Widespread reductions in human labor capacity after 1.5°C warming

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Article

Keywords: Heat Stress, Large Ensemble Experiments, Earth System Models, Internal Climate Variability, Global Mean Surface Temperature

Posted Date: July 14th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-679807/v1>

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Title: Widespread reductions in human labor capacity after 1.5°C warming

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Abstract

Rising temperatures and specific humidity are compounding influences that increase heat stress and reduce safe labor capacity. Here, we evaluate reductions in summertime labor capacity using Large Ensemble experiments from two Earth System Models (ESMs). Vulnerable regions, including the Indian subcontinent, Southeast Asia, and West Africa, are expected to begin experiencing 25% reductions as early as the 2040s. Internal climate variability can cloud the timing of such reductions, with differences in onset between ensemble members exceeding 40 years in high-variability locations. At regional scales, onset times are more certain, with differences between ensemble members typically less than 20 years. We demonstrate the benefits for maintaining human labor capacity associated with limiting the increase in global mean surface temperature (ΔGMST) to 1.5°C , consistent with the Paris Agreement. If ΔGMST exceeds 3.5°C , at least 15% of the global population is projected to experience 50% reductions in summertime labor capacity.

Main Text

Extreme temperatures paired with high relative humidity pose a particular threat to human health, since these conditions limit the evaporative cooling that regulates core body temperature^{1,2}. Existing studies project a rise in global heat stress exposure as anthropogenic warming leads to increases in temperature and specific humidity^{2–7}. In addition to exacerbating human morbidity and mortality due to heat-related illnesses^{8,9}, heat stress is predicted to pose severe limitations on the safe conduct of human activity, including labor productivity^{10–13}. Industrial organizations have established safety guidelines limiting the duration of continuous labor above threshold levels of humid heat, as quantified through wet-bulb globe temperature

(WBGT) ^{13–15}. Dunne et al. (2013) estimate that under a high-emissions scenario, global labor capacity in the hottest months will be reduced to 63% by 2100, with impacts extending across the tropics and mid-latitudes ¹⁰. Such reductions have been estimated to reduce GDP by up to 4.0% on a global scale ¹², and up to 20% in highly-affected regions ¹¹.

Faced with increasing WBGT in the coming decades, nations and industries must develop strategies to minimize economic and health impacts ¹⁶. Recent research has evaluated alternative adaptation options to reduce heat stress in working environments without compromising labor capacity ¹⁷. Many behavioral responses, such as shifting working hours away from the hottest part of the day, are currently practiced but may become infeasible as critical regions begin experiencing heat stress for longer stretches of time. Air conditioning is an effective technical solution to maximize labor productivity that is already widely available in the United States, and that has recently become increasingly prevalent in countries such as China ^{18,19}. However, air conditioning penetration levels remain low in developing nations where electricity access may be inconsistent or unaffordable ^{16,17}. Many of these nations are also densely populated, located in tropical or subtropical regions, and heavily reliant on manual labor in factories and workshops^{16,20}. Air conditioning is also less applicable for outdoor workers, which leaves large populations vulnerable to intensified workplace heat stress due to climate change. Without adequate cooling access and other adaptation solutions, labor capacity reductions thus threaten to disproportionately impact developing nations.

Development plans in these countries require not only an understanding of the magnitude of worktime losses, but also a timeframe of when these losses are likely to occur. Here, we analyze Large Ensemble (LE) experiments from two independent Earth System Models (ESMs) to assess when summertime labor capacity reductions in vulnerable regions will become severe

enough to necessitate interventions such as workplace air conditioning. Beyond single realizations of an ESM, LEs allow us to evaluate uncertainty due to internal climate variability, with ensemble members representing equally likely realizations of meteorological uncertainty superimposed on future warming. Consequently, LE experiments provide additional constraints on both the expected timing of labor reduction onset and the corresponding spread. Recently, Li et al. (2020) made use of an LE experiment from a single ESM to consider the occurrence of heat stress extremes over the coming century⁷. Using LEs from two quasi-independent climate models allows us to also consider uncertainty stemming from climate model design and its influence on the rate and patterns of warming. In particular, the two ESMs we consider have divergent transient climate sensitivities that capture a significant portion of uncertainty among CMIP6 models in end-of-century warming²¹.

We utilize LE experiments from the Geophysical Fluid Dynamics Laboratory Earth System Model (ESM2M) and the Community Earth System Model (CESM2) under comparative high emissions scenarios (RCP 8.5 and SSP 3-7.0, respectively) to calculate daily mean simplified WBGT. Employing a continuous algorithm that quantifies labor capacity based on WBGT¹⁰, we introduce a new diagnostic we denote as Time of Expected Onset (TExO) for when summertime labor capacity is likely to first be reduced by 25% and 50% relative to recent historical (1980-2000) levels (see Methods). For ease of notation, we hereafter refer to these two thresholds as “moderate” and “severe” reduction, respectively. We choose to discretize the continuous decline in summertime labor capacity into thresholds of moderate (25%) and severe (50%) for two reasons. First, human psychology is better equipped to respond to distinct threats than to gradually mounting threats²². Second, centering the analysis around threshold reductions allows us to quantify internal variability in an intuitive way by providing a window over which

these reductions in summertime labor capacity are expected to occur. This approach makes explicit how climate uncertainty informs the “timing of action” required for adaptation efforts²³.

The historical WBGT and summertime labor capacity projections of these models are validated against reanalysis estimates and demonstrate agreement in their mean state, anthropogenic trend, and variance, both globally and on aggregate within the regions considered in this study (Supplementary Fig. 1-4). Previous studies also demonstrate the ability of global climate models to simulate regional increases in extreme wet-bulb temperature, a metric closely related to WBGT and labor capacity^{24,25}.

Results

Over the course of the 21st century, large areas in the tropics and subtropics—spanning from 30° south to 45° north and representing 31% (ESM2M) to 44% (CESM2) of global land area—are expected to experience moderate (at least 25%) reductions in summertime labor capacity due to mounting heat stress (Fig. 1a-b). Consistent with previous work^{7,10,12}, we identify at-risk regions including the Indian subcontinent, Southeast Asia, Oceania, West Africa, and the Middle East. The earliest expected onset of moderate local-scale reductions occurs in the 2030s in Southeast Asia, Northern Australia, India, the Persian Gulf, West Africa, the Amazonian Basin, and the Southeastern United States, with the entire country of India and much of the Southeastern United States projected to experience a moderate reduction as early as the 2040s. By end-of-century, regions as far north as the United States Midwest and Northern China are projected to experience moderate reductions.

Fig. 1 Time of Expected Onset (TEXo) for moderate and severe reductions in summertime labor capacity. The ensemble mean of the first occurrence times is shown for ESM2M and CESM2, representing the expected time at which locations will first experience **a, b** 25% reduction and **c, d** 50% reduction relative to the historical (1980-2000) summertime labor capacity baseline. Displayed percentages are the percent of global land area impacted by end-of-century. Stippling indicates locations where some but not all ensemble members experience the relevant level of reduction by end-of-century. White contour lines demarcate regions where the absolute labor capacity during the historical period (1980-2000) is already reduced from full capacity by at least 10% (i.e. is less than 90%).

Severe (at least 50%) summertime labor capacity reductions are projected to occur over 8% (ESM2M) to 28% (CESM2) of global land area between 2070 and 2100 (Fig. 1c-d). Similar regions are at risk in the two models, including Southeast Asia, India, West Africa, and northern Oceania. However, affected areas are larger in the higher-sensitivity model (CESM2) and, for regions that are vulnerable in both models, TEXo tends to be earlier in CESM2 by an average of

12 years. Historically hot and humid regions with baseline (1980-2000) summertime labor capacity already somewhat reduced ($>10\%$; white contours, Fig. 1) are predisposed to future summertime labor capacity reductions (both moderate and severe)

Through assessment of the ensemble distribution, we quantify the range of first-occurrence time in vulnerable locations (Fig. 2). The ensemble average in Fig. 1 represents the expected time of onset based on historical and future climate forcing, whereas the ensemble range reflects how the realized occurrence time may be earlier or later due to internal climate variability. For 48% of vulnerable locations in the ESM2M projections and 76% of vulnerable locations in the CESM2 projections, the timing of moderate reduction onset converges to within 30 years across ensemble members. In other affected locations, internal climate variability produces a large spread in the onset time of summertime labor capacity reductions. The spatial extents of internal variability hotspots differ between the two models (orange and yellow regions of Fig. 2). The ensemble range is greater than 40 years for ESM2M in parts of India, Northern Australia, West Africa, and the Amazon basin, but for CESM2 in Northern Africa, the Middle East, Southern Australia. The difference between models in locations of enhanced variability largely reflects the margins of the spatial extent of moderate reductions expressing increased variance. These margins are more poleward in CESM2 due to its stronger climate sensitivity, as historically tropical conditions breach further into the extratropics.

Fig. 2 Ensemble range in first occurrence times. Range is calculated as the difference in years between the earliest and latest first occurrence time among the ensemble members. Only locations where at least half of the members experience the given reduction threshold by end-of-century are colored. Stipples indicate that not all members experience threshold reduction by 2100. In colored regions that are stippled, the total range is estimated by scaling the spread of members that do experience threshold reduction prior to 2100.

The full ensemble spread of first occurrence times is displayed for some of the most densely populated metropolitan areas distributed across vulnerable regions (Fig. 3a). The first occurrence of moderate (25%) labor capacity reduction takes place within the next decade in at least one model ensemble member for the grid-cells containing Delhi, Lagos, Dubai, and Guangzhou, and before 2040 for all seven cities. By 2060, nearly all members across all cities and in both models experience their first occurrence of moderate reduction. A severe (50%) reduction occurs in Dubai as soon as 2045 in the earliest emerging CESM2 ensemble member,

and before 2060 in nearly all CESM2 members. In Dubai as well as in Delhi, all members of both models experience their first occurrence of severe reduction by the end of the century. Consistent with Fig. 2, significant internal variability is exhibited at the “city” scale. For the first onset of moderate reductions, a range of over 40 years is projected with ESM2M in Delhi, Lagos, and Dubai. These are also the cities with the earliest first occurrence times and left-skewed distributions, indicating that they are more susceptible to early occurrences of meteorological events such as heat waves than the other vulnerable cities shown. In Bangkok, Jakarta, New Orleans, and Guangzhou, ensemble range is smaller (17-25 years) with the first occurrences of moderate reduction likely to occur between 2040 and 2060. The multi-decadal spread in first occurrence times emphasizes the challenges of anticipating the onset of labor capacity reductions at the local scale.

Regional-scale projections take the population-weighted average first occurrence time over grid cells that experience threshold reduction in vulnerable regions (regions boxed in Fig. 1a). This can be conceptualized as when the “average citizen” of a region, as defined based on the regional population distribution, will experience the benchmark levels of summertime labor capacity reduction. It also implies when a region, on aggregate, is expected to begin experiencing widespread reductions. For the at-risk regions presented here (Fig. 3b), moderate reductions begin in the 2040s, and severe reductions begin in the 2080s. The Amazonian Basin, while at-risk, is not analyzed because population is scarce in the overwhelming majority of the affected locations (Supplementary Figure 5), which precludes robust population-weighted results. Consistent with Fig. 1, regional onset times predicted by CESM2 are earlier than those predicted by ESM2M. Aggregating local reductions in labor capacity to the regional scale acts to reduce the ensemble range relative to the range given for individual localities. For example, while the

ESM2M/CESM2 ensemble range for moderate reductions in Delhi is 51/32 years, the range for the Indian subcontinent on aggregate is only 19/11 years. The seven displayed regions generally exhibit a spread of 10-20 years for the moderate threshold and 5-10 years for the severe threshold, with some exceptions (e.g. the Middle East in ESM2M, where early outliers in the ensemble distribution for severe reduction widen the range). The smaller ensemble ranges when considering severe as opposed to moderate reductions reflect the timing of such severe reductions being influenced less by meteorological events and more by the shared, forced climate signal inherent to all ensemble members. For nearly all domains presented in Fig. 3, the ensemble ranges are larger than the difference in expected onset (median or mean) between ESM2M and CESM2, underscoring the sensitivity of onset timing to internal variability.

Across all global vulnerable land area, a moderate labor capacity reduction is projected by 2060 on average, while a severe reduction is projected between 2080 and 2090 (Fig. 3c). The ensemble spread is further reduced relative to regional estimates to <10 years and <5 years for moderate and severe reduction, respectively. Consistent with the established framework for projection uncertainty of climate-related state-variables, such as surface temperature²⁶, the timing of reductions in summertime labor capacity demonstrate strong internal variability at local scales that reduces at large spatial scale through aggregation of local negative and positive anomalies. Thus, projection of onset time is more confident at the regional and global levels than the local level.

Fig. 3 Ensemble spread of first occurrence times at the city, regional, and global scales.

Vertical bars denote projected first occurrence times for individual ensemble members.

Regional/global metrics represent the population-weighted average time of first occurrence across vulnerable grid cells within each region. The locations of selected cities and regions are shown in Fig. 1a (black dots and boxes).

Finally, we examine the relationship between global mean surface temperature (GMST) and the fraction of global and regional populations projected to experience summertime labor capacity reductions (Fig. 4). Under projected levels of end-of-century warming (3.7°C for ESM2M and 4.6°C for CESM2), the fraction of the global population having experienced a

moderate (25%) reduction in summertime labor capacity is projected to be between 54% and 72% for the ESM2M and CESM2 ensemble means, respectively. Between 20% and 53% of the population is expected to have summertime labor capacity reduced by half. Impacts are even more pervasive in at-risk regions such as India, Southeast Asia, and northern Oceania, where 90% of the population experiences at least a moderate labor reduction. Both the global and regional trajectories exhibit a consistent trend of abrupt onset. Once summertime labor capacity reductions of a certain threshold begin, slight levels of further warming cause the affected fraction to increase rapidly before saturating, beyond which the remaining population is not located in the model's climatologically vulnerable areas. This means that while there is uncertainty in the precise time of onset (Fig. 2, 3), there is high confidence that the progression of summertime labor capacity reductions will sweep across regions once they begin, or once a critical warming level has been realized. It should be noted that saturation at the severe threshold does not imply cessation of the implications of heat stress, which continue as temperature and humidity rise. By end-of-century in the CESM2 model, extreme 75% reductions become relevant on the global scale and are projected to affect 9% of the world's population, with particular impact over the Indian subcontinent and the Middle East.

When normalizing by temperature rather than time, results from the two models show increased convergence, suggesting that model discrepancy in the first occurrence time is primarily a result of different transient climate sensitivities. Because the relationship with ΔGMST is robust, projections of the progression of summertime labor capacity reductions can be made with relatively high confidence given the degree of anthropogenic warming; this is consistent with recent work showing that WBGT and WBT extremes can be assessed as a function of GMST independent of forcing pathway^{7,24}. Specifically, the fraction of the

population affected by moderate reductions increases rapidly beginning at 1.5°C of warming, a trend that is observed at both the global and regional scale. Globally, less than 4% of the population is expected to see moderate summertime labor capacity reductions at 1.5°C of warming; however, this rises to nearly 20% at 2°C of warming. After 2°C, the extent of summertime labor capacity reductions is projected to increase dramatically across nearly all at-risk regions, with larger populations exposed to moderate reductions and higher thresholds, such as 75% reduction, introduced.

Fig. 4 Rapid rise in fraction of population having experienced first occurrence of reduced summertime labor capacity with increased warming. The affected fraction of regional and global populations is plotted against the degree of global warming by mapping each year to its corresponding ΔGMST. Dark circles represent the ensemble mean, while light circles represent individual ensemble members. The year 2050 is plotted for both ESMs to convey the difference in the speed of warming between the two models.

Discussion

The Paris Agreement calls to limit warming of global average temperature from pre-industrial levels to well below 2°C, and to pursue efforts to keep it within 1.5°C²⁷. Substantial work has been performed linking 2°C of warming to severe consequences that could be preventable or significantly reduced at 1.5°C, including coral reef losses of over 99%, possible irreversible loss of the Greenland ice sheet, increased risk of flooding, forest fires, drought, and heatwaves, and an additional several hundred million people susceptible to poverty due to climate-related reasons²⁸. Here, we identify summertime labor capacity reductions as another imminent repercussion that will be extensive at the current rate of warming, but largely alleviated if global targets are met. Convergence of results across LE experiments from two ESMs demonstrates a robust relationship between ΔGMST and the onset of summertime labor capacity reductions, with 20% of the global population expected to experience moderate reductions at 2°C. However, consistent with recent findings that a 1.5°C limit to warming will likely exempt most tropical areas from survival limits of humid heat²⁴, this threat can be minimized by meeting a 1.5°C target that would keep the projected fraction of the global population affected by moderate reductions below 4% and avoid more severe levels of reduction (50% and higher) altogether.

In the high-emissions scenarios analyzed, moderate (25%) regional-scale reductions are reached as early as the 2040s (Fig. 3). Widespread adoption of precautionary measures, such as workplace air conditioning, would thus be necessary in the coming decades to prevent economic loss from reduced summertime labor capacity while protecting worker safety. Developing regions such as the Indian subcontinent, where between 54 and 77% of the population is expected to be affected by moderate summertime labor capacity reductions by 2050 (Fig. 4), may

face pressing challenges in infrastructure planning since penetration levels of air conditioning are currently low ². Even in developed regions such as the Southeastern United States, where air conditioning is already widely available ¹⁹, projected reductions in summertime labor capacity by mid- to late-century (Fig. 3) imply that usage rates could increase substantially in the coming decades; this has clear ramifications for energy demand and associated greenhouse gas emissions ²⁹. Implications are most severe for manual labor occupations that are necessarily outdoors, including farming and construction, in which the use of air conditioning is infeasible. This disproportionately threatens developing nations such as India, where over 40% of all employment is in the agricultural sector ³⁰. With between 65 and 95% of the regional population projected to have summertime capacity reduced by half at the end of the century (Fig. 4), it is highly likely that the nation's farming communities will be significantly impacted. Economic repercussions of this could be severe and should serve as a subject for further study.

In addition to projecting expected onset times with greater certainty through analysis of the ensemble mean, we use the LE experimental design to assess the influence of internal climate variability on the onset and extent of summertime labor capacity reductions. We find that at large (regional to global) spatial scales, the ensemble range in the timing of summertime labor capacity reductions is modest (approximately 20 years or less; Fig. 3). While model uncertainty in the precise time of onset still exists due to the differing climate responses of ESMs, analyzing the bounds of irreducible uncertainty offers insight into the time horizons over which regional stakeholders and decision makers might have to prepare. On the other hand, at local hotspots of natural climate variability, there is significant uncertainty in the first occurrence time of summertime labor capacity reductions (Fig. 2). In these areas, uncertainty from internal climate variability does not mean that repercussions will be less severe. Rather, because an early

occurrence is equally as likely as an unexpectedly late occurrence of significant (e.g. 25-50%) reductions in summertime labor capacity, timely adoption of protective measures becomes even more critical in infrastructure planning.

A number of assumptions involved in our calculations make aspects of these results a conservative estimate. We do not account for the disproportionate population growth projected to occur in vulnerable regions³¹, which would increase the affected fraction of the global population. In our quantification of WBGT, we assume shade is available¹⁴. As this may not be the case in agricultural and construction work, impacts are expected to occur earlier in time and at lower GMST for certain outdoor occupations. Onset and severity of reductions in labor capacity for urban regions is underestimated in our approach as well, since the “urban heat island effect” is not included. We also employ daily mean WBGT as opposed to daily maximum metrics, which have been utilized in prior studies². Furthermore, because the quantification of labor capacity is based on an average, acclimated worker, it does not capture more severe limitations for unacclimated individuals or individuals with pre-existing health conditions¹⁰. Among vulnerable worker populations, the onset of conditions that reduce labor capacity will be swifter, and additional precautions are needed to ensure safety.

Overall, our results illustrate a relationship between the magnitude of global warming and the extent of summertime labor capacity reductions. Under the high-emissions scenarios analyzed here, this can be translated into a timeframe for adaptation. Uncertainty due to natural climate variability emphasizes the potential for single extreme heat stress events—with concurrent economic losses and threats to worker safety—to occur much earlier than would be anticipated from the forced climate change signal. We find that timely strategies to (a) limit global warming to 1.5°C and (b) facilitate heat resilience in regions identified as especially

vulnerable serve to minimize economic and health impacts arising from projected increases in humid heat.

Methods

Calculation of labor capacity reduction and associated statistics. We first calculate daily average wet-bulb temperature (WBT_d) from daily mean 2 m reference temperature (T_{ref}), specific humidity, and pressure, using the method of Stull (2011)³². This represents the lowest temperature attainable through evaporative cooling. Wet-bulb globe temperature adjusts WBT to account for the thermal effects of radiation and wind speed¹⁴. Daily average wet-bulb globe temperature ($WBGT_d$) for indoor environments is calculated as follows, in which T_{ref} is used to approximate black globe temperature^{10,14}:

$$WBGT_d = 0.7 \times WBT_d + 0.3 \times T_{ref,d} \quad (1)$$

Similar to Dunne et al. (2013)¹⁰, we conceptualize labor capacity as the theoretical capacity of an individual to perform heavy labor during an 8-hour work day, defined on a continuum from 0% (no amount of labor is safe) to 100% (continuous heavy labor is safe). A labor capacity of 50% indicates equal parts rest time and heavy labor time are necessary to maintain worker safety. We calculate daily average labor capacity (λ_d) from $WBGT_d$ using the continuous representation developed by Dunne et al.¹⁰:

$$\lambda_d = 100 - 25 \times \max(0, WBGT_d - 25)^{2/3} \quad (2)$$

In this representation, labor capacity is reduced from 100% starting at 25°C and is defined up until 33°C, at which capacity bottoms out at 0%. λ_d is defined for each longitude (x), latitude (y),

daily timestep (t_d), and ensemble member (e) as $\lambda_d(x, y, t_d, e)$. We obtain monthly average labor capacity, $\lambda_m(x, y, t_m, e)$, by averaging over λ_d for all days in a given month.

We define annual mean summertime labor capacity, $\lambda_s^*(x, y, t_s, e)$, to be the average of the three months with the lowest labor capacity in a given year. Note that the indices of these three months need not be consecutive and may vary over time. This approach allows us to identify the months of greatest heat stress in localities without a clearly defined summer season (e.g. in monsoon climates), as well as to account for the possibility of changing climatologies over the course of the century.

Summertime labor capacity reductions are computed relative to the historical (1980-2000) summertime labor capacity baseline, $\lambda_b^*(x, y)$. This is defined as the mean of $\lambda_s^*(x, y, t_s, e)$ computed over the time and ensemble dimensions for the period 1980-2000, minus two times the standard deviation computed in the same manner:

$$\lambda_b^*(x, y) = \underset{t_s \in [1980, 2000), e \in [1, 30]}{\text{mean}}\{\lambda_s^*(x, y, t_s, e)\} - 2 \times \underset{t_s \in [1980, 2000), e \in [1, 30]}{SD}\{\lambda_s^*(x, y, t_s, e)\} \quad (3)$$

Time of first occurrence, τ_α , is defined as the first year in which summertime labor capacity is reduced by $\alpha\%$ relative to the historical baseline. We consider time of first occurrence for two reduction thresholds: $\alpha = 25\%$ and $\alpha = 50\%$:

$$\tau_{25}(x, y, e) = \min\{t_s : \lambda_s^*(x, y, t_s, e) < 0.75\lambda_b^*(x, y)\} \quad (4)$$

$$\tau_{50}(x, y, e) = \min\{t_s : \lambda_s^*(x, y, t_s, e) < 0.5\lambda_b^*(x, y)\} \quad (5)$$

Since data from the ESM simulations is truncated at year 2100, in cases where the relevant level of reduction is not attained by end-of-century, 2101 is assigned to τ_α as a filler

value. We define the vulnerable area, A , for reduction threshold α as the subset of grid cells satisfying the condition that at least 15 ensemble members (i.e. half) experience their first occurrence of reduced summertime labor capacity by 2100:

(6)

$$A_\alpha = \{(x, y) : \sum_e \mathbf{I}\{\tau_\alpha(x, y, e) \leq 2100\} \geq 15\}$$

where the indicator function, $\mathbf{I}$, is 1 when the inner condition is met and 0 otherwise. This allows for inclusion of grid cells and regions for which the ensemble indicates it is more likely than not that threshold levels of reduction are experienced by the end of the century.

The projected or “expected” onset year of summertime labor capacity reductions is obtained by taking the mean over the ensemble dimension:

(7)

$$\bar{\tau}_\alpha(x, y) = \text{mean}_{e \in [1, 30]} \{\tau_\alpha(x, y, e)\}$$

The impact of internal climate variability on the timing of reductions is considered by calculating the range, $\Delta\tau_\alpha$, over the ensemble dimension:

(8)

$$\Delta\tau_\alpha(x, y) = \left(\frac{30}{n_{\text{reduced}, \alpha}}\right) \times \left(\max_{e \in [1, 30]} \tau_\alpha(x, y, e) - \min_{e \in [1, 30]} \tau_\alpha(x, y, e)\right)$$

where $n_{\text{reduced}, \alpha}$ is the number of ensemble members that experience their first occurrence of $\alpha\%$ reduction by 2100. For grid cells where all ensemble members experience threshold reduction by 2100, this is equivalent to the difference between the earliest and latest individual member onset years. For grid cells where not all ensemble members experience first occurrence by 2100, the range up until 2101 is scaled by the number of reduced members to estimate the full range. At these grid cells, therefore, the ensemble range is an estimate based on the statistics of

the reduced members. As indicated by equation (6), the range in first occurrence time across ensemble members is only estimated in grid cells for which at least half of the ensemble has experienced threshold reduction.

We also define time of first occurrence for labor capacity reduction at the regional scale, $\tau_{\alpha,R}$, by taking the population-weighted average of grid cells within each region r :

(9)

$$\bar{\tau}_{\alpha,R}(r, e) = \frac{1}{\sum_{(x,y) \in r} p(x, y)} \sum_{(x,y) \in r} \bar{\tau}_{\alpha}(x, y, e) \times p(x, y)$$

where $p(x,y)$ is the 2020 population per grid cell, obtained from Columbia University's Socioeconomic Data and Applications Center Gridded Population of the World dataset ³³.

To normalize by ΔGMST , we utilize monthly average near-surface air temperature data (TAS), available for one ESM2M ensemble member and three CESM2 ensemble members. We average spatially and temporally to calculate the area-weighted global annual mean. Pre-industrial GMST is calculated by averaging global mean TAS over the period 1860-1900. After 1900, we isolate the forced climate signal in CESM2 by averaging global annual mean TAS over the three available ensemble members, and in ESM2M by taking a 10-year rolling average. ΔGMST is then defined for each year after 1900 as the increase from pre-industrial GMST to the smoothed data values.

An annual time series for the fraction of the population in region r having experienced $\alpha\%$ labor capacity reduction ($\rho_{\alpha,r}$) is calculated by aggregating the population from grid cells where $\bar{\tau}_{\alpha} \leq t_s$, for t_s between 2000 and 2100.

(10)

$$\rho_{\alpha,r}(t_s) = \frac{I}{\sum_{(x,y) \in r} p(x, y)} \sum_{(x,y) \in r} \mathbf{1}\{\bar{\tau}_{\alpha}(x, y) \leq t_s\} \times p(x, y)$$

The same procedure is performed using τ_α for individual ensemble members rather than the ensemble mean $\bar{\tau}_\alpha$ in order to obtain an ensemble range. By mapping each year to its associated ΔGMST , we also directly translate this annual time series to express the fraction of the population having experienced $\alpha\%$ labor capacity reduction as a function of ΔGMST .

Overview of Modeling Framework. We use projections of historical and future climate from Initial Condition Large Ensembles (ICLEs) of two Earth System Models (ESMs): GFDL-ESM2M and CESM2. ESM2M is described by Dunne et al. (2012)³⁴ and Dunne et al. (2013)³⁵ with the LE documented in Rodgers et al. (2015)³⁶. CESM2 is described in Danabasoglu et al., (2020)³⁷ with the LE documented in Rodgers et al. (2021)³⁸. Both models reproduce historical patterns and variation of surface conditions^{37–40}, essential benchmarks for their utility in projecting future warming and humid heat. We validate historical WBGT and summertime labor capacity projections of these models against reanalysis estimates and demonstrate agreement in their mean state, anthropogenic trend, and variance, both globally and on aggregate within the regions considered in this study (Supplementary Fig. 1-4). A study by Zhang et al. (2021) also demonstrated the ability of global climate models to simulate with high fidelity regional increases in extreme wet-bulb temperature, a metric closely related to WBGT and labor capacity²⁴.

The two LEs were initialized in unique ways. The GFDL LE was initialized through modest perturbation to the initial climate state (ocean, atmosphere, land, sea-ice). The first ensemble member was branched into 29 additional members in 1950, using January 2nd-30th of year 1950 in the first ensemble member for the initial conditions of members 2-29³⁶. The 30

members cover the historical period (1950-2005) and at year 2006 are branched into RCP8.5 extensions which span the time period 2006-2100. This can be considered a micro-perturbation ensemble initialization procedure.

The CESM2 LE was initialized through a combination of macro- and micro-perturbations. Initial conditions are taken from 10 disparate years from years 1001-1301 of a 2000-year pre-industrial control simulation with CESM2³⁷. These 10 macro-perturbation initial conditions are branched into 9 additional ensemble members at year 1850 through micro-perturbations to the initial conditions of each member. Each member simulates the years 1850-2014 (historical forcing) and 2015-2100 (SSP3-7.0 forcing). We use a 30-member subset of the ensemble, which contains 3 macro-perturbation members and their respective 27 micro-perturbation ensemble members. The imprint of micro- and macro- perturbations is not apparent within the projections of surface temperature and humidity fields analyzed in this study (Supplementary Fig. 6). We choose the 30-member subset of the CESM2 LE for consistency with the 30-member GFDL LE and due to initial limited availability of the CESM2 LE.

For the CESM2 LE, WBT was calculated online. For the GFDL LE, WBT was calculated offline with the request fields (temperature, humidity, pressure, etc.). The change in global mean surface temperature (ΔGMST) is computed as the difference between the pre-industrial state (1850-1900) and the ensemble mean GMST at each point during the subsequent years. The definition was chosen for consistency with the IPCC Global Warming of 1.5°C report⁴¹.

Atmospheric Reanalysis Product. We validate the historical representation of GFDL-ESM2M and CESM2 wet-bulb globe temperature with an atmospheric reanalysis product, ERA5 (Supplementary Fig. 3-4). The European Centre for Medium-Range Weather Forecasts

(ECMWF) ERA5 reanalysis product involves assimilation of observed meteorological and surface conditions into a forward forecast model to reproduce the trajectory of the climate over recent decades. ERA5 is found to well represent low-frequency (decadal) variability and high frequency (daily-to-monthly) variability of standard surface meteorological fields, such as temperature and humidity⁴².

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Acknowledgments

K.Y. was funded by the High Meadows Environmental Institute of Princeton University. S.S. was supported by NASA award NNX17AI75G. S.S. and G.M. were supported through the Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM) Project under the NSF Award PLR-1425989, with additional support from NOAA and NASA. Logistical support for the SOCCOM Project in the Antarctic was provided by the NSF through the U.S. Antarctic Program.

Author Contributions

K.Y., S.S., and G.M. designed the study with input from K.R., K.S., and J.D. K.Y. performed the

analysis and drafted the initial manuscript. All authors contributed to manuscript revision. R.S. ran the GFDL-ESM2M RCP8.5 LE Experiment. S.-S.L., N.R., and J.E. ran the CESM2 LE Experiment.

Competing Interests

The authors declare no competing interests.

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