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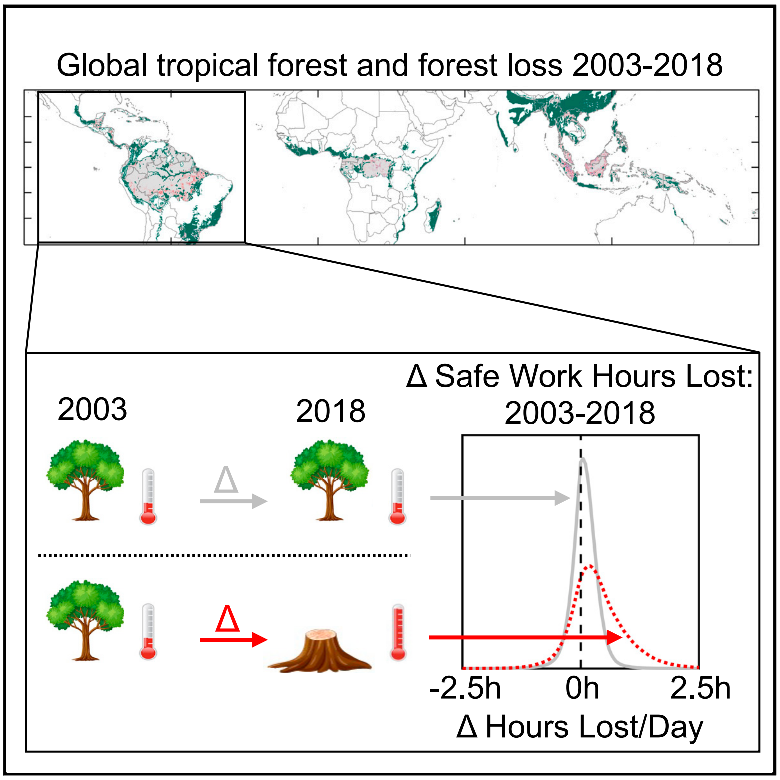
Article

Tropical deforestation accelerates local warming and loss of safe outdoor working hours

Graphical abstract



Highlights

- Recent tropical deforestation increased heat exposure relative to forested areas
- Work in deforested areas was associated with disproportionate lost safe work time
- Deforestation was associated with >0.5 h/day of lost safe work for 4.9 million people
- Additional global climate change will worsen heat exposure in deforested areas

Authors

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In brief

Tropical deforestation is associated with local warming, but the extent to which this warming impacts populations across the tropics remains understudied. We examine deforestation-associated increases in heat exposure across the tropics. We find that recent tropical deforestation was associated with an increase in heat exposure for 4.9 million people, including 2.8 million outdoor workers. Furthermore, future global warming will exacerbate these impacts. These results highlight the importance of the local cooling services that tropical forests provide for populations vulnerable to climate change.

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Article

Tropical deforestation accelerates local warming and loss of safe outdoor working hours

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SCIENCE FOR SOCIETY Recent research has highlighted the effects of global warming on low- and middle-income countries in the tropics. Additionally, tropical deforestation remains an issue of global concern for climate change mitigation. We link these bodies of research by examining how tropical deforestation exacerbates local impacts of global warming and leads to unsafe thermal environments for outdoor workers. We show that deforestation across the tropics is associated with increases in humid heat exposure large enough to exceed established thresholds for outdoor worker health. These findings suggest that tropical deforestation is hastening the arrival of climate change impacts. Furthermore, this work shows that local ecosystem services provided by tropical forests are important for the resilience of vulnerable populations.

SUMMARY

Climate change has increased heat exposure in many parts of the tropics, negatively impacting outdoor worker productivity and health. Although it is known that tropical deforestation is associated with local warming, the extent to which this additional heat exposure affects people across the tropics is unknown. In this modeling study, we combine worker health guidelines with satellite, reanalysis, and population data to investigate how warming associated with recent deforestation (2003–2018) affects outdoor working conditions across low-latitude countries, and how future global climate change will magnify heat exposure for people in deforested areas. We find that the local warming from 15 years of deforestation was associated with losses in safe thermal working conditions for 2.8 million outdoor workers. We also show recent large-scale forest loss was associated with particularly large impacts on populations in locations such as the Brazilian states of Mato Grosso and Pará. Future global warming and additional forest loss will magnify these impacts.

INTRODUCTION

Tropical forests serve as global carbon sinks and provide critical ecosystem services for local communities,[1,2] but tropical deforestation driven by the expansion of agriculture and logging has accelerated in recent decades.[3] Trees help regulate the local thermal environment.[4,5] The loss of tropical forests removes these important cooling services and leads to increased temperatures,[4,6–11] mediated by changes in shade, evapotranspiration, and surface reflectivity.[12] Tropical deforestation often occurs in contiguous patches of land that are cleared to create agriculture or pasture land. The magnitude of local warming in these patches is strongly associated with their area, with annually averaged maximum temperatures that are up to 10°C warmer in large (>100 km^2) deforested patches,[13] and warming effects that can extend for kilometers beyond deforested sites.[9]

Deforestation-induced loss of cooling services may be particularly detrimental to the health and well-being of communities in the tropics, as they are often dependent on outdoor work and have comparatively low adaptive capacity to adjust to environmental change.[14,15] Increased exposure to higher temperatures can threaten the resilience of communities, particularly if temperatures regularly exceed thresholds for human safety.[16,17] Contributors to heat stress include ambient exposure to high temperature and humidity, internal heat generated by heavy physical work, and nonbreathable clothing.[18] Working in hot environments can increase core body temperatures, leading to heat strain and potentially fatal heat stroke, even among young and otherwise healthy

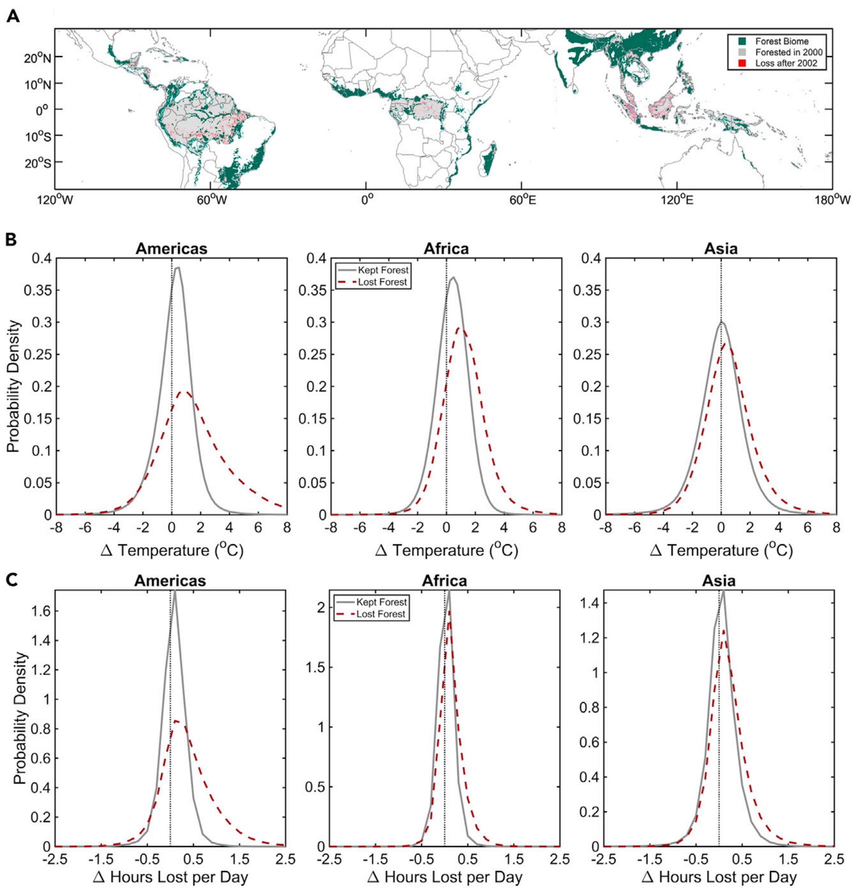

Figure 1. Tropical forest cover loss and associated changes in temperatures and safe work hours lost

(A–C) Map (A) shows tropical and subtropical forest biome, and distributions (B, C) show temperature and lost safe work hours differences 2003–2018. Map (A) illustrates regions with forest cover (Hansen et al.)[34] in the year 2000 (gray), regions deforested between 2003 and 2018 (red), and locations with tropical and subtropical forest biome (Dinerstein et al.)[33] that were deforested before the start of the study period (green). Differences in temperature (B) and differences in safe work hours lost (C) between 2018 and 2003 are shown for the three main tropical forest regions. Gray curves show PDFs of areas that maintained forest cover ("kept forest", corresponding to gray locations on map), and red curves show locations that lost forest cover ("lost forest", corresponding to red locations on map). PDFs showing changes in hours lost per day show distributions from locations with greater than 0.25 h lost per day in 2003 (PDFs with all locations shown in Figure S10). Americas includes 34 countries, Africa includes 32 countries, and Asia includes 27 countries (full list of countries in Table S6).

individuals. Although it is well established that working outdoors in higher temperatures reduces productivity and increases heat strain,[19,20] the extent to which deforestation-driven temperature change affects human populations across the tropics is unknown. This is noteworthy because high temperature and humidity already create daytime unsafe working conditions across much of the tropics.[21–26,27]

Studies on deforestation and temperature changes have focused on quantifying warming from tropical deforestation at regional scales,[13,28] and the relationship between deforestation and increasing temperatures in the tropics is well established.[4,7–11,29,30] However, only a few small-scale studies have evaluated deforestation effects on heat exposure and the well-being of nearby populations in rural communities,[8,31,32] limiting our understanding of whether these effects extend globally in similar settings across low-latitude countries.

In this modeling study, we quantify the magnitude and geographic extent of deforestation-associated changes on local thermal environments across 94 low-latitude countries with tropical forests. We estimate the safe work hours (the amount of time in a day during which heavy physical outdoor labor can be performed safely under established heat exposure thresholds) that have been lost due to increases in humid heat exposure associated with recent deforestation by combining satellite-derived temperature with reanalysis-based estimates of humidity to calculate Heat Index (HI) in both forested and deforested locations. We find that in the last 15 years alone (2003–2018), tropical deforestation was associated with disproportionate increases in heat exposure, which were associated with losses in safe work hours for outdoor workers. We show that almost 5 million people, including 2.8 million outdoor workers, in recently deforested areas experienced at least half an hour of lost safe work time per day. Furthermore, estimated safe work hour losses were greater in areas experiencing extensive deforestation. We also show that future global warming will increase local exposure to unsafe outdoor working conditions in recently deforested areas, leading to more lost safe work hours. Our findings further emphasize the valuable cooling services of tropical forests, which will be increasingly important for climate change resilience for outdoor workers who may have limited capacity to adapt to warming.

RESULTS

Low-latitude deforestation and temperature increases

Of the ~23.07 million km^2 encompassing the tropical and subtropical forest biome (green regions in Figure 1A show tropical forest biome that was deforested before the year 2000; Dinerstein et al.),[33] 13.9 million km^2 was covered in >75% tree cover in the year 2000 (gray regions in Figure 1A, experimental procedures; Hansen et al.).[34] Between 2003 and 2018, 8.7% of this tropical forest cover (1.22 million km^2) was lost or degraded (red regions in Figure 1A), with 6.9% forest cover loss in the Americas (~0.56 million km^2), 6.5% loss in Africa (~0.14 million km^2), and 13.6% loss in Asia (~0.52 million km^2).

Throughout the tropics and subtropics, deforestation is associated with local warming that exceeds interannual climate variability near the equator,[13] particularly for afternoon temperatures

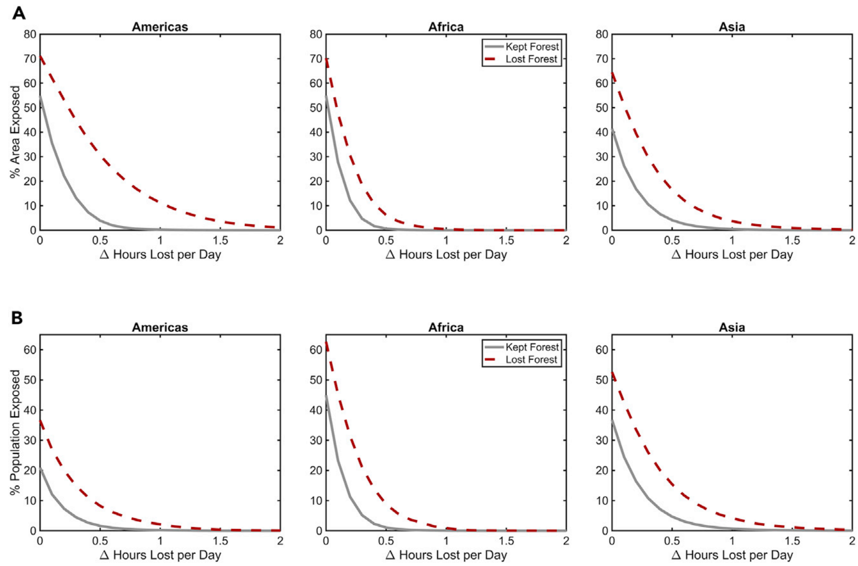

Figure 2. Land area and population in forested and deforested locations exposed to increases in loss of safe work hours

(A and B) Percent of land area (A) and percent of population (B) that experienced increases in loss of safe work hours between 2003 and 2018 in forested and deforested areas in the Americas, Africa, and Asia.

from satellite data analyzed here (experimental procedures). Specifically, the low-latitude locations in the Americas, Africa, and Asia that maintained forest cover between 2003 and 2018 experienced mean temperature variations of ~0.2°C, ~0.4°C, and ~-0.01°C, respectively. These changes at forested locations are consistent with climate model representations of internal climate variability and anthropogenic climate change; for example, temperature observations show that global-mean, near-surface air temperature increased less than 0.4°C over this time period.[35] By contrast, deforested locations experienced mean increases in afternoon temperatures of 1.6°C, 1.2°C, and 0.55°C, in the Americas, Africa, and Asia, respectively (Figure 1B; see also Prevedello et al.);[12] these mean temperature changes at deforested locations exceed warming experienced at nearby forested locations as well as estimates of global climate variability and change over the same time period. The impacts of deforestation are even more apparent in the tails of the distributions showing the largest year on year temperature increases.[13] For example, in the Americas, ~78% of locations that experienced afternoon temperature increases greater than 6°C were deforested between 2003 and 2018, despite these areas accounting for less than 9% of the original forested area. Although forest cover gain is associated with temperature decreases similar in magnitude to temperature increases from forest loss,[12] here, we focus on deforestation because data on the timing of tree regrowth are limited (experimental procedures).

Decreases in safe work hours for outdoor labor

Temperature increases in deforested areas are associated with losses in safe work hours. Here, "lost safe work hours" is defined as the amount of time per day deemed unsafe for heavy physical outdoor work, which includes labor conducted in the agriculture and construction sectors[21,25] for given HI values. These lost safe work hours reflect heat exposure during working hours rather than individually verified working hours (experimental procedures). We find that, on average, between 2003 and 2018 deforested areas in the Americas, Africa, and Asia experienced mean increases in safe work time lost of 0.33, 0.13, and 0.16 h per day, respectively, due to temperature increases associated with deforestation. By contrast, locations that maintained forest cover experienced mean increases in lost safe work time of 0.05, 0.03, and 0.03 h per day, respectively (Figure 1C).

Large areas of land in the tropics experience some degree of year to year weather and climate variability and therefore some variation in lost safe work hours[25] regardless of forest cover (Figure 1C), but a striking increase in unsafe thermal environments in recent decades has occurred in locations that have experienced deforestation.[11] Between 2003 and 2018, the proportion of land areas experiencing more than 30 min of safe work time lost per day was higher in deforested compared with forested areas. For example, in the Americas, 4% of forested land areas experienced this magnitude of work hours lost, whereas 31% of deforested land areas experienced the same loss (Figure 2A).

Using Gridded Population of the World version 4 (GPWv4) data,[36] we estimate how many people live in areas experiencing increases in lost safe work hours (Figure 2B). We conducted sensitivity tests with LandScan data,[37] which assume a different spatial distribution of populations, and our main results remain unchanged (experimental procedures). We find that during the analysis period, the proportion of the population living in areas experiencing increases of at least 0.5 h per day of safe work time lost was higher in deforested compared with forested areas. For example, in the American tropics, 1.6% of people living in forested areas experienced a loss of 0.5 h per day of safe work time between 2003 and 2018, whereas 8.2% of people living in deforested areas experienced similar losses. We find similarly disproportionate lost work hours in Africa and Asia. In Africa, 8.8% of people living in deforested areas experienced a loss of 0.5 h per day of safe work time, compared with only 1.1% of people in forested areas. In Asia, 15.4% of people living in deforested areas experienced a loss of 0.5 h per day of safe work time, whereas 4.7% of people in forested areas experienced a loss of 0.5 h per day of safe work time (Figure 2B).

Loss of more than 0.5 h per day of safe work time in 2018 compared with 2003 is relatively common in deforested areas, where large fractions of the working day were lost in some places. Similar increases in lost safe work hours in areas that maintained forest cover are virtually nonexistent (Figures 1C and 2A). For example, of regions in the Americas where more than two safe work hours per day were lost between 2003 and 2018, 93.8% had experienced deforestation.

Human populations are highly concentrated in certain geographic areas. Therefore, we also examine the total number

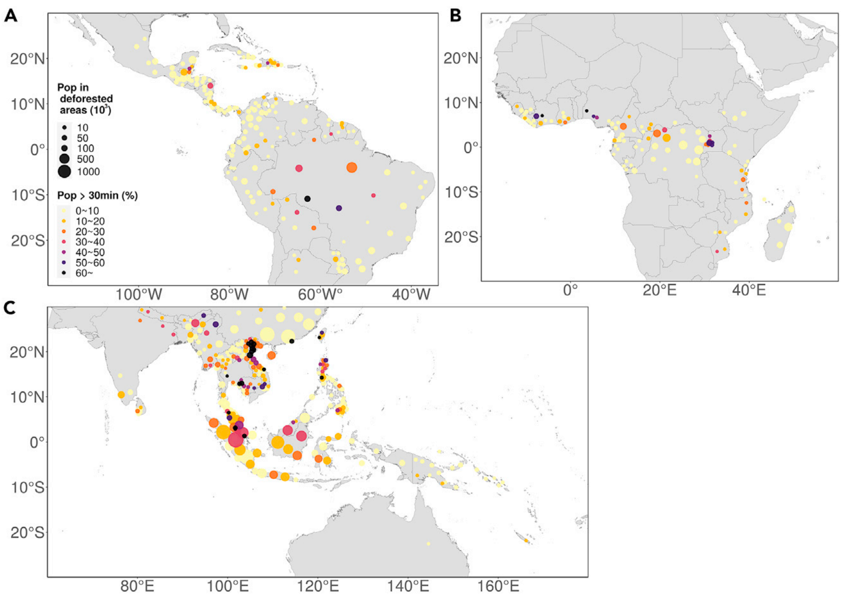

Figure 3. Population in deforested areas with greater than 0.5 h of safe work time lost

Population living in deforested areas (in thousands) and percent of population living in deforested areas where more than 0.5 h of safe work time was lost between 2003 and 2018. Circle size increases with higher total population, and darker color corresponds to increased percent of population exposed to >0.5 h of safe work time lost per day.

of people living in regions where more than 0.5 h per day of safe work time were lost between 2003 and 2018 by country administrative division 1—the highest subnational unit for each country.[36] The size of the circles on the maps in Figure 3 denotes the total number of people living in deforested areas by administrative division; the color of these circles denotes the percent of people in deforested areas who have lost at least 0.5 h per day of safe work time between 2003 and 2018. Darker red colors in Figure 3 highlight "hotspots," or administrative divisions with >30% of population in recently deforested areas, where deforestation-associated warming affects large portions of the population. We find "hotspots" in Brazil, Belize, Cambodia, Vietnam, Malaysia, Myanmar, Nigeria, and Cameroon. Comparing our predicted work loss impacts with the Global Rural-Urban Mapping Project (GRUMP) assessment of urban areas and settlements shows that heat exposure in forest loss areas has increased both in rural and more densely populated areas. Increased heat exposure in the latter areas is not surprising given that the rapid urban expansion observed in recent decades in many tropical countries has come partially—and in some cases—predominantly at the expense of forests.[38]

During 2003–2018, tropical deforestation was associated with a total of ∼4.9 million people losing more than 0.5 h per day of safe work time, and ∼91,000 people losing more than 2 h per day of safe work time (Table S1). By combining general population data with outdoor worker statistics (i.e., proportion of population working in agriculture, forestry, and fisheries sectors),[39] we can also estimate the number of outdoor workers living in areas experiencing increases in lost safe work hours associated with deforestation; data are available for 41 countries (experimental procedures). We find that the proportion of outdoor workers who have lost more than 0.5 h per day of safe work time between 2003 and 2018 is higher in deforested compared with forested locations. In the Americas, Africa, and Asia, we find that 7.9%, 4.3%, and 10.8%, respectively, of outdoor workers in areas deforested during 2003–2018 lost at least 0.5 h per day of safe work time due to forest loss, with tropical deforestation during 2003–2018 causing increases in 0.5 h of safe work time lost for over 2.8 million outdoor workers in all three regions combined (Table S2). By contrast, only 1.24%, 0.16%, and 2.79%, respectively, of outdoor workers in areas that maintained forest cover experienced similar losses in safe work hours.

Global warming impacts in recently deforested areas

Climate models project continued warming in the coming decades.[40] Under the high-emissions scenario Representative Concentration Pathway 8.5 (RCP 8.5), global annual mean warming of 2°C relative to the present is expected as early as 2057, and as early as 2083 in RCP 4.5, a scenario with lower emissions.[32] Future warming will exacerbate effects on unsafe thermal environments via lost safe work hours, even if we assume that there is no further tropical deforestation—an unrealistically conservative baseline given current trends.[41] At the current population, global climate change of +1°C, +1.5°C, and +2°C beyond 2018 temperatures will increase the total number of people in recently deforested locations experiencing 0.5 h per day of unsafe work time by 5, 6.5, and 7.7 million people, respectively. The number of people in recently deforested locations with >2 h lost safe work time increases by 2.8, 5.6, and 9.6 million people, relative to the number of people with >2 h lost safe work time in 2018 in these areas (Table S1). The impact of additional warming on the subsample of outdoor workers in deforested areas experiencing >0.5 h per day of lost safe work time increases by 0.35, 0.47, and 0.55 million people, respectively. Any increases in future population or further deforestation will increase these numbers.

Figure 4 shows results for the fraction of the population living in recently deforested regions that will experience >2 h unsafe work lost with an additional +1°C, +1.5°C, and +2°C of future global warming. Global warming will exacerbate the impacts of deforestation-induced local warming across much of the tropics in the Americas, Asia, and eastern Africa. Across all three regions, safe work hours lost in recently deforested areas increase by about half an hour per degree of global warming (Table S3).

Extensive deforestation exacerbates impacts in Brazil

We examine Mato Grosso and Pará states in Brazil to illustrate how deforestation-associated temperature effects are pronounced in areas that have experienced extensive tropical deforestation (Figure 5; brief contextual background in Text S1). Both states are at Brazil's forest frontier,[42] and together, they accounted for 63% of all deforestation in the Amazon

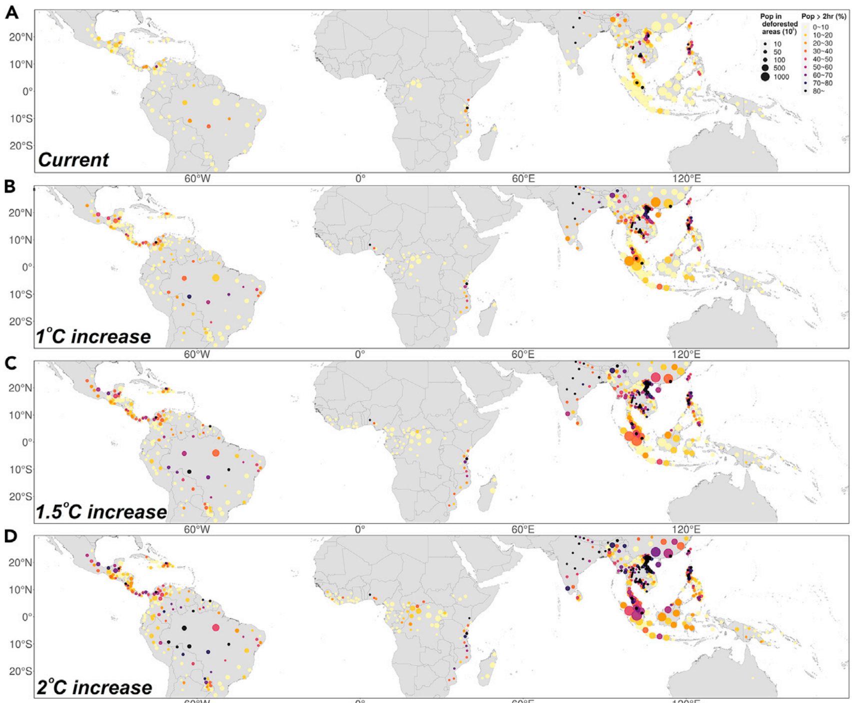

Figure 4. Population in deforested areas with greater than 2 h work time lost currently and with additional global warming

(A–D) Percent of population living in deforested areas exposed to >2 h of safe work time lost in deforested areas in 2018 (A) and with an additional 1°C (B), 1.5°C (C), and 2°C (D) of global warming, assuming no further deforestation or population change. Circle size increases with higher total population, and darker color corresponds to increased percent of population exposed to >2 h of safe work time lost per day.

from 2008 to 2019, with an average of over 5,000 km^2 of forest cleared per year.[43]

Our analysis indicates that in these states, 335,914 km^2 (20.6% of land area) was deforested before 2003 and 166,890 km^2 (10.2% of land area) was deforested between 2003 and 2018, whereas 1,123,850 km^2 kept forest cover (68.8% of the area) and 7,021 km^2 gained forest cover (0.4% of the area). Temperature increases over 2°C in these two states were found in 57.9% of recently deforested locations compared with just 7.6% of forested locations (Table S4). In total, 215,460 km^2 of the Amazon forest region of Mato Grosso and Pará states—an area approximately the size of France—has experienced increases of >0.5 h per day of lost safe work time since 2003. In our study period, 46.6% of the deforested area experienced >0.5 h per day of lost safe work time compared with only 4.1% of the area that maintained forests. In total, approximately 0.21 million people in Mato Grosso and Pará states lost >0.5 h per day of safe work time between 2003 and 2018 in recently deforested locations. Outdoor workers (here, defined as workers in the agricultural, forestry, and fishery sectors) accounted for 20.5% of the population in these states. The increased lost hours in these two Brazilian states accounts for ~37% of the total deforestation-associated heat exposure in the American tropics; in our study period, deforestation was associated with 0.56 million people losing >0.5 h of safe work time per day in the entire American tropics.

There are 3,632 km^2 of deforested area where more than 2 h of safe work time have been lost since 2003, impacting an estimated 2,922 people. With future global warming of +1°C, +1.5°C, and +2°C (under the assumption of no further deforestation), deforested areas where more than 2 h of safe work time is lost per day will increase to 37,112, 56,948 and 82,941 km^2, respectively. Assuming no further population growth, this will lead to 144,010, 213,914, and 288,239 people living in areas losing more than 2 h per day of safe work time compared with 2003. Compared with our analysis of Brazil overall, the warming impacts from deforestation in Mato Grosso and Pará states are proportionally larger. For example, when considering regions where more than 2 h per day were lost in forested and deforested areas since 2003, Mato Grosso and Pará state had 2.3 times more relative land area and 3.9 times more relative people impacted than Brazil overall.

DISCUSSION

Warming is already impacting worker health and productivity across the tropics, with climate change expected to reduce "workability" in the coming century.[22,23,26,44–46] Yet, research so far has overlooked how deforestation and associated loss of cooling services will impact some of the world's most vulnerable populations—rural communities in low-latitude countries. This modeling study provides estimates of population impacts of combined humid heat exposure from recent deforestation and climate change. Just 15 years of deforestation (2003–2018) is associated with local warming in many locations equivalent to a century of unabated global warming (Figure 1B; see also Vargas Zeppetello et al.).[13] We find that this warming is associated with widespread expansion of conditions less conducive for safe heavy physical outdoor labor (Figures 1C, 2, and 3). Warming from deforestation is most pronounced in tropical South America due to large contiguous patches of deforestation associated with the expansion of industrial agriculture. By contrast, in Africa, temperature changes associated with deforestation are less extreme, which is consistent with the expansion of deforestation by smaller farm operations.[13,41]

Our results indicate that recent tropical deforestation is associated with losses of >0.5 h per day of safe work time for ~2.8 million outdoor workers. To contextualize our findings, we compare these results with the findings from the 2019 Lancet Countdown on Health and Climate Change,[24] which reports that humid heat exposure in 2018 led to 133.6 billion potential global lost work hours (an increase of ~45 billion global lost work hours since

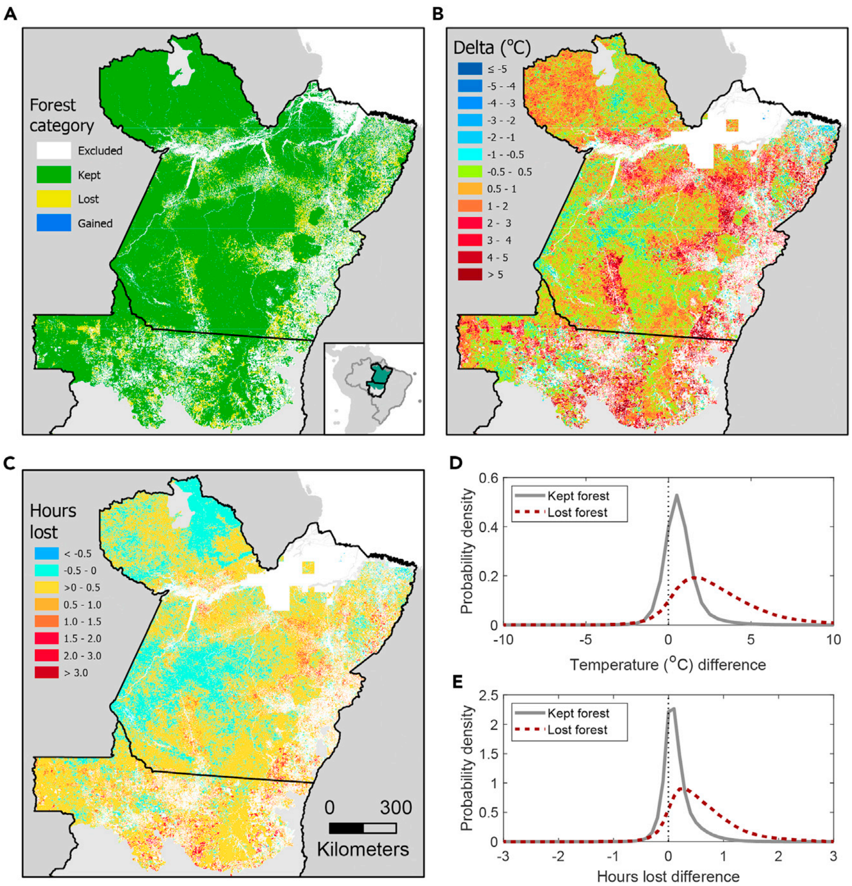

Figure 5. Changes in forest cover, temperatures, and lost safe work hours between 2003 and 2018 in Mato Grosso and Pará states

(A–E) Forest cover change (A), temperature change (B), lost safe work hours change (C), and distributions showing temperature changes (D) and lost safe work hour changes (E). Differences shown for locations that maintained forest and lost forest in Mato Grosso and Pará states in Brazil between 2003 and 2018. PDFs showing changes in hours lost per day (E) show distributions from locations with greater than 0.25 h lost per day in 2003 (PDFs with all locations shown in Figure S11).

2000). Under similar assumptions (360 days of work per year), we find that recent tropical deforestation may have been associated with up to 0.5 billion lost potential safe work hours per year for outdoor workers. Our estimates of potential lost safe work hours are unsurprisingly lower than the Lancet Countdown global estimates for several reasons. Most importantly, we are only considering the outdoor worker population in locations that have experienced 21st century deforestation, whereas the Lancet Countdown considers all workers in all locations. Despite the different focus and methods of these studies, our findings suggest that tropical deforestation magnifies the local impacts of background global warming.

Tropical deforestation may be hastening the arrival of heat effects on workability for some of the most vulnerable populations in the world in countries that are expected to bear the brunt of adverse climate change impacts. The majority of people exposed to increased losses of at least 2 h of safe work time per day live in Asia (Table S1), where there is relatively high population density in recently deforested tropical forest biome. With an additional 2°C of global warming, the number of people living in areas experiencing 2 h of lost safe work time per day in recently deforested areas will increase by over 9.6 million, without taking into account likely increases in local populations or further deforestation. As with other research that evaluates population exposure of environmental changes or threats,[25,44,47] our approach provides a reasonable estimate of the number of people living in areas with unsafe thermal environments. We hope our results motivate further research to provide more granular estimates, which require micro-level data that are currently unavailable for the scope of our analysis. Specifically, although we have used HI to estimate safe work hours lost due to humid heat exposure, future work could consider other humid heat metrics[48–51] such as the Universal Thermal Comfort Index (UTCI), which accounts for radiant temperature in addition to air temperature and humidity.[52–55]

Large portions of the population across the tropics and subtropics currently work outdoors throughout the year (Table S5) and are therefore likely to be impacted by the temperature increases presented here. In American, African, and Asian low-latitude countries, ~15.5%, ~55.3%, and ~56.1%, respectively, of the population work in the agriculture, fisheries, and forestry sectors (Integrated Public Use Microdata Series);[56] these numbers are underestimates because they do not include outdoor workers in other sectors. Additionally, not considered here are those people engaged in informal labor, such as water and fuelwood collection for the household, who may also work in hot outdoor environments.

In addition to heat exposure impacts on work productivity,[57,58] heat exposure can cause numerous downstream health impacts. Work in deforested versus forested settings in Indonesia is associated with heat strain, lower cognitive performance, and declines in labor productivity[10,20,31] as well as an increase in all-cause mortality.[32] Individuals working under heat stress are also more likely to experience occupational heat strain and kidney disease or acute kidney injury.[19,59,60] Globally, high ambient temperatures increase mortality,[61,62] with large increases in heat-attributable excess mortality projected in tropical countries due to global climate change.[17,62] Heat exposure can also interact with other factors to amplify adverse health outcomes, such as traumatic injuries among outdoor working populations.[63] Taken together, these findings suggest that heat stress due to deforestation may exacerbate the negative effects of climate change on the well-being of individuals and families that rely on outdoor work for their livelihood.

The magnitude of deforestation-associated warming reported here (Figure 1B) and elsewhere[12,13,29] has implications for economic impacts of labor lost[45,64] and raises questions about long-term adaptation to global warming for these hard-hit regions. Beyond the possible downstream health impacts outlined above, local warming exacerbated by deforestation may have implications for migration,[65,66] economic production,[67,68] and human capital.[69]

Tropical deforestation remains an issue of global concern for global climate change and biodiversity conservation.[70–73] Additionally, tropical deforestation and forest cover restoration can impact local climate via changes in rainfall[74,75] and cloud cover,[76] which could exacerbate the impacts of local temperature changes. A growing body of work has highlighted how deforestation is associated with local warming, particularly at low latitudes.[9,12,13,28,29] Our results suggest warming from tropical deforestation may already impact outdoor workers through the loss of safe work hours across the tropics, and this impact will be exacerbated by future warming and possible increases in deforestation. Specifically, humid heat exposure, as measured by HI or wet bulb globe temperature (WBGT), is expected to increase as the globe warms,[46,51] which will have implications for productivity of both agricultural workers, crops,[77] and livestock,[78] as well as the intensity of heat waves and associated heat stress in the tropics and subtropics.[79] There is an urgent need to bolster the climate resilience of rural populations in tropical low- and middle-income countries whose populations are often identified as contributing the least to climate change, but are expected to bear a disproportionate burden of its negative effects.[80,81] Activities that drive deforestation, such as the expansion of agriculture or logging, are relatively predictable and can be mitigated by proactive land use planning that takes into account the cooling services provided by trees. Forest protection, reforestation, agroforestry on existing agricultural lands, and agricultural intensification with zero deforestation commitments may all be viable strategies that maintain or add trees that provide cooling services that benefit local populations. Indeed, although not examined here due to lack of information about timing of tree regrowth (experimental procedures), tree cover gain is associated with temperature decreases[12] and associated potential increases in safe work hours in the tropics (Figure S1). These activities also serve as natural climate solutions[82]—that is, land management actions that can contribute to climate mitigation and adaptation needs. Policy efforts, such as the United Nations' Decade of Ecosystem Restoration, may serve as a pathway to accelerating this process.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information should be directed to and will be fulfilled by the lead contact, Luke Parsons (luke.parsons@duke.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

The datasets used for this study are free and available online. MODIS land surface temperature data: https://oceancolor.gsfc.nasa.gov/data/aqua/, ERA5 humidity data: https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, CMIP5 data: https://esgf-node.llnl.gov/search/cmip5/, Hansen forest cover data: https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.7.html. Region-specific spatial data at a 1 km horizontal spatial resolution, including tropical forest biome, population, hours lost, and mean afternoon temperatures for Africa, Americas, and Asia, have been deposited at Zenodo under https://doi.org/10.5281/zenodo.5707740. Code used to analyze and plot data have been deposited at https://github.com/LukeAParsons/deforestation_heatexposure. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

Methods overview

Our primary analytic framework (Figure S2) combines spatially explicit datasets on forest cover, temperature, and population characteristics and counts, as well as established relationships between humid heat exposure (Heat Index) and safe work hours. Below, we outline each component of our analytic framework and the methods used to estimate the impact of increased heat exposure on safe work hours. All data are interpolated to a common 1 km horizontal spatial resolution (the unit of analysis) to facilitate comparison. The following methods are employed at all spatial scales (e.g., global, national, state-level, and local analyses) using data at this common 1 km spatial scale.

Countries in analysis

Our study examines the local warming impacts of low-latitude (here referred to as "tropical") deforestation (or lack thereof) and future global climate change. We focus on countries that are within 30° of the equator and have tropical forest biome[33] present within their borders with greater than 75% forest cover in the year 2000.[34] This totals to 94 countries, including 34 countries in North, Central, and South America (referred to as "Americas"), 31 countries in Africa, and 27 countries in Southeast Asia (referred to as "Asia"). These tropical countries (listed in Table S6) represent approximately 4 billion people, of which ~2.2 billion people live in tropical forest biome,[33] and ~300 million people live in tropical forest biome that was >75% forested in the year 2000.

Forest cover, loss, and gain

We use tree cover data from Hansen et al.,[34] hereafter H13, to examine regions that maintained and lost forest cover in the tropics and subtropics (30°S–30°N) within the tropical and subtropical forest biome defined in Dinerstein et al.[33] The original forest loss data from H13 have been updated since 2013, with data up to and including 2019 in the v. 1.7 dataset used here. As in H13, here, we define a location as forested if a location was >75% forested in the year 2000 (first year of forest data coverage) and contains tropical forest biome. A forested location was then reclassified as "maintained" if it did not experience any forest loss over the time period of analysis (2003–2018), "loss" when it lost cover and showed no forest gain (2003–2018), and "gain" if it was included in the H13 "gain" category. The forest gain dataset in H13 only contains binary information ("gain" or "no gain") at each location between the years 2000 and 2012. Hence, a location that is labeled "gain" in the dataset might have gained forest prior to our reference year 2003. Therefore, we only assess the change in temperatures and heat stress associated with forest loss (Figures 1B and 1C). The effects of the geographic scale of deforestation have not been accounted for here and may explain some of the variability in temperature changes associated with deforestation.[13] Forest cover data are provided at a 30 m spatial resolution. We use bilinear weighting to regrid deforestation data to the 1 km resolution MODIS data so the dataset could be compared at the same grid resolution ("interp.surface.grid" in the R "fields" package v. 10.3). We tested the sensitivity of our results to the 75% forest cover threshold by using >10%[83] and >50%[9] forest cover thresholds, and we find that our main conclusions do not change (Figure S3).

Population data and impacts

We calculate changes in local temperature associated with deforestation and the subsequent lost safe work hours for heavy outdoor labor. This methodology follows on past large-scale studies of broadscale effects of environmental conditions (e.g., particulate matter, heat exposure), by estimating the number of people in the areas experiencing notable environmental changes.[24-26,44,47] Table S6 lists the total population and outdoor worker population estimate by country.

We calculate the temperature changes associated with changes in forest cover and overlay these changes on the GPWv4 and IPUMS Terra dataset.[36] The GPW provides spatially explicit population data at approximately 1 km^2 resolution based on population counts between 2005 and 2014 (for details see http://sedac.ciesin.columbia.edu/data/collection/gpw-v4), which we assume to be evenly distributed across administrative unit. The main conclusions (e.g., populations living in areas experiencing deforestation lost more safe work hours than those in locations that maintained forest cover) remain robust if we use LandScan data (https://landscan.ornl.gov/) that locates populations in 1 km^2 pixels instead of spreading these populations across administrative zones (Figure S7).

We use the 2015 GPW population data along with the IPUMS Terra data[39,56] to estimate impacts of deforestation-associated temperature changes on workers in the agriculture, fishing, and forestry sectors (referred to as "outdoor workers" in text). IPUMS Terra extracts information from census and survey microdata on individuals and households to provide spatially explicit human population characteristics, such as employment in specific sectors. Industrial classifications are categorized into twelve occupational groups and are adapted to roughly meet the groupings outlined in the International Standard Industrial Classifications system. Our primary variable of interest is the proportion of the population in ages 16–65 employed in agriculture, fishing, or forestry sectors in a given geographic unit (e.g., county). We apply this percentage to the corresponding geographic unit from the GPW population data that are between 16 and 65 years of age to get the number of people in any given geographic unit that is working in the agriculture, fishing, or forestry sectors. It is possible that this process contains some negligible errors that resulted from administrative boundary mismatch and data conversion. Note that estimates of outdoor worker numbers represent a conservative estimate of the number of people working outside. Our estimates assume that people's daytime locations on average correspond to the 1 km^2 pixels to which global spatial population datasets assign them. Outdoor worker impact estimates are limited to countries that have data on industrial classifications, which are available for 41 countries (44% of the countries in our analysis), with data on 21 countries in the Americas, 13 countries in Africa, and 7 countries in Asia. The GPWv4 population data are several years old (2015), and outdoor worker statistics[39,56] do not cover all countries containing tropical forest biome in the tropics (Table S6). However, the main conclusions of our results do not change if we use more recent LandScan population data in place of the GPWv4 data (Figure S7).

Diurnal cycles of temperature and humidity

The National Oceanic and Atmospheric Administration (NOAA) uses HI, which includes temperature and relative humidity, as a criterion for issuing safety warnings and predicting health impacts associated with heatwaves. Although the MODIS satellite dataset provides twice daily values for temperature, higher temporal resolution temperature and humidity data are needed to estimate work hours lost. Following the methodology of Wolff et al.,[32] we use the fifth generation of the European Center for Medium-Range Weather Forecast atmospheric reanalysis data product[84] to obtain the diurnal (24-h) cycle of temperature and humidity over low-latitude land areas in the years 2003 and 2018. For each grid point over land (30°S–30°N, 120°W–170°E), we calculate the average hourly temperature and relative humidity in 2003 and 2018 by using the local specific humidity from the ERA5 data combined with the diurnal cycle of temperature and the assumption that the amount of water vapor in the atmosphere was constant. With the shape of the diurnal cycle from ERA5 and the two values for daytime and nighttime temperatures obtained from MODIS data, we generate hourly estimates of heat indices and estimate the total time per day spent above the heat stress threshold limit for heavy physical work (see section on HI distributions below). Although *in situ* measurements indicate that humidity can be higher in forested areas than in clearings in the tropics,[85] Masuda et al.[11] have shown that humid heat exposure for workers is significantly higher in cleared areas than forested areas despite these spatial differences in humidity.

We use MODIS data from the three hottest months of the year (as defined by ERA5 climatology 1979–2018) to study temperature changes from 2003 to 2018, because the tropical and subtropical forest biome extends into regions characterized by more pronounced seasonality (Figure 1A). An analysis of ERA5 hourly data shows that inclusion of 12-m mean temperatures at these locations would mask temperature impacts by averaging cool and warm seasons (Figure S9). We use any MODIS 8-d composite observations that overlap with the three hottest months of the year from the ERA5 climatology to define the maximum (MODIS Aqua) and minimum (MODIS Terra) values of the diurnal cycle of temperature. However, most of our analysis focuses on the tropics, so the main results related to temperature changes in forested versus deforested locations are similar if we analyze more months of the year (Figure S1). We also show results for the three hottest months, because, although outdoor work occurs throughout the year in low-latitude countries (Table S5), agricultural workers must work outside in these months. Although we use 2-m air temperature to define the hottest months of the year, if we use HI to define the hottest months, the results are nearly identical (Figure S8).

Although 2-m air temperature is often used to calculate HI, here we rely on land surface temperature from satellite data, because 2-m air temperature is not available at the necessary spatial resolution to conduct this analysis. Here, we focus on differences in land surface temperature before and after deforestation, which should help eliminate much of the 2-m versus land surface temperature differences. Near the equator, temperatures at the top of the tree canopy in tropical forests can be up to 5°C–10°C higher than the 1.5-m air temperatures beneath the canopy at the same location,[6,86] and land surface temperatures that are measured by the MODIS satellite can be up to 5°C–10°C higher than the local 1.5-m air temperature in croplands and on bare land.[6] Because both of our available temperature measurements are biased toward warmer values that are strongly correlated with near-surface air temperature in the tropics, we do not expect our estimates of near-surface air temperature differences between forested and deforested regions to be meaningfully biased.[6]

We select two years (2003 and 2018) near the beginning and end of the satellite record to estimate the change in temperatures associated with changes in forest cover. These are El Niño "neutral" years and are separated by 15 years to maximize the signal of deforestation. Hence, these years minimize the contribution of natural variability to the temperature change. The main findings remain robust if different years are analyzed (e.g., 2004 versus 2017; Figure S4), indicating that temperature and associated lost work hours results are not due to year to year, natural climate variability.

HI distributions

HI was estimated from diurnal cycles of temperature and relative humidity (see diurnal cycles of temperature and humidity above) and a refinement of Rothfusz's multiple linear regression analysis of Steadman's complex, multi-parameter equations (see https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml for the equations used). As in Wolff. et al.[32], we assess lost safe work time due to unsafe work conditions using an implementation of the American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Value (TLV), intended for computation of time-weighted average exposure levels and adapted for use with HI assuming sun exposure.[87] We assume workers are acclimatized, able to rest in the shade, utilize regular single-layer work clothes, conduct 415-W metabolic rate work, based on literature for heavy physical work in agriculture or construction.[16,21] We estimate the amount of time considered unsafe for continuous labor in each hour (work–recovery cycle), then sum all lost safe work time to calculate total safe work time lost per day for each location. We use NOAA HI rather than WBGT to measure heat stress, because WBGT is impractical in our study contexts. WBGT requires wind speed, sun angle, and cloud cover data that are not available. Recent work has evaluated[88,89] the use of HI values compared with WGBT and concluded that HI provides a reasonable alternative to WBGT when WBGT is not practical or available.

In some locations, light labor could be scheduled during the hottest part of the day, which we have not examined here. For work hours lost estimates, we used the same underlying assumptions (e.g., work intensity, clothing) for all industries. Although our results do not provide estimates of work productivity by specific industries, occupations, or tasks (which drive absolute heat stress levels), the relative changes in hours lost due to changes in the outdoor work environment from deforestation and climate change in different populations and geographical areas reported here provide important information about populations at highest risk.

Future temperature changes

We used output from 31 Coupled Model Intercomparison Project—Phase 5 (CMIP5; Taylor et al.)[90] models to estimate local surface temperature and specific humidity changes per degree of global warming ("pattern scaling" method)[26,46,91] under a "high" climate change scenario (RCP 8.5). The method allows us to estimate local temperature and humidity changes under an additional 1°C, 1.5°C, and 2°C of warming to derive future estimates of heat indices and hours lost. The RCP 8.5 experiment can include land use changes, so local temperature and humidity changes from RCP 8.5 were compared with changes from 1% CO_2 experiments, and multi-model mean results were found to be nearly identical (Figure S5). We have tested the sensitivity of our results using the CMIP5 skin surface temperature ("ts") variable and the 2-m air temperature variable ("tas") and find no significant differences in our results (not shown). Regional pattern scaling results for surface temperature are shown in Figure S6. We limited our analysis to the 31 models that provided surface temperature and humidity output: ACCESS1-0, ACCESS1-3, bcc-csm1-1-m, bcc-csm1-1, BNU-ESM, CCSM4, CESM1-BGC, CESM1-CAM5, CMCC-CESM, CMCC-CMS, CMCC-CM, CNRM-CM5, CSIRO-Mk3-6-0, CanESM2, EC-EARTH, FGOALS-g2, FGOALS-s2, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-R, HadGEM2-AO, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC-ESM-CHEM, MIROC-ESM, MIROC5, MPI-ESM-LR, MPI-ESM-MR, MRI-CGCM3, MRI-ESM1, NorESM1-ME, NorESM1-M.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2021.11.016.

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AUTHOR CONTRIBUTIONS

Conceptualization: L.A.P., N.H.W., L.V.Z., D.S.B., T.K., Y.J.M., and J.T.S.; methodology: L.A.P., N.H.W., L.V.Z., D.S.B., T.K., Y.J.M., and J.T.S.; investigation: J.J., L.A.P., T.K., N.H.W., and L.V.Z.; visualization: L.A.P., J.J., and N.H.W.; writing—original draft, L.A.P., J.J., N.H.W., L.V.Z., D.S.B., T.K., Y.J.M., and J.T.S.; writing—review and editing, L.A.P., J.J., N.H.W., L.V.Z., D.S.B., T.K., Y.J.M., and J.T.S.; funding acquisition: N.H.W., D.S.B., Y.J.M., and J.T.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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