strain index. *International Archives of Occupational and Environmental Health*, *89*(2), 299–306. https://doi.org/10.1007/s00420-015-1073-7

Chan, A. P. C., Zhang, Y., Wang, F., Wong, F. F. K., & Chan, D. W. M. (2017). A field study of the effectiveness and practicality of a novel hybrid personal cooling vest worn during rest in Hong Kong construction industry. *Journal of Thermal Biology*, *70*, 21–27. https://doi.org/10.1016/j.jtherbio.2017.07.012

Chelminski, I., Ferraro, F. R., Petros, T., & Plaud, J. J. (1997). Horne and Ostberg questionnaire: A score distribution in a large sample of young adults. *Personality and Individual Differences*, *23*(4), 647–652. https://doi.org/10.1016/s0191-8869(97)00073-1

Crowe, J., Manuel Moya-Bonilla, J., Román-Solano, B., & Robles-Ramírez, A. (2010). Heat exposure in sugarcane workers in Costa Rica during the non-harvest season. *Global Health Action*, *3*(1), 5619. https://doi.org/10.3402/gha.v3i0.5619

Crowe, J., Wesseling, C., Solano, B. R., Umaña, M. P., Ramírez, A. R., Kjellstrom, T., et al. (2013). Heat exposure in sugarcane harvesters in Costa Rica. *American Journal of Industrial Medicine*, *56*(10), 1157–1164. https://doi.org/10.1002/ajim.22204

Delgado Cortez, O. (2009). Heat stress assessment among workers in a Nicaraguan sugarcane farm. *Global Health Action*, *2*(1), 2069. https://doi.org/10.3402/gha.v2i0.2069

Dimaranan, B. V. (2006). *Global trade, assistance, and production: The GTAP 6 data base*. West Lafayette, IN: Center for global trade analysis.

Dunne, J. P., Stouffer, R. J., & John, J. G. (2013). Reductions in labour capacity from heat stress under climate warming. *Nature Climate Change*, *3*(6), 563–566. https://doi.org/10.1038/nclimate1827

Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Wang, X.-R., & Lin, C.-J. (2008). LIBLINEAR: A library for large linear classification. *Journal of Machine Learning Research*, *9*(Aug), 1871–1874.

Folkard, S. (2003). Shift work, safety and productivity. *Occupational Medicine*, *53*(2), 95–101. https://doi.org/10.1093/occmed/kqg047

Folkard, S. (2008). Do permanent night workers show circadian adjustment? A review based on the endogenous melatonin rhythm. *Chronobiology International*, *25*(2–3), 215–224. https://doi.org/10.1080/07420520802106835

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., et al. (2017). SSP3: AIM implementation of shared socioeconomic pathways. *Global Environmental Change*, *42*, 268–283. https://doi.org/10.1016/j.gloenvcha.2016.06.009

Fujimori, S., Masui, T., & Matsuoka, Y. (2012). AIM/CGE [basic] manual. In *Center for social and environmental systems research*, *Discussion Paper Series* (2012–01). Tsukuba Japan: NIES.

Granneman, J. H. (2013). *Construction noise: Overview of regulations of different countries*. Paper presented at the INTER-NOISE and NOISE-CON Congress and Conference Proceedings, Innsbruck, Austria.

Hasegawa, T., Fujimori, S., Takahashi, K., Yokohata, T., & Masui, T. (2016). Economic implications of climate change impacts on human health through undernourishment. *Climatic Change*, *136*(2), 189–202. https://doi.org/10.1007/s10584-016-1606-4

Hasegawa, T., Park, C., Fujimori, S., Takahashi, K., Hijioka, Y., & Masui, T. (2016). Quantifying the economic impact of changes in energy demand for space heating and cooling systems under varying climatic scenarios. *Palgrave Communications*, *2*, 16013. https://doi.org/10.1057/palcomms.2016.13

Hassan, A.-M., Javad, J. M., Abdollah, G., Heidar, T. G., & Soheila, K. (2017). Heat stress level and physiological parameters among an open-pit mine workers in Razavi Khorasan, Iran. *Annals of Medical and Health Sciences Research*, *7*, 54–59.

Haus, E. L., & Smolensky, M. H. (2013). Shift work and cancer risk: Potential mechanistic roles of circadian disruption, light at night, and sleep deprivation. *Sleep Medicine Reviews*, *17*(4), 273–284. https://doi.org/10.1016/j.smrv.2012.08.003

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., & Piontek, F. (2013). A trend-preserving bias correction—The ISI-MIP approach. *Earth System Dynamics*, *4*(2), 219–236. https://doi.org/10.5194/esd-4-219-2013

IEA (2013a). *Energy balances for non-OECD countries*. Paris, France: OECD/IEA.

IEA (2013b). *Energy balances for OECD countries*. Paris, France: OECD/IEA.

Inaba, R., & Mirbod, S. M. (2007). Comparison of subjective symptoms and hot prevention measures in summer between traffic control workers and construction workers in Japan. *Industrial Health*, *45*(1), 91–99. https://doi.org/10.2486/indhealth.45.91

Ioannou, L. G., Tsoutsoubi, L., Samoutis, G., Bogataj, L. K., Kenny, G. P., Nybo, L., et al. (2017). Time-motion analysis as a novel approach for evaluating the impact of environmental heat exposure on labor loss in agriculture workers. *Temperature*, *4*(3), 330–340. https://doi.org/10.1080/23328940.2017.1338210

Isaac, M., & van Vuuren, D. P. (2009). Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy*, *37*(2), 507–521. https://doi.org/10.1016/j.enpol.2008.09.051

ISO (1989). Hot environments—Estimation of the heat stress on working man, based on the WBGT-index (wet bulb globe temperature) *ISO 7243:1989*.

Jones, B., & O'Neill, B. C. (2016). Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environmental Research Letters*, *11*(8), 084003. https://doi.org/10.1088/1748-9326/11/8/084003

Kantermann, T., Juda, M., Merrow, M., & Roenneberg, T. (2007). The human circadian clock's seasonal adjustment is disrupted by daylight saving time. *Current Biology*, *17*(22), 1996–2000. https://doi.org/10.1016/j.cub.2007.10.025

Kc, S., & Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, *42*, 181–192. https://doi.org/10.1016/j.gloenvcha.2014.06.004

Kenny, G. P., Schissler, A. R., Stapleton, J., Piamonte, M., Binder, K., Lynn, A., et al. (2011). Ice cooling vest on tolerance for exercise under uncompensable heat stress. *Journal of Occupational and Environmental Hygiene*, *8*(8), 484–491. https://doi.org/10.1080/15459624.2011.596043

Kjellstrom, T. (2016). Impact of climate conditions on occupational health and related economic losses: A new feature of global and urban health in the context of climate change. *Asia-Pacific Journal of Public Health*, *28*(2 Suppl), 28S–37S. https://doi.org/10.1177/1010539514568711

Kjellstrom, T., Kovats, R. S., Lloyd, S. J., Holt, T., & Tol, R. S. (2009). The direct impact of climate change on regional labor productivity. *Archives of Environmental & Occupational Health*, *64*(4), 217–227. https://doi.org/10.1080/19338240903352776

Lemke, B., & Kjellstrom, T. (2012). Calculating workplace WBGT from meteorological data: A tool for climate change assessment. *Industrial Health*, *50*(4), 267–278.

Liljegren, J. C., Carhart, R. A., Lawday, P., Tschopp, S., & Sharp, R. (2008). Modeling the wet bulb globe temperature using standard meteorological measurements. *Journal of Occupational and Environmental Hygiene*, *5*(10), 645–655. https://doi.org/10.1080/15459620802310770

Maiti, R. (2008). Workload assessment in building construction related activities in India. *Applied Ergonomics*, *39*(6), 754–765. https://doi.org/10.1016/j.apergo.2007.11.010

Masui, T., Matsumoto, K., Hijioka, Y., Kinoshita, T., Nozawa, T., Ishiwatari, S., et al. (2011). An emission pathway for stabilization at 6 Wm−2 radiative forcing. *Climatic Change*, *109*(1), 59. https://doi.org/10.1007/s10584-011-0150-5

Meade, R. D., D'Souza, A. W., Krishen, L., & Kenny, G. P. (2017). The physiological strain incurred during electrical utilities work over consecutive work shifts in hot environments: A case report. *Journal of Occupational and Environmental Hygiene*, *14*(12), 986–994. https://doi.org/10.1080/15459624.2017.1365151

Meade, R. D., Lauzon, M., Poirier, M. P., Flouris, A. D., & Kenny, G. P. (2015). An evaluation of the physiological strain experienced by electrical utility workers in North America. *Journal of Occupational and Environmental Hygiene*, *12*(10), 708–720. https://doi.org/10.1080/15459624.2015.1043054

Miller, V., Bates, G., Schneider, J. D., & Thomsen, J. (2011). Self-pacing as a protective mechanism against the effects of heat stress. *The Annals of Occupational Hygiene*, *55*(5), 548–555. https://doi.org/10.1093/annhyg/mer012

Naito, T., Iribe, Y., & Ogaki, T. (2017). Ice ingestion with a long rest interval increases the endurance exercise capacity and reduces the core temperature in the heat. *Journal of Physiological Anthropology*, *36*(1), 9. https://doi.org/10.1186/s40101-016-0122-6

Neutens, T., Schwanen, T., Witlox, F., & de Maeyer, P. (2010). Evaluating the temporal organization of public service provision using space-time accessibility analysis. *Urban Geography*, *31*(8), 1039–1064. https://doi.org/10.2747/0272-3638.31.8.1039

NIOSH (2016). Criteria for a recommended standard: Occupational exposure to heat and hot environments. *2016–106*.

Nurul Habib, K. M. (2012). Modeling commuting mode choice jointly with work start time and work duration. *Transportation Research Part A: Policy and Practice*, *46*(1), 33–47. https://doi.org/10.1016/j.tra.2011.09.012

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., et al. (2013). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, *122*(3), 387–400. https://doi.org/10.1007/s10584-013-0905-2

OSHA (2014). Protecting workers from the effects of heat. *OSHA Fact Sheet, FS-3743*.

Reppert, S. M., & Weaver, D. R. (2002). Coordination of circadian timing in mammals. *Nature*, *418*, 935. https://doi.org/10.1038/nature00965

Roson, R., & Van der Mensbrugghe, D. (2012). Climate change and economic growth: Impacts and interactions. *International Journal of Sustainable Economy*, *4*(3), 270–285.

Sahu, S., Sett, M., & Kjellstrom, T. (2013). Heat exposure, cardiovascular stress and work productivity in rice harvesters in India: Implications for a climate change future. *Industrial Health*. advpub. https://doi.org/10.2486/indhealth.2013-0006

Sipilä, J. O. T., Ruuskanen, J. O., Rautava, P., & Kytö, V. (2016). Changes in ischemic stroke occurrence following daylight saving time transitions. *Sleep Medicine*, *27*, 20–24. https://doi.org/10.1016/j.sleep.2016.10.009

Stowie, A. C., Amicarelli, M. J., Crosier, C. J., Mymko, R., & Glass, J. D. (2015). Circadian analysis of large human populations: Inferences from the power grid. *Chronobiology International*, *32*(2), 255–261. https://doi.org/10.3109/07420528.2014.965316

Strazdins, L., Clements, M. S., Korda, R. J., Broom, D. H., & D'Souza, R. M. (2006). Unsociable work? Nonstandard work schedules, family relationships, and children's well-being. *Journal of Marriage and Family*, *68*(2), 394–410. https://doi.org/10.1111/j.1741-3737.2006.00260.x

Suzuki-Parker, A., & Kusaka, H. (2016). Future projections of labor hours based on WBGT for Tokyo and Osaka, Japan, using multi-period ensemble dynamical downscale simulations. *International Journal of Biometeorology*, *60*(2), 307–310. https://doi.org/10.1007/s00484-015-1001-2

Takakura, J., Fujimori, S., Takahashi, K., Hijioka, Y., Hasegawa, T., Honda, Y., et al. (2017). Cost of preventing workplace heat-related illness through worker breaks and the benefit of climate-change mitigation. *Environmental Research Letters*, *12*(6), 064010.

Torriti, J., Hanna, R., Anderson, B., Yeboah, G., & Druckman, A. (2015). Peak residential electricity demand and social practices: Deriving flexibility and greenhouse gas intensities from time use and locational data. *Indoor and Built Environment*, *24*(7), 891–912. https://doi.org/10.1177/1420326X15600776

UNFCCC (2015). Adoption of the Paris agreement. 1/CP.21.

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011). The representative concentration pathways: An overview. *Climatic Change*, *109*(1), 5. https://doi.org/10.1007/s10584-011-0148-z

Vatani, J., Golbabaei, F., Dehghan, S. F., & Yousefi, A. (2016). Applicability of universal thermal climate index (UTCI) in occupational heat stress assessment: A case study in brick industries. *Industrial Health*, *54*(1), 14–19. https://doi.org/10.2486/indhealth.2015-0069

Waite, M., Cohen, E., Torbey, H., Piccirilli, M., Tian, Y., & Modi, V. (2017). Global trends in urban electricity demands for cooling and heating. *Energy*, *127*, 786–802. https://doi.org/10.1016/j.energy.2017.03.095

Wenz, L., & Levermann, A. (2016). Enhanced economic connectivity to foster heat stress–related losses. *Science Advances*, *2*(6).

Xiang, J., Hansen, A., Pisaniello, D., & Bi, P. (2015). Perceptions of workplace heat exposure and controls among occupational hygienists and relevant specialists in Australia. *PLoS One*, *10*(8), e0135040. https://doi.org/10.1371/journal.pone.0135040

Yi, W., & Chan, P. A. (2017). Effects of heat stress on construction labor productivity in Hong Kong: A case study of rebar workers. *International Journal of Environmental Research and Public Health*, *14*(9). https://doi.org/10.3390/ijerph14091055