Effects of climate change on combined labour productivity and supply: an empirical, multi-model study

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Summary

Background Although effects on labour is one of the most tangible and attributable climate impact, our quantification of these effects is insufficient and based on weak methodologies. Partly, this gap is due to the inability to resolve different impact channels, such as changes in time allocation (labour supply) and slowdown of work (labour productivity). Explicitly resolving those in a multi-model inter-comparison framework can help to improve estimates of the effects of climate change on labour effectiveness.

Methods In this empirical, multi-model study, we used a large collection of micro-survey data aggregated to subnational regions across the world to estimate new, robust global and regional temperature and wet-bulb globe temperature exposure-response functions (ERFs) for labour supply. We then assessed the uncertainty in existing labour productivity response functions and derived an augmented mean function. Finally, we combined these two dimensions of labour into a single compound metric (effective labour effects). This combined measure allowed us to estimate the effect of future climate change on both the number of hours worked and on the productivity of workers during their working hours under 1·5°C, 2·0°C, and 3·0°C of global warming. We separately analysed low-exposure (indoors or outdoors in the shade) and high-exposure (outdoor in the sun) sectors.

Findings We found differentiated empirical regional and sectoral ERF's for labour supply. Current climate conditions already negatively affect labour effectiveness, particularly in tropical countries. Future climate change will reduce global total labour in the low-exposure sectors by 18 percentage points (range –48·8 to 5·3) under a scenario of 3·0°C warming (24·8 percentage points in the high-exposure sectors). The reductions will be 25·9 percentage points (–48·8 to 2·7) in Africa, 18·6 percentage points (–33·6 to 5·3) in Asia, and 10·4 percentage points (–35·0 to 2·6) in the Americas in the low-exposure sectors. These regional effects are projected to be substantially higher for labour outdoors in full sunlight compared with indoors (or outdoors in the shade) with the average reductions in total labour projected to be 32·8 percentage points (–66·3 to 1·6) in Africa, 25·0 percentage points (–66·3 to 7·0) in Asia, and 16·7 percentage points (–45·5 to 4·4) in the Americas.

Interpretation Both labour supply and productivity are projected to decrease under future climate change in most parts of the world, and particularly in tropical regions. Parts of sub-Saharan Africa, south Asia, and southeast Asia are at highest risk under future warming scenarios. The heterogeneous regional response functions suggest that it is necessary to move away from one-size-fits-all response functions to investigate the climate effect on labour. Our findings imply income and distributional consequences in terms of increased inequality and poverty, especially in low-income countries, where the labour effects are projected to be high.

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Introduction

Labour is a major channel through which climate change might affect the global workforce and thus economic output[1] Warming directly affects labour supply (working hours) by changing the allocation of time to labour beyond certain thresholds, especially in working conditions that are highly exposed to the climate—eg, in the agriculture sector[2–4]—to avoid lasting damages to health due to heat exhaustion or heat stroke, or even death.[5,6] Climate change also reduces performance during working hours (labour productivity) when workers under severe heat stress slow down and take more breaks to rehydrate and cool down.[5–7] Additionally, excessive body temperature and dehydration can increase the number of mistakes made, resulting in increased accidental injuries.[8–10] As labour accounts for a substantial share of the total valued added, as much as 50% in some sectors depending on the sector and country,[11] studies using economic models have found that the climate effects on labour are among the most important drivers of total economic costs of climate change.[1,11] Possible effects on the working population due to temperature shocks that are unmitigated through adequate thermoregulatory infrastructure will lead to a reduction in economic activity and reduce the capacity for economic growth, especially in low-income and middle-income countries.[3,4,12] These

Research in context

Evidence before this study

Heat stress affects both labour supply and productivity. Although the literature on the effect of heat on labour is extensive, exposure-response functions (ERFs) based on a small number of observations and almost no systematic inter-comparison of existing response functions remain. We searched PubMed, Embase, SpringerLink, and ScienceDirect for literature on heat and labour effects from inception until Sept 30, 2020, using the following search terms: ("temperature*", "climate" OR "heat") AND ("*labour", "*labor", "*worker", "supply", "productivity", "capacity"). We also considered official reports from the International Labour Organization and the Joint Research Centre. Previous studies applied a single function globally and most of the existing literature has studied labour supply and labour productivity independently—only one study has used multiple impact models for labour productivity before, and none have empirically estimated response functions globally.

Added value of this study

Our study is the first to empirically estimate response functions with globally representative data for labour supply and assess the uncertainty related to labour productivity by applying multiple response functions. We combined our heterogenous regional response functions for labour supply with an augmented mean response function of existing impact models of labour productivity to compute a single compound metric for effective labour effects. This metric allowed us to project the effect of future climate change on both the number of hours worked and on the productivity of workers during their working hours under various warming scenarios. We showed that current warming already limits effective labour across the globe. Global warming will exacerbate these effects, especially in sub-Saharan Africa, south Asia, and southeast Asia.

Implications of all the available evidence

Labour is directly affected by changes in environmental conditions. Our study shows differentiated historical effects of temperature on labour across the world, indicating that future warming will have substantial adverse effects on effective labour. These effects will be heterogenous across regions and sectors, with the highest declines expected in Africa and Asia. Our findings indicate that there is a need to use regional ERFs because of the heterogeneity between regions. Furthermore, the combined effect on both the number of hours worked and the productivity of the workers implies consequences for long-term economic growth and inequality. Future studies should focus on improving the impact models for labour productivity and to contextualise the role of adaptation. The results can be used to improve the assessment of the economic consequences of future climate change impacts on labour.

effects have distributional implications in terms of increased inequality and poverty.[1,12]

Most of the existing literature focuses on the effect on labour productivity, where the terms labour productivity, work productivity, work capacity, and worker productivity are used interchangeably without clear delineations.[10] Analyses of the effect of warming on the number of hours worked are largely absent and, if available, focus mostly on individual countries.[3,4,13–16] A representative global assessment of total labour effects is missing (panel).

We used novel exposure-response functions (ERFs) for the effect of warming on global and regional labour supply, using both mean temperature and wet-bulb globe temperature (WBGT). Although climate change is a global phenomenon, the effects are localised and depend largely on local physical and sociocultural contexts; hence, region-specific response functions must be estimated. The high-resolution spatial data on labour supply and climate used in this study allowed us to estimate climate effects on labour with greater robustness compared with previous literature, capturing various heterogeneities and aiding the evidence-based policy process. We used these regional functions with projections of climate change to assess future changes in labour supply. Combining these changes with estimates of changes in labour productivity derived from published temperature-productivity response functions yields a metric for the effect of climate change on effective labour. We assessed the large uncertainty regarding labour productivity effects by doing a multi-model comparison following the approach of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP).[23] We computed the future effects of climate change under 1·5°C, 2·0°C, and 3·0°C of global warming scenarios (relative to the pre-industrial era) on labour productivity and labour supply, and then combined these two effects into effective labour.

For more on **IPUMS** see https://international.ipums.org/international

Methods

Exposure-response functions of labour supply

In this empirical, multi-model study, we analysed over 300 micro surveys from Integrated Public Use Microdata Series (IPUMS)-International, the world's largest archive of publicly available micro-survey data. The archive comprises data for many countries for 30 years, including the number of hours worked per week (defined as the number of hours an individual respondent worked per week at all jobs). Although data on number of hours worked are available, the timing of the surveys are not always available; thus, we aggregated the data on hours worked to the annual level. For some European countries, we were only able to obtain data at the annual level.

In terms of gender breakdown, the number of female respondents ranges from 26·0% in east Asia to 47·2% in

Panel: Definitions used in the existing literature

Previous research has not carefully defined the subject of interest and terms such as labour productivity, labour supply, and labour capacity have been used interchangeably. Definitional clarity is certainly needed and for this reason we include the following definitions.

The existing literature focuses on labour productivity, where the terms labour productivity, work productivity, work capacity, worker performance, and worker productivity are used interchangeably without clear delineations.[11] Dunne and colleagues[17] define labour capacity as the occupational capacity to safely perform sustained labour under environmental heat stress. Kjellstrom and colleagues[18] define labour capacity as the reduction of hourly work capacity at different levels of work intensity. Sahu and colleagues[7] measure a reduction in work productivity as a reduction in hourly work output whereas Li and colleagues[19] define labour productivity as a relationship between the output and the associated input in a production process (focusing on construction work in China). Pilcher and colleagues[20] did not provide a specific definition for worker performance but they studied the effects of temperature on performance for reasoning, learning, and memory tasks.

In economic theory, labour supply is defined as the amount of labour, measured in person-hours, offered for hire in a given time period.[21] Warming directly affects labour supply (working hours) by reducing the allocation of time to labour beyond certain thresholds, especially in weather-exposed sectors such as agriculture,[3,4,22] to avoid lasting damages to health due to heat exhaustion, heat stroke, or even death.[5,6] Climate change might also reduce performance (labour productivity) during these working hours when workers under severe heat stress slow down and take more breaks to rehydrate and cool down.[5–7] We combined these two dimensions (supply and productivity) of labour into a single compound metric, which we call effective labour. This compound metric allowed us to estimate the effect of future climate change on both the number of hours worked and on the productivity of workers during their working hours.

Heal and Park[13] use the term "effective labour supply", which they define as a composite of labour hours, task performance, and effort. However, their empirical analysis is based on country-level data on per-capita income and temperature and the authors estimate willingness to pay for heating and cooling in the USA. We took a similar approach but used subnational data on labour supply and published labour productivity models from the literature.

northern Europe. Thus, we believe our numbers are robust. One limitation of the data used is that not all samples required that the person be currently working at the time of the census. Many samples include people who did not work during the reference week but are usually employed. The labour supply data are geo-referenced at the second administrative level, allowing us to use the individual weights from the surveys to aggregate the individual responses of labour supply (hours worked) data to the region-year level. As a result, the aggregated dataset is representative at subnational level.

We re-categorised the occupational codes for primary occupation into low-exposure working conditions (labour outside in the shade or indoors—eg, manufacturing) and high-exposure working conditions (outside with no shade—eg, agriculture and construction). We used a panel regression controlling for both location (subnational region) and time (survey year) fixed effects using an unbalanced panel at the region-year level:

$$ln(LS_{ist})=f_s(temp_{ist}) + \alpha_{is} + \gamma_{ts} + \varepsilon_{it} \quad (1)$$

In this regression, the dependent variable is the log of the total number of hours worked in working condition s in region i in survey year t. $f_s(temp_{ist})$ represents the non-linear effect of regional annual mean temperature or WBGT on labour supply. This effect is controlled for by including both linear and quadratic dependencies on temperature. Previous findings showed a non-linear, concave response of labour supply to local temperatures;[2–4,24,25] for low temperatures labour supply increases with temperature but once a certain threshold temperature is surpassed supply declines when temperature is further increased. Time-invariant subnational region fixed effects are denoted by α_{it}, while γt are survey-year fixed effects. Our standard errors were clustered at the country level. We used equation 1 for high-exposure and low-exposure working conditions globally and for Africa, Asia, the Americas, and Europe. As robustness tests, we used binned regressions and population-weighted temperature instead of individual survey weights.

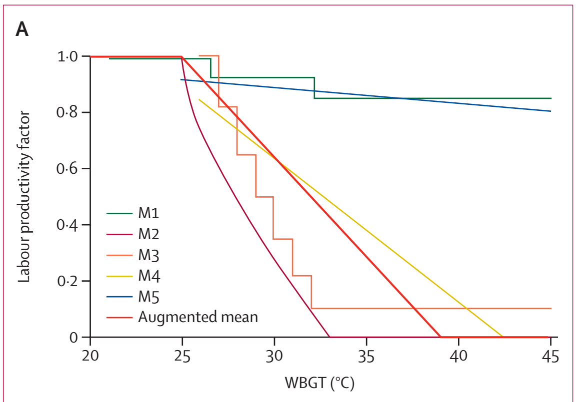
For the econometric analysis, we extracted mean temperature (T_{mean}), maximum temperature (T_{max}), and near-surface relative humidity from ERA5, fifth generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate data at a spatial resolution of 0·25°×0·25° and hourly temporal resolution, which was overlaid on the subregional shapefile from IPUMS.

For **ERA5 data** see https://cds.climate.copernicus.eu/cdsapp#!/home

Exposure response functions for labour productivity

We assessed the effect of climate change on labour productivity using five different ERFs established in the literature (figure 1B). All these ERFs are driven by changes in WBGT rather than mean temperature. Wyndham[26] is similar to Sahu and colleagues,[7] in terms of the shape of the ERFs (ie, the location and gradient of each function

A



B

Study	Response variable	Spatial scale
M1: Pilcher et al[20] (2002)	Psychological performance—eg, reaction time, tracking, or memory tasks	Global
M2: Dunne et al[17] (2013)	Individual capacity to safely perform heavy labour under heat stress	Global
M3: Kjellstrom et al[18] (2014)	Reduction of hourly work capacity for heavy work following the ISO standard	Global
M4: Sahu et al[7] (2013)	Work output per hour of rice farmers calculated by number of rice bundles laid down	India
M5: Li et al[19] (2016)	Time efficiency measures; direct, indirect, and idle time of rebar construction workers	China

C

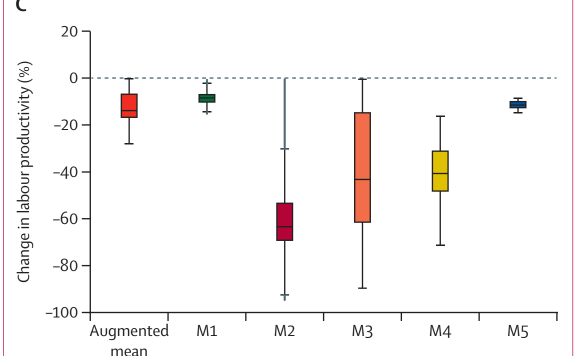


Figure 1: **Exposure-response functions for labour productivity**
(A) The five individual exposure response functions from selected impact models used to calculate the augmented mean response function (red line) used to quantify the effect of WBGT (°C) on labour productivity in this study. (B) Labour productivity impact models, with their response variable and spatial scale. (C) Global effects of climate change on labour productivity for the augmented mean response function and labour productivity impact models at 3·0°C compared with the historical baseline period (1986–2005). Boxes show the quartiles and the horizontal line in the box shows the median, whiskers denote the most extreme non-outlier data points and denote fliers are the points representing data that extend beyond the whiskers. WBGT=wet bulb globe temperature. ISO=International Standards Organisation.

For **ISIMIP** see https://www.isimip.org/

on a WBGT-productivity axis). Kjellstrom and colleagues[18] state that "The Sahu data (on agricultural workers) fit reasonably close to the fitted Wyndham curve but generally indicates additional work capacity loss, possibly due to more heavy labour in this type of work."

These five ERFs cover a range of functions applied in past assessments of the effect of climate change on labour productivity,[14–16,19,27] including one multi-model assessment using all five models together.[27] The ERFs represent the range of work intensities that occur in different working environments and the functional form and scope of the models are rather different.[28] In some models, labour productivity decreases continuously with WBGT, whereas in other models it decreases in discrete steps (figure 1A). Somanathan and colleagues[1] did a detailed empirical study on different types of manufacturing in India and found results that broadly fall in the range covered by the functions here (with a threshold of approximately 25–27° WBGT and reductions in productivity of 3–8% for every additional degree of WBGT), showing that indoor labour can also be heavily affected. Most models show some form of saturation with increasing WBGT, albeit at different levels. These effects need to be considered when aggregating the effect of individual models because a simple multi-model mean would show artefacts of saturation.

In the economic assessment of the effect of climate change on labour productivity, typically only one ERF is applied.[11] A detailed uncertainty analysis on individual impact channels is a challenge for many complex economic models. However, using only an individual ERF might lead to extreme results because doing so does not allow the representation of uncertainties resulting from the different approaches. We here propose an augmented mean response function. In line with the ERFs, we assumed zero effects for values of the WBGT below 25·0°C, and for values above 25·0°C we did a linear fit with equal weighting of all five ERFs with zero intercept. We then assumed that labour productivity declines above 25·0°C linearly with the slope of the fit until it reaches zero around WBGTs of 39·5°C. Sensitivity checks revealed that our augmented mean response function lies well between the existing impact models and even compensates for the more extreme response functions (figure 1C).

For the impact analysis, we quantified daily WBGT by first assessing the wet-bulb temperature Tw from daily mean relative humidity and T_{max} following the empirical relationship by Stull:[29]

$$Tw = T_{max}\,\text{atan}(0{\cdot}151977\,[RH + 8{\cdot}313659]^{1/2}) + atan(T_{max} + RH) - atan(RH - 1{\cdot}676331) + 0{\cdot}00391838(RH)^{3/2}\,atan(0{\cdot}023101\,RH) - 4 \qquad (2)$$

Ideally, WBGT is calculated from sub-daily temperature and humidity data to account for diurnal variability in both variables. However, daily is the highest resolution provided by the ISIMIP2b input data. We used daily mean relative humidity and daily T_{max}, as done by Saeed and colleagues,[30] because we wanted to provide an indication of the maximum possible WBGT experienced on any given day. The maximum relative humidity and maximum temperature are unlikely to occur at the same time of day because there can be an inverse diurnal relationship between the two variables, so these two variables were not used together, and the use of the daily mean of each variable would miss out the extremes experienced each day. A combination of daily mean relative humidity and T_{max} is thus considered appropriate. We then used Tw to quantify WBGT for outdoor conditions in the shade using the formula of Bernard and Pourmoghani:[31]

$$WBGT_{shade}=0\cdot67T_w+0\cdot33T_{max} \tag{3}$$

Stull's[29] empirical relationship in equation 2 is for the calculation of wet-bulb temperature. Equation 3 is based on Lemke and Kjellstrom,[32] who define the same equation except that in Lemke and Kjellstrom[32] the wet-bulb temperature is replaced with the psychometric wet-bulb temperature T_{pwb}. It is, however, reasonable to use Tw in equation 3 because Stull's[29] relationship was derived from a fit to a psychrometric graph for standard sea-level pressure of 101·325 kPa and Stull[29] notes that a rationale for the empirical relationship shown in equation 2 is for its use in the calculation of WBGT. However, we acknowledge that Tw as estimated in our study will be slightly different from Tw that might be estimated using meteorological instruments because ours was based on an empirical relationship. Tw is normally estimated with a wetted bulb instrument in natural wind conditions in the shade, whereas T_{pwb} is normally estimated from a wetted bulb in the shade, aspirated with a fan at 3–5 m/s or by rotating a wetted thermometer in the air. Equation 3 assumes a wind speed of 1 m/s and when wind speed is greater than 3 m/s the $WBGT_{shade}$ computed with T_{pwb} reduces by approximately 6% of the 1 m/s value.[32] Thus, we expected the use of empirically derived Tw in equation 3 instead of T_{pwb} to have a negligible effect on the estimation of $WBGT_{shade}$. WBGT for outdoor in the sun was approximated following Kjellstrom and colleagues:[18]

$$WBGT_{sun}=WBGT_{shade}+3° \tag{4}$$

We focus on the results for $WBGT_{shade}$ because we found the method of quantifying $WBGT_{sun}$ (the approximation of +3°C) oversimplistic. Nevertheless, the results for $WBGT_{sun}$ can be found in the appendix (pp 4–5).

	1·5°C warming	2·0°C warming	3·0°C warming
IPSL-CM5A-LR	2015–35	2027–47	2046–66
GFDL-ESM2M	2028–48	2043–63	2073–93

Table: **Year each temperature level is projected to be reached for each global climate model**

Effect of climate on effective labour

To compute the effect of climate on effective labour, we combined the effect of climate change on labour

See Online for appendix

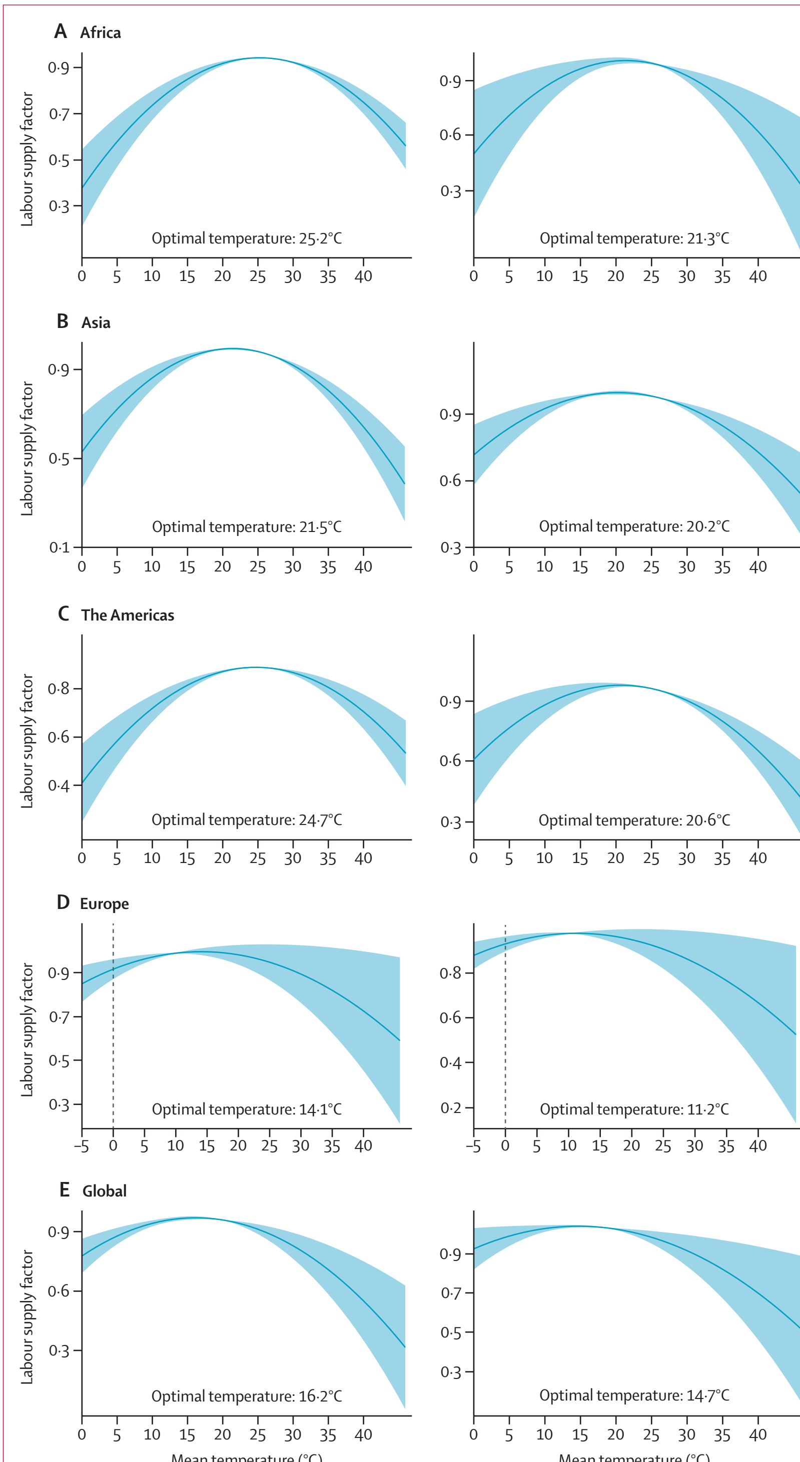


Figure 2: **Relationship between temperature and labour supply**
Shading shows 95% CI. Our specification controlled for temperature, region, and survey year fixed effects. Standard errors were clustered at the country level.

productivity (percentage point decline from present) with the loss of hours worked (labour supply) using the impact models from the literature and our own labour-supply response functions. Heal and Park[13] use the term "effective labour supply", which they define as a composite of labour hours, task performance, and effort but the authors did empirical analysis using country-level data on per-capita income and temperature, and households' estimated willingness to pay for heating and cooling in the USA. We take a similar approach but use subnational data on labour supply and published labour productivity models from the literature:

$$\textit{Change in Effective Labour} = (100\% + \textit{Change in Labour Supply}) * \textit{Change in Labour Productivity} \quad (5)$$

Both labour productivity and labour supply are affected by several factors aside from climatic stressors, such as clothing and the intensity of work being undertaken;[12] however, we were unable to account for them in our analysis because of data constraints.

Climate change projection data and warming levels

To estimate the effect of future climate change, we used statistically downscaled (0·5°×0·5°) simulations of daily global climate data from two global climate models (GCMs) from the CMIP5 ensemble (IPSL-CM5A-LR and GFDL-ESM2M) that are part of the input dataset of the ISIMIP2B.[23] The simulations were bias-corrected toward observational data.[33] Daily WBGT was estimated across the global land surface at the grid-cell level for all GCMs and warming levels, following the method already described.

We considered three global warming levels in the assessment; 1·5°C, 2·0°C, and 3·0°C increase in global mean temperature above pre-industrial levels. Following Schleussner and colleagues,[34] we assessed these warming levels by assessing warming over the observational period until the reference period 1986–2005 (0·6°C) and modelled warming for the individual GCMs relative to the reference period. We first calculated the absolute effects for the reference period and then assessed the relative changes for 1·5°C, 2·0°C, and 3·0°C (table). All the effects are averaged for a 20-year period to account for climate variability. The effects were population weighted using the shared socioeconomic pathway 2 (SSP2) scenario because the change in labour is more significant in locations with higher population. SSP narratives describe how the future might unfold in terms of broad societal trends.[35] SSP2 describes the middle-of-the-road scenario with medium challenges to mitigation and adaptation. To allow for inter-comparability, we used one future population estimate, SSP2 projected population for 2100, for all warming levels and GCMs. We acknowledge that only including SSP2 in ISIMIP is a limitation. However, given the voluntary nature of ISIMIP, the number of runs required by participating modelling teams needed to be kept to a manageable level. In the upcoming round of ISIMIP, ISIMIP3, multiple SSPs will be included. In a follow-up paper we plan to focus on adaptation using multiple SSPs.

Role of the funding source

The funder of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

We found a non-linear, concave relationship between mean temperature and labour supply. We normalised the labour supply and labour productivity response functions to one. Our findings show that global labour supply under low-exposure work conditions is maximised at a mean temperature of 16·2°C and under high-exposure work conditions at 14·7°C (figure 2E). Labour supply increases up to these temperature thresholds; further temperature increases then result in a decrease in the number of hours worked (figure 2E).

Importantly, we found evidence that the effect of temperature on labour supply is heterogeneous across regions and work conditions. For Africa (figure 2A), labour supply is maximised at a mean temperature of 25·2°C, whereas the optimal temperature is 21·5° for Asia (figure 2B), 24·7°C for the Americas (figure 2C), and 14·1°C for Europe (figure 2D).

In the case of high-exposure work conditions, the non-linearity of the ERFs held true for each of the regions, the optimal temperature being lower than

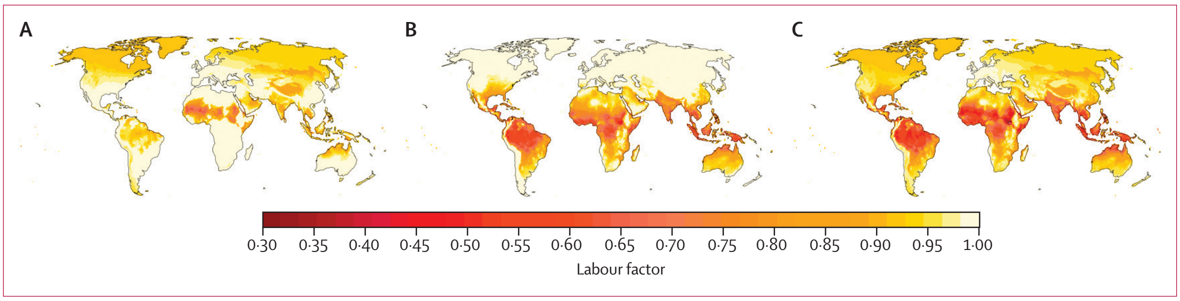


Figure 3: **Effects of climate on labour, 1986–2005**
Labour supply factor (A), labour productivity factor (B), and effective labour factor (C; as a combination of A and B).

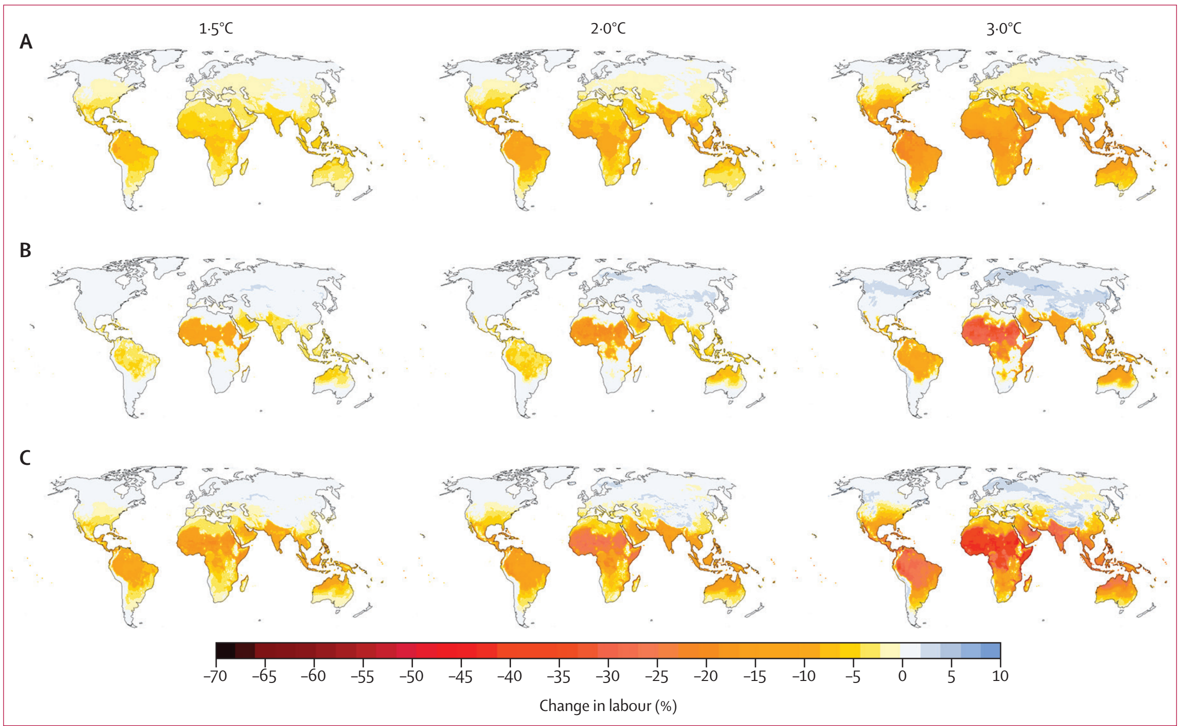


Figure 4: **Effects of climate change relative to the period 1986–2005 on labour**
Labour supply (A), labour productivity (B), and effective labour for outdoor working conditions in the shade or indoors (C) for 1·5°C, 2·0°C, and 3·0°C global warming.

the optimal for the low-exposure work conditions (21·3°C for Africa, 20·2°C for Asia, 20·6°C for Europe, and 11·2°C for the Americas) because for high-exposure work conditions, workers are subjected to higher heat stress compared with low-exposure conditions. For the USA, we estimated that labour supply in the high-exposure working conditions is maximised at 14·3°C, whereas the optimal temperature in the low-exposure working conditions was estimated to be 14·8°C (appendix p 3).

The estimated ERFs for WBGT and labour supply were similar to those estimated using mean temperature, both globally and regionally (appendix pp 1–2). The optimal global WBGT for the low-exposure work conditions was estimated at 18·2°C and for high-exposure conditions 15·8°C, slightly higher than the mean optimal temperature (appendix pp 1–2). We further found that inter-annual variations in temperature result in a decline of labour supply at both global and regional levels, with the highest effects on Africa under high-exposure work conditions (appendix pp 1–2).

The heterogeneity in the regional response-functions, which are estimated from a large dataset, suggests that applying global response functions (as is common in the literature) to project local climate effects on labour is likely to provide biased results. Therefore, in our study we used novel regional response-functions to estimate the effects of future climate change, separately for each study region.

As a sensitivity test, we used a binned temperature regression, in which daily temperature was sorted into discrete bins of 5°C and two additional ones: below 5°C and above 30°C. The results from these regressions support our main findings, with additional days of mean temperature in the bins below the reference bin resulting in an increase in labour supply (appendix p 3). Additional temperature days in the bins in the higher temperature level bins result in a decrease in labour supply (appendix p 3).

As a further robustness test, we used population-weighted temperature instead of individual survey weights. We used population of the subnational regions to compute the population weights to ensure that the labour supply response functions reflect the average global labour supply. The results from regressions using subnational population weights suggest that labour supply is non-linear and concave in mean temperature, with only slight differences in the temperature levels maximising labour supply.

We used the ERFs to study the limits posed on labour by present day climate compared with the optimal temperature (for labour supply) and a WBGT level of 25°C (for labour productivity), acknowledging that the latter ERFs do not account for the possible effects of low temperatures on productivity (figure 3).

In the historical period (1986–2005), we found that labour supply is affected negatively in the tropics but also in colder regions because of temperatures below the

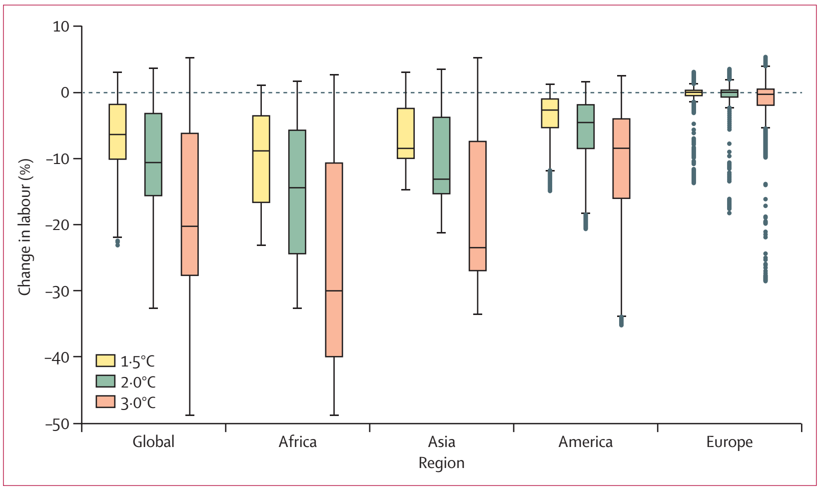


***Figure 5:* Population-weighted (SSP2) changes (percentage points) in global and regional effective labour under various global warming scenarios compared with pre-industrial levels, 1986–2005**
Boxes show the quartiles, the horizontal line in the box shows the median, whiskers denote the most extreme non-outlier data points and denote fliers are the points representing data that extend beyond the whiskers. SSP2=Shared Socioeconomic Pathway 2.

optimum (figure 3A). Further, using the augmented mean ERF, we found that global average labour productivity is reduced by 0·08 for low-exposure work conditions in regions with WBGT above 25°C, and up to 0·64 around the equator (figure 3B). Particularly affected are regions in South America, central Africa, India, and southeast Asia, where labour productivity is by a factor of 0·50 below the optimum. These estimates are in line with studies that find moderate-to-high risk for in-shade work in many tropical and subtropical regions.[15,16,36] By combining both metrics, we found that global mean annual effective labour is by a factor of 0·23 below the optimum (figure 3C).

Close to the equator, effective labour is below the optimum by a factor of 0·80 (combining the two negative effects), whereas it is only by a factor of 0·20 below the optimum in the northern and southern hemispheres (mainly driven by labour supply). These results suggest that effective labour is substantially limited by high temperatures, particular in regions around the equator. As climate change will intensify heat stress in already hot regions, there is a need to understand the possible future effects of climate change, which could have adverse effects on both health protection and economic output in these regions, in the absence of further adaptation measures.

To investigate the effect of future climate change, we computed the relative effects of additional warming compared with the reference period under three warming scenarios of 1·5°C, 2·0°C, and 3·0°C for labour supply (figure 4A), labour productivity (figure 4B), and effective labour (figure 4C).

Global effective labour indoors or outdoors in the shade will decrease by 6·7 percentage points (range –23·1 to 3·1) under 1·5°C of warming, by 10·3 percentage points (–32·6 to 3·6) under 2·0°C, and by 18·3 percentage points (–48·8 to 5·3) under a 3·0°C warming scenario compared with present day. Figure 5 shows the population-weighted regional differences for effective labour. Increasing warming is projected to result in substantial declines in Africa, Asia, and the Americas (effects are averaged over the region; figure 5). Figures 4 and 5 also emphasise the heterogeneity in climate effects across the regions. Africa is expected to experience the highest reductions in effective labour, with a reduction of 9·9 percentage points (–23·1 to 1·2) under 1·5°C warming, 14·9 percentage points (–32·6 to 1·7) under 2·0°C, and 25·9 percentage points (–48·8 to 2·7) reduction under 3·0°C warming (figures 4, 5). The highest effects in Africa will be in sub-Saharan Africa, with declines of up to 50·1 percentage points in effective labour under a 3·0°C scenario (figure 4C). In Asia, the second most affected region, effective labour is projected to reduce by 6·7 percentage points (–14·7 to 3·1) at 1·5°C warming, by 10·4 percentage points (–21·2 to 3·6) at 2·0°C, and by 18·6 percentage points (–33·6 to 5·3) under 3·0°C warming. Countries in Asia around the equator (India and southeast Asia) will experience the largest reductions in effective labour due to future climate change. In the case of the Americas, the average decline will be 3·5 percentage points (–14·9 to 1·3) at 1·5°C of warming, 5·6 percentage points (–20·6 to 1·8) at 2·0°C, and 10·4 percentage points (–35·0 to 2·6) at 3·0°C warming. The strongest effects are expected in South America (figure 4). Europe is expected to be the least affected region, with an average decrease in effective labour of 0·1 percentage points (–13·6 to 3·1) under 1·5°C, 0·3 percentage points (–18·2 to 3·6) under 2·0°C, and 1·0 percentage point (–28·5 to 5·3) under 3·0°C warming. However, these effects greatly vary across the continent, with a decline of up to 28·5 percentage points in effective labour at 3·0°C of warming expected in southern Europe (figures 4, 5). Note that increasing temperatures in the northern regions improve labour supply up to the optimal temperature, although we cannot quantify this for labour productivity. The effects were estimated to be significantly higher under high-exposure work conditions and a 3·0°C warming scenario, with the average reductions in effective labour is projected to be 32·8 percentage points in Africa, 25·1 percentage points in Asia, and 16·7 percentage points in the Americas (appendix pp 7–8). Europe is expected to have a decline of 5·8 percentage points in effective labour under a global warming scenario of 3·0°C (appendix pp 6–7, 14).

Discussion

Labour is one of the sectors most heavily exposed to, and affected by, climate change. Although labour is regularly included in economic assessments of climate change effects using macroeconomic models, our understanding of this channel and the reliability of the response functions are limited by being based on a small number of observations without systematic inter-comparison of existing response functions. We estimated robust empirical regional ERFs for labour supply using several micro surveys. First, the heterogeneous regional response functions indicate that it is necessary to move away from one-size-fits-all response-functions to investigate the effect of climatic stressors on labour, especially at the global level. Second, we compared multiple existing response functions on labour productivity. Finally, we combined these two dimensions of labour into a single compound metric (effective labour), which allowed us to estimate the effect of future climate change on both the number of hours worked and on the productivity of workers during their working hours.

Our findings show that current climate has a negative effect on effective labour compared with optimal conditions as given by the ERFs. These effects will be exacerbated by climate change, with future warming projected to reduce effective labour output in most parts of the world during the 21st century.

An immediate consequence of these declines in labour (supply and productivity) will be income reductions,[37] and in turn the associated inequality and poverty effects are also likely to be severely affected, especially in low-income areas of Africa and Asia, where labour effects are projected to be high. The relatively higher reductions in effective labour under high-exposure work conditions might also have distributional consequences because incomes in the associated sectors (eg, agriculture and construction) are relatively low.

Furthermore, our results provide a basis for improving the economic assessments of labour effects;[11] in particular, our results stress the need to account for the large uncertainty across labour productivity ERFs, but also provide a robust foundation to include regional labour supply effects, which so far is largely missing.

In such a complex global analysis there are multiple sources of uncertainty that might influence the results, such as uncertainties with regards to the climate models as well as uncertainties resulting from the modelling of the impact metrics (appendix p 23). The assessment of additional uncertainty dimensions as, for instance, uncertainties regarding socioeconomic development are beyond the scope of this paper. We found that the large heterogeneity between the projected climate effects on labour productivity for the five impact models compared with the augmented mean response (appendix pp 13–21) is a major driver of uncertainty, underlining the need for more research in this field. To some extent, this result is not surprising because the five models we used were derived for different types of labour and calibrated for different regions of the world. The existing literature has used the models independently, which means past understanding on the sensitivity of labour productivity to climate change has been based on the use of disparate labour productivity models. For the first time, we showed the differences in projections when the models were used with consistent climate change projections. This conclusion leads us to two recommendations: (1) that future studies carefully consider which labour productivity models they use and that they consider using several models so uncertainty can be quantified; and (2) that the scientific community work towards developing a set of more statistically robust models of labour productivity. A notable example is the detailed empirical study by Somanathan and colleagues;[1] however, this study focuses only on certain types of manufacturing in India. For application in global integrated assessment, robust global estimates are necessary, such as the labour supply functions we developed here. The former models thus inherently have significant statistical biases (indeed, CIs are not available for these models), which significantly impinges on the robustness of the projections calculated from them.

Our estimates of effective labour under climate change are based on projections of daily WBGT estimated from climate model projections based on empirical relationships, rather than using meteorological instruments for which WBGT is intended. To this end some authors[38,39] suggest avoiding the indirect use of WBGT without instrumental globe temperature, whereas Havenith and Fiala[40] suggest that non-instrumental measurements of WBGT should be avoided. Furthermore, WBGT can be estimated empirically in multiple different ways[28] and the application of WBGT assumes that workers wear light clothing.[40] These limitations imply that the calculation of WBGT from climate model data should be treated with caution and that climate change impact assessments for labour productivity with climate variables that are not based on the WBGT, but other heat indices, could be worthwhile.

The augmented labour productivity function we developed considers step, linear, and non-linear models of labour productivity. We assumed a linear fit beyond 25°C because two of the input models are linear and because we sought to develop a simple function that broadly considered the ERFs used in previous climate change impact assessments. However, we acknowledge that the physiological basis for this assumption is limited and that although simplicity offers practicality, it does not guarantee robustness.[41] In this respect, the application of a heat index based on human heat balance, which can include known physiological and behavioural modifiers of heat dissipation, might be more robust. We recommend such an approach in future labour productivity studies, but the purpose of our study was to capture some of the uncertainty that arises from using models used previously in climate change impact assessments.

An important omission to our method is that future adaptation is not included because of a dearth of published empirical evidence on the extent to which people in working environments have acclimatised or adapted to increases in atmospheric temperature (or other variables like WBGT) in recent decades. This evidence contrasts with that of temperature-related mortality, where there is evidence of a reduction in slope of the temperature—mortality dose—response relationship.[42,43] A significant opportunity exists therefore to quantify the extent to which physiological acclimatisation, as well as planned adaptations (eg, shift working and air conditioning) has occurred in different working environments historically.[41] A good example is the work by Somanathan and colleauges,[1] showing that climate control reduces negative effects on labour productivity in manufacturing plants in India, but not on supply. The paper also shows the complexity of the topic because different wage structures influence outcomes. More research in this direction will inform how labour productivity and supply models should be modified in climate change impact assessments so that uncertainties associated with adaptation can be considered. This is an emerging approach in epidemiological studies of temperature-related mortality,[44] where the dose-response curves are flattened or shifted by varying amounts when they are used with climate projections, to account for possible future adaptation. Our projections should be interpreted as effects in the absence of any future adaptation and might, if adaptation is successful, therefore be upper estimates of the effect. Although mechanisms exist for dealing with temperature extremes—eg, the US Occupational Safety and Health Administration advice to consider the adjustment of work shifts to allow for earlier start times or evening and night shifts[45]—the extent to which such adaptations can be implemented will vary by labour sector. Furthermore, individual susceptibility to heat varies significantly and can be influenced by factors such as physical fitness and clothing.[46] Although there have been some suggestions to model adaptation for labour productivity by shifting the hours of work (eg, to earlier starts, later finishes, or night-time working when temperatures are cooler than during the day[27]) it is important to acknowledge that evidence shows shift working can cause disturbances of the normal circadian rhythms of psychophysiological functions; interference with work performance; difficulties in maintaining relationships; disturbances of sleeping and eating habits; chronic fatigue, anxiety, and depression; and longer-term effects such as coronary heart disease.[47–50] These issues need to be carefully considered along with the technical aspects of how to model adaptation in future studies on labour productivity and supply.

We suggest that future studies focus on using the detailed sectoral breakdown so that ERFs for each sector can be compared on the basis of exposure level of industries. In the future, new globally estimated ERFs based on robust empirical assessment should be used. Further work is also needed to contextualise the role of adaptation on the basis of various factors such as indoor versus outdoor work and rural versus urban. In terms of technical adaptation (eg, air conditioning), behavioural changes (eg, shift in work patterns), and infrastructure and regulatory interventions (eg, installation of green roofs) should be considered by future research.

Contributors

All authors contributed to the idea, approach, methodology, and interpretation of results. SD and NvM led the writing of the paper, with further writing input and comments from all other authors. SD constructed the labour supply functions. NvM led the analysis of the labour productivity model inter-comparison. NvM ran the simulations and produced the maps, graphs, and tables. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Declaration of interests

We declare no competing interests.

Data sharing

The labour supply data are available from IPUMS. The labour productivity data are available from authors on reasonable request.

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References

1 Somanathan E, Somanathan R, Sudarshan A, Tewari M. The impact of temperature on productivity and labor supply: evidence from Indian manufacturing. *J Polit Econ* 2021; **129:** 1797–827.

2 Schleypen J, Mistry M, Saeed F, Dasgupta S. Sharing the burden: quantifying climate change spillovers in the European Union under the Paris Agreement. *Spat Econ Anal* 2021; published online April 16. https://doi.org/10.1080/17421772.2021.1904150.

3 Shayegh S, Manoussi V, Dasgupta S. Climate change and development in South Africa: economic productivity and labor availability. *Clim Dev* 2020; published online Dec 14. https://doi.org/10.1080/17565529.2020.1857675.

4 Antonelli C, Coromaldi M, Dasgupta S, Emmerling J, Shayegh S. Climate impacts on nutrition and labor supply disentangled—an analysis for rural areas of Uganda. *Environ Dev Econ* 2020; published online March 4. https://doi.org/10.1017/S1355770X20000017.

5 Parsons K. Human thermal environment. The effects of hot, moderate and cold temperatures on human health, comfort and performance. New York: CRC Press, 2014.

6 Kjellstrom T, Kovats RS, Lloyd SJ, Holt T, Tol RSJ. The direct impact of climate change on regional labor productivity. *Arch Environ Occup Health* 2009; **64:** 217–27.

7 Sahu S, Sett M, Kjellstrom T. Heat exposure, cardiovascular stress and work productivity in rice harvesters in India: implications for a climate change future. *Ind Health* 2013; **51:** 424–31.

8 Schulte PA, Bhattacharya A, Butler CR, et al. Advancing the framework for considering the effects of climate change on worker safety and health. *J Occup Environ Hyg* 2016; **13:** 847–65.

9 Schulte PA, Chun H. Climate change and occupational safety and health: establishing a preliminary framework. *J Occup Environ Hyg* 2009; **6:** 542–54.

10 Bouchama A, Knochel JP. Heat stroke. *N Engl J Med* 2002; **346:** 1978–88.

11 Orlov A, Sillmann J, Aaheim A, de Bruin K. Economic losses of heat-induced reductions in outdoor worker productivity: a case study of Europe. *Econ Disaster Clim Chang* 2019; **3:** 191–211.

12 Takakura J, Fujimori S, Hanasaki N, et al. Dependence of economic impacts of climate change on anthropogenically directed pathways. *Nat Clim Chang* 2019; **9:** 737–41.

13 Heal G, Park J. Feeling the heat: temperature, physiology and the wealth of nations. 2014. https://ideas.repec.org/p/ces/ceswps/_4673.html (accessed June 21, 2021).

14 Kjellström E, Thejll P, Rummukainen M, et al. Emerging regional climate change signals for Europe under varying large-scale circulation conditions. *Clim Res* 2013; **56:** 103–19.

15 Kjellstrom T, Briggs D, Freyberg C, Lemke B, Otto M, Hyatt O. Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts. *Annu Rev Public Health* 2016; **37:** 97–112.

16 Kjellstrom T, Freyberg C, Lemke B, Otto M, Briggs D. Estimating population heat exposure and impacts on working people in conjunction with climate change. *Int J Biometeorol* 2018; **62:** 291–306.

17 Dunne J, Stouffer R, John J. Reductions in labour capacity from heat stress under climate warming. *Nat Clim Chang* 2013; **3:** 563–66.

18 Kjellstrom T, Lemke B, Otto M, Hyatt O, Dear K. Occupational heat stress contribution to WHO project on "Global assessment of the health impacts of climate change" 2014. http://www.climatechip.org/sites/default/files/publications/TP2014_4_Occupational_Heat_Stress_WHO.pdf (accessed Sept 21, 2020).

19 Li X, Chow KH, Zhu Y, Lin Y. Evaluating the impacts of high-temperature outdoor working environments on construction labour productivity in China: a case study of rebar workers. *Build Environ* 2016; **95:** 42–52.

20 Pilcher JJ, Nadler E, Busch C. Effects of hot and cold temperature exposure on performance: a meta-analytic review. *Ergonomics* 2002; **45:** 682–98.

21 Sapsford D, Tzannatos Z. The distribution of pay. In: The economics of the labour market. Basingstoke: The MacMillan Press, 1993: 173–208.

22 Zivin JG, Neidell M. Temperature and the allocation of time: implications for climate change. *J Labor Econ* 2014; **32:** 1–26.

23 Frieler K, Lange S, Piontek F, et al. Assessing the impacts of 1.5°C global warming—simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). *Geosci Model Dev* 2017; **10:** 4321–45.

24 Burke M, Hsiang SM, Miguel E. Global non-linear effect of temperature on economic production. *Nature* 2015; **527:** 235–39.

25 Dasgupta S, Emmerling J, Shayegh S. Inequality and growth impacts from climate change— insights from South Africa. https://www.eiee.org/portfolio/inequality-and-growth-impacts-from-climate-change-insights-from-south-africa (accessed Oct 20, 2020).

26 Wyndham CH. Adaptation to heat and cold. *Environ Res* 1969; **2:** 442–69.

27 Gosling SN, Zaherpour J, Ibarreta D. PESETA III: climate change impacts on labour productivity, 2018; EUR 29423 EN. Luxembourg: Publications Office of the European Union, 2018.

28 Bröde P, Fiala D, Lemke B, Kjellstrom T. Estimated work ability in warm outdoor environments depends on the chosen heat stress assessment metric. *Int J Biometeorol* 2018; **62:** 331–45.

29 Stull R. Wet-bulb temperature from telative humidity and air temperature. *J Appl Meteorol Climatol* 2011; **50:** 2267–69.

30 Saeed F, Schleussner C-F, Ashfaq M. Deadly heat stress to become commonplace across south Asia already at 1·5°C of global warming. *Geophys Res Lett* 2021, **48:** e2020GL091191.

31 Bernard TE, Pourmoghani M. Prediction of workplace wet bulb global temperature. *Appl Occup Environ Hyg* 1999; **14:** 126–34.

32 Lemke B, Kjellstrom T. Calculating workplace WBGT from meteorological data: a tool for climate change assessment. *Ind Health* 2012; **50:** 267–78.

33 Lange S. EartH2Observe, WFDEI and ERA-interim data merged and bias-corrected for ISIMIP (EWEMBI). V. 1.1. GFZ Data Services. 2019. https://doi.org/10.5880/pik.2019.004 (accessed July 15, 2020).

34 Schleussner C-F, Lissner TK, Fischer EM, et al. Differential climate impacts for policy-relevant limits to global warming: the case of 1.5°C and 2°C. *Earth Syst Dyn* 2016; **7:** 327–51.

35 Riahi R, van Vuuren DP, Kriegler E, et al. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob Environ Change* 2017; **42:** 153–68.

36 Andrews O, Le Quéré C, Kjellstrom T, Lemke B, Haines A. Implications for workability and survivability in populations exposed to extreme heat under climate change: a modelling study. *Lancet Planet Health* 2018; **2:** e540–47.

37 Diffenbaugh NS, Burke M. Global warming has increased global economic inequality. *Proc Natl Acad Sci USA* 2019; **116:** 9808–13.

38 d'Ambrosio Alfano FR, Malchaire J, Palella BI, Riccio G. WBGT index revisited after 60 years of use. *Ann Occup Hyg* 2014; **58:** 955–70.

39 Budd GM. Wet-bulb globe temperature (WBGT)—its history and its limitations. *J Sci Med Sport* 2008; **11:** 20–32.

40 Havenith G, Fiala D. Thermal indices and thermophysiological modeling for heat stress. *Compr Physiol* 2015; **6:** 255–302.

41 Vanos JK, Baldwin JW, Jay O, Ebi KL. Simplicity lacks robustness when projecting heat-health outcomes in a changing climate. *Nat Commun* 2020; **11:** 6079.

42 Gasparrini A, Guo Y, Hashizume M, et al. Temporal variation in heat-mortality associations: a multicountry study. *Environ Health Perspect* 2015; **123:** 1200–07.

43 Schwartz JD, Lee M, Kinney PL, et al. Projections of temperature-attributable premature deaths in 209 US cities using a cluster-based Poisson approach. *Environ Health* 2015; **14:** 85.

44 Gosling SN, Hondula DM, Bunker A, et al. Adaptation to climate change: a comparative analysis of modeling methods for heat-related mortality. *Environ Health Perspect* 2017; **125:** 087008.

45 Occupational Safety and Health Administration. Protective measures to take at each risk level. 2021. https://www.osha.gov/SLTC/heatillness/heat_index/protective_high.html (accessed May 25, 2021).

46 Havenith G, Holmér I, Parsons K. Personal factors in thermal comfort assessment: clothing properties and metabolic heat production. *Energy Build* 2002; **34:** 581–91.

47 Akerstedt T. Shift work and disturbed sleep/wakefulness. *Sleep Med Rev* 1998; **2:** 117–28.

48 Costa G. The impact of shift and night work on health. *Appl Ergon* 1996; **27:** 9–16.

49 Stevens RG. Circadian disruption and health: shift work as a harbinger of the toll taken by electric lighting. *Chronobiol Int* 2016; **33:** 589–94.

50 Vetter C, Devore EE, Wegrzyn LR, et al. Association between rotating night shift work and risk of coronary heart disease among women. *JAMA* 2016; **315:** 1726–34.