The effect of deforestation and climate change on all-cause mortality and unsafe work conditions due to heat exposure in Berau, Indonesia: a modelling study

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Summary

Background **Previous studies focusing on urban, industrialised regions have found that excess heat exposure can increase all-cause mortality, heat-related illnesses, and occupational injuries. However, little research has examined how deforestation and climate change can adversely affect work conditions and population health in low latitude, industrialising countries.**

Methods **For this modelling study we used data at 1 km² resolution to compare forest cover and temperature conditions in the Berau regency, Indonesia, between 2002 and 2018. We used spatially explicit satellite, climate model, and population data to estimate the effects of global warming, between 2002 and 2018 and after applying 1·0°C, 1·5°C, and 2·0°C of global warming to 2018 temperatures, on all-cause mortality and unsafe work conditions in the Berau regency, Indonesia.**

Findings **Between 2002 and 2018, 4375 km² of forested land in Berau was cleared, corresponding to approximately 17% of the entire regency. Deforestation increased mean daily maximum temperatures by 0·95°C (95% CI 0·97–0·92; p<0·0001). Mean daily temperatures increased by a population-weighted 0·86°C, accounting for an estimated 7·3–8·5% of all-cause mortality (or 101–118 additional deaths per year) in 2018. Unsafe work time increased by 0·31 h per day (95% CI 0·30–0·32; p<0·0001) in deforested areas compared to 0·03 h per day (0·03–0·04; p<0·0001) in areas that maintained forest cover. With 2·0°C of additional future global warming, relative to 2018, deforested areas could experience an estimated 17–20% increase in all-cause mortality (corresponding to an additional 236–282 deaths per year) and up to 5 h of unsafe work per day.**

Interpretation **Heat exposure from deforestation and climate change has already started affecting populations in low latitude, industrialising countries, and future global warming indicates substantial health impacts in these regions. Further research should examine how deforestation is currently affecting the health and wellbeing of local communities.**

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For the Bahasa translation of the abstract see Online for appendix 1

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Introduction

Heat exposure is a major human health risk, especially for people living in low latitude tropical countries where the ability to adapt to higher temperatures (ie, adaptive capacity) can be hindered by inadequate access to water, electricity, and other infrastructure. In the general population, particularly older people, very young children, and those with chronic diseases, heat-related mortality is projected to increase as a result of climate change.[1,2] These mortality effects are projected to be particularly pronounced in south-east Asia.[3] In working populations, including young and otherwise healthy workers, excess ambient heat exposure, combined with internal heat generated from physical labour, can lead to increased morbidity and mortality,[4] decreased productivity,[5,6] and increased risks of traumatic injury.[7] A growing body of research indicates that in tropical countries, both climate change and deforestation are increasing temperatures and heat exposure,[4,8–11] but the combined risks of these changes have so far been underappreciated. For example, forest clearing in tropical countries can cause immediate increases in local temperatures of up to 8°C and exacerbate diurnal temperature variation.[11] The amount of warming can scale with larger deforested patches (>100 km²),[12] and the effects of warming can extend up to 50 km beyond deforested sites.[13] Yet, little is known about how warming associated with deforestation affects human health at large geographical scales (eg, >10 000 km²), or how these risks are likely to change in the future due to climate change.

Research on the human health risks of climate change has largely focused on urban areas in industrialised settings and on the potential health effects associated with heatwaves, other extreme weather events, and vector-borne

Research in context

Evidence before this study

Although no formal literature search was done before undertaking the study, there is a vast body of published literature indicating that the effect of increasing temperatures on human health and wellbeing is a growing concern. Previous studies have found that excess heat exposure can increase all-cause mortality, heat-related illnesses, and occupational injuries, and can decrease productivity. Past work, however, has largely only examined heat events in urban, industrialised country settings. Little to no research has examined how deforestation, which causes substantial local temperature increases and also contributes to climate change, can adversely affect work conditions and population health in low latitude, industrialising countries.

Added value of this study

To the best of our knowledge, our modelling study is the first to estimate the effects of deforestation and climate change on all-cause mortality and unsafe work conditions from increases in heat exposure in some of the least resilient populations to climate change—populations in low latitude, industrialising countries. A major barrier to understanding and addressing how local (ie, deforestation) and global (ie, climate change) factors driving temperature increases affect the health of these populations is the paucity of representative human health data needed to understand the impact of these changes over large temporal and spatial scales. Our study overcomes this barrier by using spatially explicit data on tree cover change, land surface temperatures, and population distribution. We used established thresholds of heat health for worker safety to estimate the number of lost safe work hours in a day and used established heat-mortality slopes to estimate changes in all-cause mortality from changes in mean daily temperatures. Finally, we used realistic projections for future temperature increases to assess the impact of climate change on people living in low latitude, industrialising countries.

Implications of all the available evidence

Our results indicate that heat exposure from deforestation has already significantly increased all-cause mortality and decreased safe work hours. Future temperature increases from climate change, even with the assumption of no further deforestation, will probably lead to an even more serious public health concern. Taken together, these results highlight the major challenge of the combined effects of deforestation and climate change for populations in low latitude, industrialising countries. Threats to health caused by increasing heat exposure will affect entire households and communities. Older people, very young children, and those with chronic diseases are particularly vulnerable to heat-related mortality, while reduced productivity among otherwise healthy workers will compound these impacts. Our findings point to an urgent need for action for the approximately 800 million people living in the world's tropical forest nations—a population that is expected to substantially increase by 2050. Importantly, these populations contribute the least to climate change but will bear a disproportionate amount of its adverse effects. Policy makers should therefore identify where and to what extent the local cooling effect of trees can address challenges to human health and wellbeing from increasing temperatures in low latitude, industrialising countries.

diseases.[14–16] Less research has been done to explore how environmental change that exacerbates climate change—such as deforestation—can have immediate and substantial local and regional effects on heat exposure[13] and human health for rural populations living in tropical countries. These populations are identified as being the least resilient to the effects of climate change[10] and are expected to experience substantial temperature increases,[17] indicating that they are at especially high risk of experiencing substantial adverse health effects. A primary barrier to understanding and addressing how local (ie, deforestation) and global (ie, climate change) factors driving temperature increases impact the health of these populations is the paucity of representative human health data needed to understand the impact of these changes over large temporal and spatial scales. Yet, when considered alongside recommendations such as those from the Intergovernmental Panel on Climate Change,[18] this information could have substantial implications for protecting human health as trade-offs between economic welfare, human health, and the natural environment are considered in the implementation of climate adaptation and mitigation recommendations.

See Online for appendix

The aim of this study was to estimate the effects of deforestation and climate change on all-cause mortality and unsafe work conditions due to heat exposure in the tropics. We focused our analysis on the Berau regency in Indonesia (hereafter referred to as Berau), which is emblematic of tropical forest conditions in other countries experiencing pressures on forests from expansion of agriculture, palm oil production, mining, and other activities.[19] We used satellite, climate model, and population data to quantify changes in heat exposure resulting from deforestation; estimate the effects of deforestation and climate change on all-cause mortality due to heat exposure; and estimate the effects and implications of deforestation and climate change on unsafe work conditions, assessed as changes in hours of work deemed unsafe by established occupational health guidelines for heat stress.

Methods

Study design and timeframe

For this modelling study we did a spatially explicit analysis of all-cause mortality and unsafe work conditions in Berau (appendix 2 p 6), comparing remotely sensed surface temperature between 2002 and 2018 (observed), and after applying 1·0°C, 1·5°C, and 2·0°C of global warming relative to the 2008–27 mean, hereafter referred to as the present or 2018 baseline climate. We focused our analysis on 2002 and 2018 because the El Niño Southern Oscillation probably had minimal impacts on local climate in Indonesia during these years.[20] This approach allowed us to isolate the impacts of increasing atmospheric greenhouse gas concentrations and deforestation on local temperature changes. We chose the 1·0°C warming threshold relative to the 2018 baseline climate because this threshold corresponds to the Paris Climate Accords goal of limiting warming to less than 2·0°C relative to pre-industrial levels (approximately 1·0°C of warming relative to pre-industrial levels has already occurred). We also explored the impacts of an additional 1·5°C to 2·0°C of warming relative to present-day conditions because this is an increasingly likely outcome for the planet.[21,22] Our goal was to capture the relative additional effects of climate change on heat exposure (in terms of work hours lost and mortality) and thus we kept population, land use, and other factors constant. Our climate impacts should therefore be interpreted as conservative estimates of potential future impacts. Schematics of the study design and primary study components from spatially explicit data are presented in appendix 2 (p 6), and mirror analytical approaches that estimate environmental impacts on populations over large spatial scales.[23–27] An extended version of the methods is available in appendix 2 (p 1).

This study used spatially explicit data on climate, tree cover, population distributions, and data collected via the Global Burden of Disease, Injuries, and Risk Factors Study 2017 (GBD 2017). Analyses of these data did not require ethics approval.

Data sources and approach

To estimate historical forest loss and gain, we re-gridded version 1.6 of Hansen and colleagues'[28] dataset (hereafter referred to as H13), a 30 m spatial resolution dataset based on data provided by Landsat satellite missions, to a 1×1 km resolution. The H13 dataset provides each grid cell's fractional forest cover in 2000 and the year during which forest loss (the year when cover goes from >0% to 0%) or forest gain (the year when cover goes from 0 to >50%) occurred.[28]

To estimate historical heat exposure (daily temperature and hourly heat index), we obtained values for surface daytime and night-time temperature at 1×1 km resolution using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite observations.[29] In forested regions, the MODIS satellite detects top-of-canopy temperatures, rather than temperatures near the forest floor. However, once the forest has been removed, the satellite observes temperature at the land surface. Temperatures near the forest floor are systematically lower than those at the top of the canopy,[30] so our estimates of temperature change associated with deforestation are conservative.

We obtained the diurnal cycle of land surface temperature ("skt" variable) and relative humidity over Berau using hourly data from the fifth generation of the European Centre for Medium-Range Weather Forecast atmospheric reanalysis data product (ERA5)[31] for 2002 and 2018. Using the MODIS observations as the maximum and minimum values of the sinusoidal cycle, we created continuous diurnal cycles for each day based on the two temperatures observed by the MODIS satellite (appendix 2 p 8).

We estimated daily relative humidity at a 1×1 km resolution by assuming that the amount of water vapour in the atmosphere (specific humidity) is constant over Berau at daily timescales. This assumption, combined with our diurnal cycles of temperature, generated a relative humidity diurnal cycle that closely matched the one found in ERA5 over Berau. We then generated hourly estimates of heat indices using Rothfusz's modification of Steadman's work,[32] which has also been used in recent studies estimating safe work hours for farm workers in the USA.[27]

To estimate future heat exposure, we used atmospheric surface air temperature output from global climate models that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5)[33] to estimate the average warming of Berau relative to global warming. We used output from all 39 CMIP5 models that did the RCP8·5 experiment (end-of-century radiative forcing of 8·5 W/m² relative to pre-industrial conditions), in which 21st century greenhouse gas emissions are not curtailed (appendix 2 p 12). Although we used RCP8·5 to calculate this relationship, the coefficient for warming is nearly identical in other warming experiments.

To estimate all-cause mortality, we calculated the population-weighted mean change in daily temperature for 2002–18 and for additional future global warming of 1·0°C, 1·5°C, and 2·0°C for Berau by overlaying our estimated daily mean temperature change with LandScan 2017 data,[34] which provide spatially explicit population data at 1×1 km resolution (appendix 2 p 14). We then used estimated relationships of heat-attributable and all-cause (Philippines) and non-external (Vietnam) heat-attributable excess mortality reported by Lee and colleagues[35] for the Philippines and Vietnam to construct estimates of changes in heat-related excess mortality for Berau. We selected Vietnam and the Philippines as sources of country-specific heat-related excess mortality curves for Berau because annual mean temperatures in these countries are similar to those of Berau (appendix 2 pp 16, 18) and no such curve exists for Indonesia nor can it be estimated because of the lack of daily mortality data,[1,36,37] and because these countries are similar to Berau with regard to key drivers of heat-related mortality (appendix 2 p 16).[35,38] Lee and colleagues'[35] heat-mortality slopes represent the estimated percentage-point increase in heat-attributable excess mortality (heat-attributable mortality divided by non-heat-attributable mortality) per °C increase in mean daily temperature.

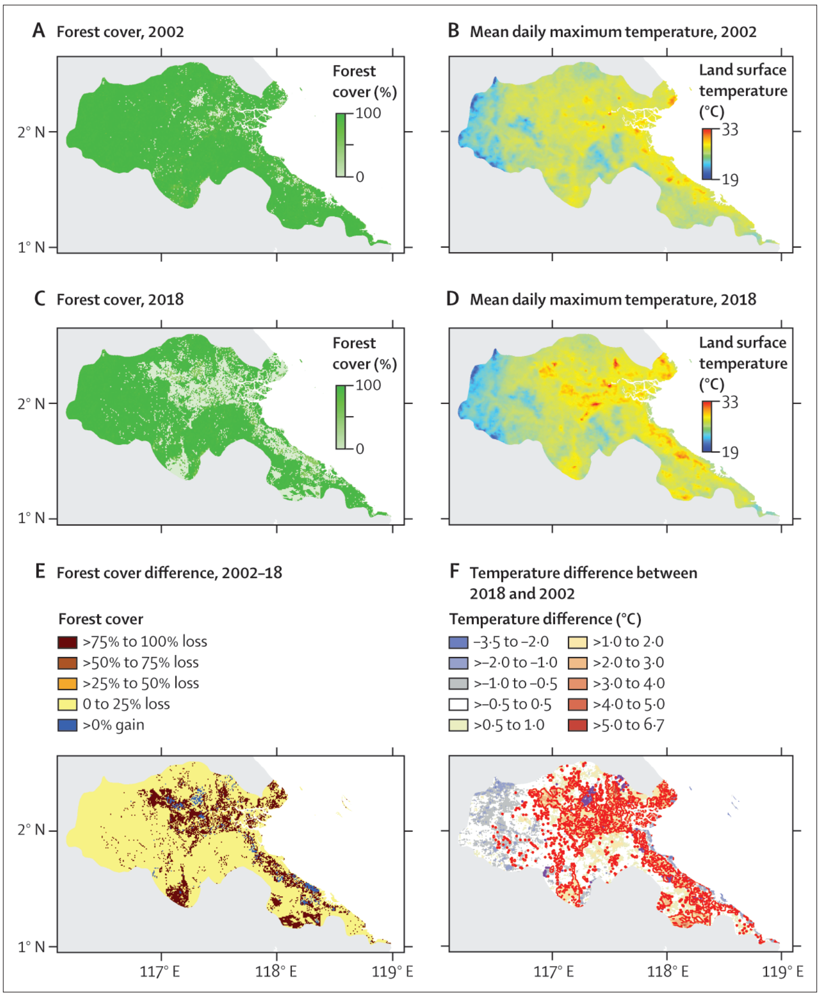

***Figure 1:* Forest cover and annual mean maximum daily land surface temperature in 2002 and 2018**
Each pixel equals 1 km² (N=25 053 pixels). Significant forest cover loss occurred between 2002 and 2018, as shown in panels A, C, and E, with a few regions of forest gain. Panels B, D, and F show that regions of greatest warming between 2002 and 2018 correspond to forest loss (red contour) and regions of greatest cooling corresponded to forest gain (blue contour).

For more on **GBD cause of death data** see http://ghdx.healthdata.org/gbd-results-tool

Mortality data for East Kalimantan were obtained from the GBD cause of death data for 2017. We used GBD mortality data for East Kalimantan because these province-level data are the highest-resolution GBD data available for Indonesia and because they provide both the all-cause and the non-external mortality rates needed for applying Lee and colleagues'[35] heat-mortality slopes for the Philippines and Vietnam. Berau publishes only all-cause mortality data, which show an all-cause mortality rate comparable to East Kalimantan's overall mortality rate (appendix 2 p 19). We used rates of all-cause (596 deaths per 100 000 people) and non-external mortality (552 deaths per 100 000 people) in 2017 for East Kalimantan after confirming that the year was not an outlier. Notably, external causes of death comprise those due to injury or poisoning or other external causes (International Classification of Diseases, Tenth Revision, Clinical Modification [ICD-10] cause-of-death codes beginning with S, T, V, X or Y).

To assess lost safe work time due to unsafe work conditions, we used an implementation of the American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Value (TLV), intended for computing time-weighted average exposure levels and adapted for use with the heat index assuming sun exposure,[39] to compute the amount of time considered unsafe (ie, lost safe work time) in each hour (work–recovery cycle). Guidance for heat exposure, such as from WHO and the ACGIH, is based on maintaining the core body temperature within a safe range (eg, within 1·0°C of normal [37·0°C]).[40] As defined in the ACGIH TLV,[41] we assumed acclimatisation, recovery and rest in the shade, regular single-layer work clothes, and 415 W metabolic rate work, based on the literature for heavy physical work in agriculture or construction.[41,42] We compared lost safe work time in each day in 2002 and 2018, and after applying 1·0°C, 1·5°C, and 2·0°C of global warming relative to present conditions. In the analysis of future lost safe work time, we assumed no further deforestation or population changes and used the shape of the diurnal cycles of the heat index derived from the MODIS observations.

Analyses

To analyse the relationship between deforestation and heat exposure, we computed 1×1 km pixel-level changes in temperature between 2002 and 2018, composited by geographical locations in Berau that experienced forest loss and maintained forest cover. These high-resolution data illustrate spatial relationships between the amount of forest cover and annual mean maximum daily land surface temperature in 2002 and 2018, and the difference between these years. We created histograms of mean daily maximum temperature differences between 2002 and 2018 for areas that kept and lost forest cover and computed the percentage of pixels with various degrees of warming that were co-located with pixels experiencing forest loss.

We also analysed the effects of deforestation and climate change on all-cause mortality due to heat exposure. Lee and colleagues[35] estimated heat-mortality slopes for the Philippines (9·15 percentage points per °C) with all-cause mortality data and for Vietnam (11·82 percentage points per °C) with non-external mortality data. We multiplied these slopes by the 2002–18 change in population-weighted mean annual temperature in Berau to estimate the percentage-point change in heat-attributable excess mortality due to the 2002–18 temperature change. We multiplied the GBD all-cause and non-external mortality rates in 2017 for East Kalimantan by Berau's 2018 population[43] from Statistics Indonesia of Berau (Badan Pusat Statistik Kabupaten Berau) to estimate Berau's all-cause and non-external mortality in 2018 (details of mortality and population data are provided in appendix 2 p 19). Because the 2018 mortality numbers already reflect the mortality impact from the 2002–18 temperature change, we calculated corrected, counterfactual (ie, without the 2002–18 temperature change) mortality numbers for Berau, as follows:

$$\text{Actual mortality} / (1 + \text{percentage} - \text{point increase}_{\text{mortality}})$$

where percentage-point increase$_{\text{mortality}}$ is equal to the product of the heat-mortality slope and the observed mean population-weighted temperature change in Berau during 2002 and 2018. We then obtained the estimated 2018 mortality attributable to the change in mean daily temperature during 2002–18, as the difference between Berau's 2018 counterfactual all-cause and non-external mortality. Future all-cause mortality from an additional 1·0°C, 1·5°C, and 2·0°C of global warming was calculated by applying the local warming multiplier to estimate future population-weighted temperature changes in Berau. This was then used to estimate future changes in all-cause mortality.

To assess the impact of changes in lost safe work time due to heat exposure from deforestation and climate change, we estimated the total population affected by lost safe work time due to increases in heat exposure by overlaying estimates of lost work time with LandScan 2017 data.[34] We define the affected population as those living within any pixel where there have been increases in exposure to higher heat indices due to deforestation and climate change.

Role of the funding source

The study was supported by a pilot research grant from the University of Washington Population Health Initiative. Researchers were independent from the funder. The funder had no role in study design, data collection, data analysis, data interpretation, writing of the report, or the decision to submit the Article for publication.

Results

Between 2002 and 2018, 4375 km² of forested land in Berau was cleared (figure 1A–C), corresponding to approximately 17% of the entire regency, and more than 28% of the land below 200 m, where 98% of the population lives. The mean annual daily maximum land surface temperatures over the entire regency were relatively similar in 2002 (26·40°C [SD 1·33]) and 2018 (26·65°C [SD 1·64]; figure 1D, E). However, at the pixel level (1 km²), large temperature differences occurred between 2002 and 2018, ranging from an increase of 6·70°C to a decrease of 3·50°C (figure 1F). Most pixels (56%) showing a greater than 1·00°C increase between 2002 and 2018 corresponded to locations that experienced deforestation, and 80% of pixels that had the most significant cooling (<–3·00°C) occurred in the few locations that experienced forest gain (figure 1C, F).

Locations that lost forest cover between 2002 and 2018 showed a far greater relative proportion of temperature increases than locations that maintained forest cover (figure 2). The mean annual daily maximum temperature difference between 2002 and 2018 across pixels that lost forest cover was 1·03°C (SD 1·03) and across pixels that kept forest cover it was 0·08°C (0·67), indicating that, on average, deforestation drove 0·95°C (95% CI 0·97–0·92; p<0·0001) of additional warming. In addition to greater mean daily maximum temperatures, deforested areas experienced the majority of extreme warming between 2002 and 2018 (figure 2). More than 84% of the pixels with temperature increases greater than 2°C were co-located with pixels experiencing forest loss. 92·4% of the pixels with warming greater than 3°C were co-located with deforestation, as were 98·1% with warming greater than 4°C, and 100% with warming greater than 5°C.

In 2018, the population-weighted mean temperature in Berau was 0·86°C higher than in 2002, an increase that contributed to an estimated 7·3–8·5% of all-cause mortality in 2018, or 101–118 additional deaths per year as a result of 2002–18 climate warming and deforestation (table). An additional increase in global mean temperature of 1·0°C would increase the proportion of all-cause mortality attributable to heat in Berau by an additional 9% compared to 2018 estimates (equivalent to 118–141 additional annual deaths at current population

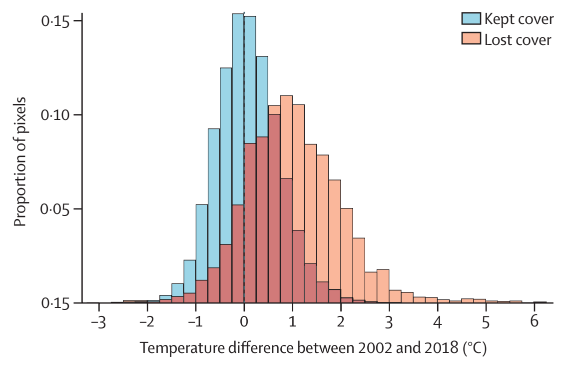

Figure 2: **Histogram comparing mean annual maximum temperature differences between 2002 and 2018**
Areas that maintained forest cover shown in blue (N=18 979 pixels), and areas that lost forest cover shown in red (N=4375 pixels). Each pixel equals 1 km².

	2002–18	>2018 warming scenarios		
		>1·0°C	>1·5°C	>2·0°C
Increase in mean daily temperature (°C)	0·41	0·9*	1·4*	1·9*
Mean increase in population-weighted mean daily temperature (°C)	0·86	0·9†	1·4†	1·9†
Heat-attributable increase in all-cause mortality (range)	7·3–8·5%	8·5–10·2%	12·8–15·3%	17·0–20·4%
Increase in heat-related mortality (deaths per year)‡	101–118	118–141§	177–212§	236–282§

*Berau warms 0·94°C for every 1°C of global warming (appendix p 2). †Assumes 2017 population distribution remains unchanged and 2018 forest extent remains unchanged. ‡Based on heat-mortality slopes for the Philippines and Vietnam from Lee and colleagues (2019).[35] §At 2018 population size.

Table: **Estimates of the increase in temperature and annual heat-related mortality from 2002, Berau regency**

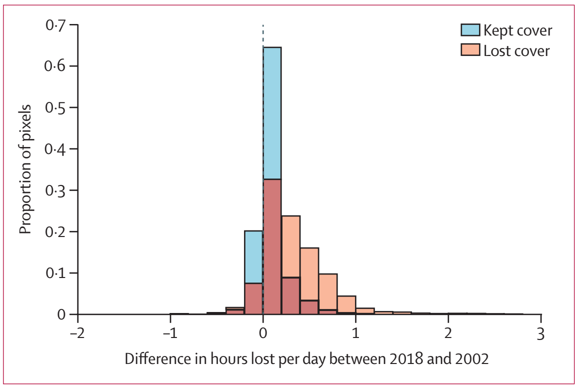

Figure 3: **Histogram comparing difference in work hours lost per day between 2002 and 2018**
Only pixels lower than 200 m are shown to reduce bias of cooler, higher elevation pixels. Each pixel equals 1 km². Pixels that kept forest cover shown in blue (N=9972 pixels) and pixels that lost forest cover shown in red (N=3914 pixels).

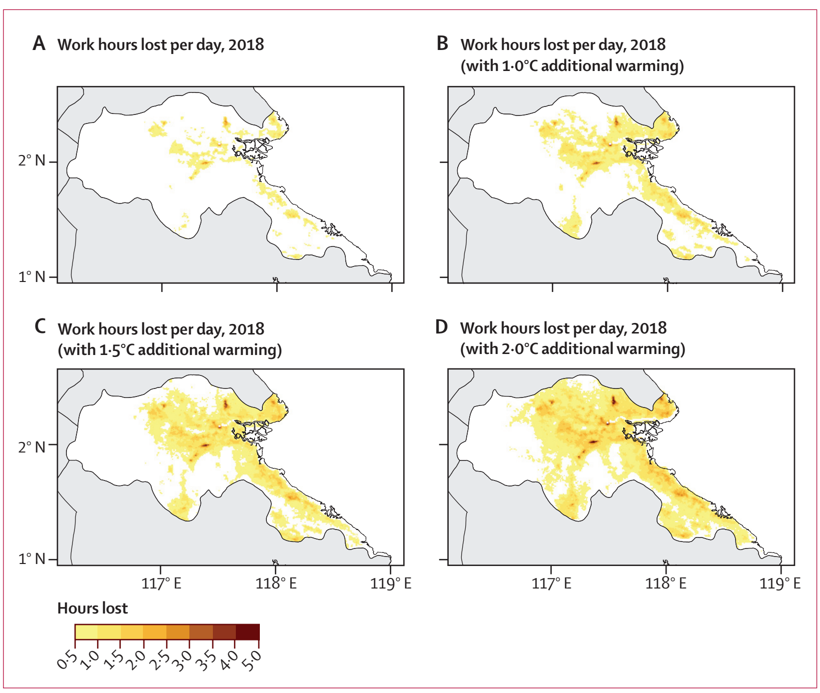

Figure 4: **Estimates of impact of expected future global warming on work hours lost per day**
Panel A shows work hours lost in 2018; the same data are shown in appendix 2 (p 23) but are rescaled here for context. Panels B–D add 1·0°C, 1·5°C, and 2·0°C of global warming, to current 2018 conditions. These results assume no additional deforestation.

levels and assuming no further deforestation), while an increase in global mean temperature of 1·5°C would increase all-cause mortality by 14% (equivalent to 177–212 additional annual deaths), and an increase in global mean temperature of 2°C would increase all-cause mortality by 19% (equivalent to 236–282 additional annual deaths).

In areas that lost forest cover, the mean difference between 2002 and 2018 in safe work hours lost per day was 0·31 h (95% CI 0·30–0·32; p<0·00001), compared to 0·03 h (0·03–0·04; p<0·00001) in pixels that kept forest cover. Compared with 2002 (appendix 2 p 23), the spatial pattern in safe work hours lost per day in 2018 (mean 0·08 h [SD 0·23]; appendix 2 p 23) closely mirrored the spatial pattern of forest loss (figure 3; appendix 2 p 23). If only pixels below 200 m elevation are considered, 67·3% of pixels with safe work time lost per day of greater than 0·5 h were co-located with forest lost pixels. When pixel-average safe work loss increased to 1·0 h lost per day, the likelihood that the pixel had experienced deforestation increased to 77·2%, whereas with 1·5 h lost per day the likelihood of deforestation increased to 88·1%, and with 2·0 h lost per day it increased to 96·2%. Although increases in forest cover between 2002 and 2018 were rare (2·1% of pixels), these areas experienced an average gain in safe work hours of 0·02 h per day.

In 2018, LandScan data showed 13·2% of the total population in deforested pixels where at least some portion of the workday had hotter conditions than recommended for safe work. By contrast, LandScan data showed 4·0% of the population in forested pixels where at least some portion of the workday had hotter conditions than recommended for safe work. In areas exceeding 0·5 h of safe work lost per day, 9·5% of the total population was in deforested locations compared with 1·3% in forested locations. In areas exceeding lost safe work hours of 1·0 h per day, 4·7% of the population was in locations that lost forest cover compared with 0·7% in forested locations. For areas exceeding 1·5 h of safe work lost per day, 0·6% of the population was in deforested locations, compared with 0% in forested locations.

Figure 4 shows the spatial distribution of lost safe work hours when 1·0°C (figure 4B), 1·5°C (figure 4C), and 2·0°C (figure 4D) of global warming is applied to average present conditions (figure 4A). With 2·0°C of global warming, some locations in Berau would lose 5 h of safe work time per day (figure 4D). The spatial extent of conditions corresponding to 2 h or more of lost safe work hours per day ranged from 20 km² in 2018 (corresponding to 11·6% of Berau's total population that lives in two major urban centres, as shown in appendix 2 p 14) to 607 km² with an additional 2·0°C of global warming (corresponding to 49·5% of the population; figure 5). With 2·0°C of warming relative to present conditions, only 74 km² of forested areas (0·7% of total forested land below 200 m) will exhibit conditions leading to 2 h or more of lost safe work hours per day. By contrast, 392 km² of land that lost cover (10% of total land that was deforested since 2002) will exhibit conditions corresponding to 2 h or more of lost safe work hours per day. Thus, 65% of the pixels that show more than 2 h of lost safe work hours per day under a 2·0°C increase in global warming are associated with deforestation.

Discussion

Forest loss in Berau is associated with significant increases in heat exposure, all-cause mortality, and unsafe work conditions. Locally, deforestation has already caused temperature increases higher than 5°C. These observed temperature increases associated with deforestation exceed local projected end-of-century warming under high emission scenarios (approximately 2·2–5·1°C warmer than the present day under RCP8·5 projections; appendix 2 p 13), highlighting the immediate and drastic effects of deforestation on heat exposure. Importantly, temperature changes from deforestation occur at much shorter timescales than global climate change, which will progress over the course of decades to centuries. Any relative comparison of local temperature changes from deforestation will shift as the planet continues to warm. In our analysis, the increases in heat exposure between 2002 and 2018 were associated with an estimated increase in all-cause mortality that will approximately double again with an additional 2°C of global warming, which is likely to occur under high greenhouse gas emissions scenarios by 2077 (±12 years; appendix 2 p 13). Finally, we found that increases in unsafe work conditions due to heat exposure from 2002 to 2018 were associated with a ten-fold increase in the amount of lost safe work hours in deforested areas compared to forested areas, and that deforested areas might exhibit conditions corresponding to up to 5 h of safe work lost during an average workday with an additional 2°C of global warming relative to present conditions. Taken together, these findings highlight an urgent need for action, as threats to health caused by increasing heat exposure and mortality risks, particularly among older people, very young children, and those with chronic diseases, are compounded by the effects on household and community wellbeing resulting from reduced productivity among otherwise healthy workers.

The associated increases in all-cause mortality from increases in heat exposure are particularly noteworthy, and provide much needed estimates of the impacts of heat-related mortality in the tropics, where data are scarce.[44,45] Our estimates of the proportion of all-cause mortality associated with temperature increases between 2002 and 2018 (7·3–8·5%) indicate the substantial impact of heat-related mortality when compared with other major health challenges in the region. For example, the GBD 2017 data for East Kalimantan reported that maternal neonatal disorders accounted for 3·6%, neglected tropical diseases and malaria accounted for 1·2%, respiratory infections accounted for 6·8%, and transportation injuries accounted for 3·8% of total deaths. Our estimates of all-cause mortality rates with 2°C of additional global warming from 2018 levels indicate increases of 24–29% compared to 2002 levels, making heat-related mortality comparable to mortality due to other long-term public health challenges in Asia. For comparison, analyses from Asia indicate that tobacco smoking, which is prevalent particularly among men in Indonesia[46] and associated with increased risks of stroke and coronary heart disease, has been estimated to account for 29·3% of all-cause mortality in individuals born on or after 1930.[47]

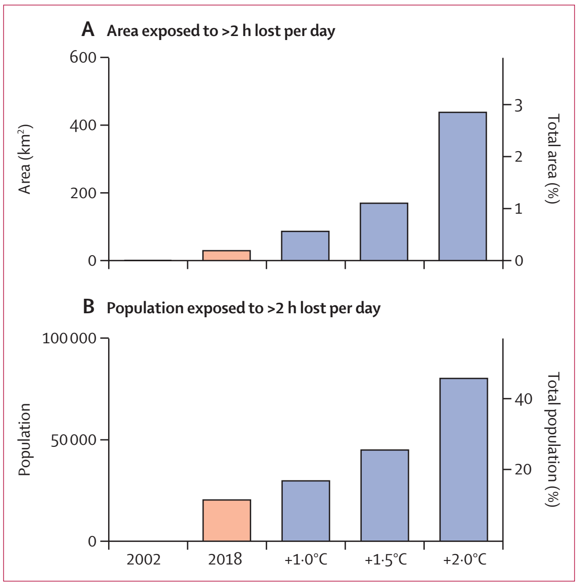

Figure 5: **Impacts of deforestation and expected global warming on area (A) and population (B) exposed to more than 2 work hours lost per day**
Although the area exposed to more than 2 work hours lost per day is small relative to the total area below 200 m (15 225 km²), the population exposed is significant. 98% of the total population lives below 200 m, where most of the deforestation has occurred to date.

Heat exposure can contribute to mortality in several ways. A vast amount of published literature has shown that higher air temperatures directly increase mortality and morbidity in the general population by causing heat stroke, heat exhaustion, and dehydration, as well as indirectly by exacerbating existing cardiovascular and renal diseases, leading to ischaemic stroke, ischaemic heart disease, cardiac dysrhythmia, hypotension, and acute renal failure.[48,49] For populations with low adaptive capacity, the relationship between temperature increases and all-cause mortality might be more pronounced, as shown by Lee and colleagues.[35] Recent studies in Berau have found that even under favourable work conditions, working in deforested versus forested areas for just 90 min can result in elevated core body temperatures exceeding 38·5°C[50] and decreased cognitive performance.[51] For outdoor workers engaged in heavy physical activities in the tropics, where heat and humidity are already high, productivity declines can occur with increasing heat stress, as the human body naturally responds to heat stress by triggering reductions in physical work intensity and internal heat generation.[4]

Our mortality projections assume that exposure to, and the mortality risk from, higher temperatures will not be mediated through additional adaptive responses beyond those already implemented.[11] Given the constraints on adaptive behaviours, this is a reasonable assumption. Although the slopes of heat-mortality dose–response curves have decreased in several high-income countries,[52,53] this decline was correlated with increases in air conditioning use,[54] advances in per-capita income or health-care access and quality,[55] reduced prevalence of cardiovascular mortality risk factors such as smoking,[56] and policies specifically targeted at reducing heat vulnerability.[55] For rural communities that largely lack access to infrastructure and markets, there is limited evidence that the slope of the heat-mortality dose–response curve will decrease in the near future.

Outdoor work is common in areas experiencing deforestation, as human-initiated land use pressures remain the primary driver of forest loss, especially in areas experiencing high land use pressure, such as Berau.[19] Deforestation is driven largely by outdoor labour-intensive industries, such as mining, farming, and palm oil production.[19] Even under the optimistic assumption of no further deforestation, which is extremely unlikely given current trends,[57] deforested areas could exhibit conditions corresponding to 5 h of unsafe work during the workday by the end of the 21st century. This finding is important, as a 2019 study in the same region[11] found that outdoor labourers worked, on average, 6·5 h a day and are already shifting work schedules to avoid the hottest times of the day. Even an average loss of 2 work hours in deforested areas would probably be detrimental to livelihoods without some adaptive strategies, such as shifting to non-outdoor livelihood activities, as that would account for a third of the time allocated to work. In subsistence agricultural settings that are common in Berau,[58] there might be more flexibility in organisation of work to allow a slower pace of work and increase rest-taking behaviours compared to industrial agricultural settings.[7] However, a study of survey data on self-reported adaptation strategies found that outdoor workers in Berau are already having to adapt to hotter temperatures due to deforestation,[11] suggesting that those engaged in outdoor work might already be approaching their adaptive capacity through behavioural adaptations.

Our findings underscore the major challenge of the combined effects of deforestation and climate change for the approximately 800 million people living in the world's tropical forest nations,[59] a population that is expected to substantially increase by 2050.[60] Rural populations in these countries contribute the least to global emissions,[17] yet bear a disproportionate burden of the adverse effects of climate change and deforestation.[61] Forests have the potential to increase community resilience to temperature increases from climate change. In our analysis, the mean annual daily maximum temperature increase was 92% lower, and lost work hours were 90% lower, in areas that maintained forest cover than in deforested areas between 2002 and 2018. Furthermore, the few areas experiencing forest cover gain saw an average gain of 0·02 h of safe work per day. There are two primary mechanisms by which forests contribute cooling services. Trees can cool local areas through shade (ie, blocking direct solar radiation) and transpiration of liquid water.[62,63] In tropical forests in particular, hundreds of litres of water a day are transpired by individual trees, creating an amount of cooling that is equivalent to two average household air-conditioning units.[63] When deforestation occurs, it removes shade from local land cover and the deep roots that contribute much of the liquid water for tree transpiration. The result is a dry surface soil layer that can no longer effectively cool through evapotranspiration.

We note several limitations of our study that future research should address. First, although our study used established methods for estimating environmental impacts on people,[25] similarly to past studies we did not estimate the causal effect of deforestation-associated heat on people due to data and other limitations. There are still no optimal approaches (eg, an ensemble of models) for large-scale studies that allow us to adequately address the uncertainty in climate and health projections that results from variability in population characteristics, adaptative capacity, and bioclimate model structures.[64] However, our approach expands on the available evidence by adapting approaches grounded in laboratory-based, controlled human studies intended for observational use that integrate consideration of factors such as clothing, metabolic rate, and work–rest cycles that are drivers of heat stress exposure, in addition to ambient conditions, among outdoor working populations.

Second, our analyses of future warming held population constant and assumed no further deforestation, and did not assume changes in urbanisation, technological change, or economic growth. Third, our estimates of changes in heat-related mortality were based on relationships of temperature and heat-related excess mortality from Vietnam and the Philippines rather than on relationships specific to Berau or East Kalimantan. Although both Vietnam and the Philippines are closely matched to Berau in terms of the climatic, social, and health characteristics strongly determinant of heat-related mortality (appendix 2 p 16), the use of data from these countries could have biased our mortality estimates. Estimation of relationships of temperature and heat-related excess mortality specific to Berau or East Kalimantan require time-series data of daily mortality and temperature, which are currently not available.[65] However, our approach followed best standard practice for estimating mortality impacts in data-scarce or data-poor environments.[65]

Fourth, we used the heat index instead of wet bulb globe temperatures (WBGT) to calculate lost safe work hours due to temperature increases. WBGT captures important elements for assessing the risk of heat stress, but at the spatiotemporal resolution needed for our study it was unfeasible to estimate WBGT without making unrealistically strong assumptions. However, recent work[66] supports the use of the heat index in lieu of WBGT when WBGT measurements are impractical, and we believe the approach we used[39] provides a valid and valuable comparison between forested and deforested areas, thus allowing us to estimate hourly heat exposure and work–recovery cycles at a more granular temporal level than has previously been published. Importantly, the heat index is also a commonly used and understood measure, as it is used in heat advisories by the US National Weather Service and the US Occupational Safety and Health Administration. Estimates of the total number of people experiencing increasing heat exposure could be improved with more detailed spatially explicit demographic data, such as data that provide age-stratified population counts. However, these data currently do not exist at the granularity that is needed.

Fifth, we recognise that heat index is more variable across space and time than captured here. The 1 km² resolution MODIS observations dampen the temperature extremes people experience on the ground, as do our use of mean diurnal cycles of ERA5 temperature. Furthermore, MODIS observations from the forest canopy are warmer than conditions in the forest understory,[30] the location of interest. Last, our assumption of constant specific humidity across Berau is most certainly a simplification of the water vapour variability (and thus relative humidity) that occurs between locations and across time. Overall, it is likely that our methodological assumptions provide conservative (high) estimates of the forest understory heat indices (appendix 2 pp 1–2). Although this limitation has no practical impact on our primary results because work hours lost are minimal in forest locations, it does suggest that we could be underestimating the cooling services provided by forests. This highlights the need for more in-situ observations comparing heat exposure across tropical landscapes.[11]

Our study raises concerns that deforestation, which exacerbates climate change, can have a substantial adverse effect on the health and wellbeing of populations in tropical countries, and indicates important public health benefits that could be achieved from the conservation or restoration of forests or forested landscapes. The benefits to public health are likely to manifest in both the short and long term, especially given current trajectories for global warming. Policy makers should actively prepare for, and manage, the health risks associated with deforestation, as deforestation events are relatively predictable and can be influenced by land use and management plans. Development of policies and land use decisions should be based on analyses that compare different land use and climate scenarios and consider the implications for human health and wellbeing. Preventive strategies to reduce health risks from heat exposure are often beyond the control of individuals, and systemic changes at multiple levels, including within the overall policy environment, are needed.[7] For rural communities in tropical countries, these ecosystem services play a particularly crucial role in maintaining health and wellbeing. Natural climate solutions,[67] which include the protection of forests and agroforestry practices, could contribute to reductions in heat exposure, improved work productivity, and reductions in mortality risks. Clinicians and policy makers should therefore carefully evaluate and prioritise interventions that maximise population health and wellbeing while addressing climate change mitigation.

Contributors

NHW, LRVZ, LAP, DSB, ETG, TK, YJM, and JTS designed the research. NHW, LRVZ, LAP, TK and YJM did the data analysis, and NHW, LRVZ, LAP, DSB, TK, YJM, and JTS interpreted data analysis outputs. NHW, LRVZ, LAP, DSB, IA, KLE, ETG, TK, YJM, and JTS wrote the Article. All authors read and approved the final manuscript. NHW, LRVZ, LAP, DSB, IA, KLE, ETG, TK, YJM, and JTS had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. NHW, LRVZ, LAP, TK, and YJM verified the underlying data. The corresponding author (YJM) attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

Declaration of interests

We declare no competing interests.

Data sharing

All data, codes, and materials used in the analysis are available from the authors upon reasonable request via email to the corresponding author.

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Supplementary appendix 1

This appendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

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Abstrak

Latar Belakang: Penelitian menemukan bahwa paparan panas yang berlebihan dapat meningkatkan seluruh penyebab kematian, penyakit terkait paparan panas, kecelakaan akibat kerja dengan fokus pada wilayah perkotaan dengan lintang rendah dan negara industri. Studi yang meneliti bagaimana deforestasi dan perubahan iklim berdampak buruk terhadap kondisi kerja dan kesehatan penduduk di negara-negara industri masih sangat terbatas.

Metode: Digunakan data pada resolusi 1 km^2 untuk membandingkan tutupan hutan tahun 2002 dan 2018 serta menggunakan kondisi temperatur/ suhu di Kabupaten Berau, Indonesia. Data populasi eksplisit secara spasial digunakan untuk memperkirakan dampak pemanasan, antara tahun 2002 dan 2018 dan setelah menerapkan peningkatan pemanasan global pada suhu 1, 1•5, dan 2ºC tahun 2018, pada semua penyebab kematian dan kondisi kerja yang tidak aman.

Hasil: Diantara tahun 2002 sampai 2018, seluas 4375 km^2 lahan hutan di Kabupaten Berau dibuka, luas tersebut setara dengan 17% dari seluruh luas kabupaten. Deforestasi meningkatkan suhu maksimum harian rata-rata sebesar 0.95°C (CI 95% : 0.97–0·92; $p<0.00001$). Rata-rata suhu harian meningkat sebesar 0.86°C dengan bobot pada populasi, terhitung sekitar 7.3–8.5% dari semua penyebab kematian (atau 101–118 kematian tambahan per tahun) pada tahun 2018. Waktu kerja yang tidak aman meningkat sebesar 0.31 jam per hari (CI 95% : 0.30–0.32; $p<0.00001$) di daerah yang terdeforestasi dibandingkan dengan 0.03 jam per hari (0.03–0.04; $p<0.00001$) di daerah yang mempertahankan tutupan hutan. Dengan tambahan 2°C pemanasan global di masa depan, dibandingkan dengan tahun 2018, area yang terdeforestasi dapat mengalami peningkatan sebesar 17–20% dalam semua penyebab kematian (sesuai dengan tambahan 236–282 kematian per tahun) dan hingga 5 jam per hari pekerjaan yang tidak aman.

Interpretasi: Efek panas dari deforestasi dan perubahan iklim mulai mempengaruhi kesehatan populasi di wilayah lintang rendah, negara-negara industri, dan pemanasan di masa mendatang menunjukkan dampak kesehatan yang signifikan. Perhatian yang lebih dibutuhkan untuk meneliti bagaimana deforestasi berdampak pada kesehatan dan kesejahteraan masyarakat lokal saat ini.

Kata kunci: deforestasi, perubahan iklim, *heat-stress,* paparan panas, semua penyebab kematian, jam kerja aman, Indonesia

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Supplementary appendix 2

This appendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

Supplement to: Wolff NH, Zeppetello LRV, Parsons LA, et al. The effect of deforestation and climate change on all-cause mortality and unsafe work conditions due to heat exposure in Berau, Indonesia: a modelling study. *Lancet Oncol* 2021; published online Nov 11. http://dx.doi.org/10.1016/S2542-5196(21)00279-5.

Appendix

Extended Methods

Study design and timeframe

We conducted a spatially explicit analysis of all-cause mortality and unsafe work conditions in Berau (appendix p 7), comparing remotely sensed surface temperature from 2002 and 2018 (observed), and after applying 1, 1·5, and 2ºC of global warming relative to the 2008-2027 mean, which we refer to as the 'present' or 2018 baseline climate in the remainder of this analysis. We focused our analysis on 2002 and 2018 because the El Niño Southern Oscillation (ENSO) likely had minimal impacts on local climate in Indonesia during these years.[1] This allowed us to isolate the impacts of increasing atmospheric greenhouse gas concentrations and deforestation on local temperature changes. We chose the 1ºC warming threshold relative to present climate because this corresponds to the Paris Climate Accord goal of limiting warming to less than 2ºC relative to pre-industrial levels (approximately 1ºC of warming relative to pre-industrial levels has already occurred). We also explored impacts of an additional 1·5 to 2ºC of warming relative to present day conditions because this is an increasingly likely outcome for the planet.[2,3] Our goal was to capture the relative additional climate change effect on heat exposure (work hours lost and mortality) and thus we kept population, land use, and other factors constant. Our climate impacts should therefore be interpreted as conservative estimates of potential future impacts. Schematics of the study design and primary study components from spatially explicit data are presented in Figure S1 (appendix p 6), and mirror analytic approaches that estimate environmental impacts on people over large spatial scales.[4–8]

Data sources and approach

Land use: historical forest loss and gain

We re-gridded version 1·6 of the Hansen et al.[9] dataset (hereafter H13), a 30m spatial resolution dataset based on data provided by Landsat satellite missions, to a 1x1 km resolution. The H13 dataset provides each grid cell's fractional forest cover in 2000 and the year during which forest loss (year when cover goes from >0 to 0), or forest gain (year when cover goes from 0 to >50%), occurred.[9] To be consistent with forest gain criteria and to minimize the number of cases where we included 1x1 km areas (pixels) with very small forest cover loss in our assessment of temperature effects of deforestation, we considered forest loss to be cases where re-gridded pixels had forest cover >50% in 2000 prior to subsequent loss between 2002 and 2018.

Heat exposure: historical (daily temperature and hourly heat index)

We obtained values for surface daytime and nighttime temperature at 1x1 km resolution using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite observations.[10] In forested regions, the MODIS satellite detects top-of-canopy temperatures, rather than temperatures near the forest floor. However, once the forest has been removed, the satellite observes temperature at the land surface. Temperatures near the forest floor are systematically lower than those at the top of the canopy,[11] so our estimates of temperature change associated with deforestation are conservative.

We obtained the diurnal cycle of land surface temperature ('skt' variable) and relative humidity over Berau using hourly data from the fifth generation of the European Centre for Medium-Range Weather Forecast atmospheric reanalysis data product (ERA5)[12] for 2002 and 2018. The diurnal temperature cycle can be well-described by a sinusoidal cycle during the day (with a period of roughly 15 hours) followed by a linear decrease in temperature between sunset and the following sunrise (appendix p 8). Using the MODIS observations as the maximum and minimum values of the sinusoidal cycle, we created continuous diurnal cycles for each day based on the two temperatures observed by the MODIS satellite (appendix p 8).

We estimated daily relative humidity at a 1x1 km resolution by assuming that the amount of water vapor in the atmosphere (specific humidity) is constant over Berau at daily timescales. Although this simplifying assumption ignores short-term fluctuations in the amount of atmospheric water vapor, Fig. S2 (appendix p 8) shows that it does not translate into a large absolute error in our estimate of surface relative humidity. This assumption, combined with our diurnal cycles of temperature, generated a relative humidity diurnal cycle that closely matched the one found in ERA5 over Berau. We then generated hourly estimates of Heat Indices using Rothfusz's modification of Steadman's work[13], which has also been done in recent studies estimating safe work hours for farm workers in the United States.[8]

Heat exposure: future

We used atmospheric surface air temperature output from global climate models that participated in the CMIP5[14] to estimate the average warming of Berau relative to global warming. We used output from all 39 CMIP5 models that conducted the RCP8.5 experiment, in which 21st century greenhouse gas emissions are not curtailed (appendix p 12). These CMIP5 simulations show that the average warming over Berau is nearly equal to global mean warming over the 2006-2099 time period. These model results indicate that for every 1ºC increase in the global average temperatures in the 21st century, the average temperature in Berau will increase by 0.94ºC. We thus used this local warming multiplier (0.94ºC/ºC) to estimate the impacts of global climate change in Berau for 1.0, 1.5 and 2.0ºC global warming scenarios. Although we used RCP8.5 to calculate this relationship, the coefficient for warming is nearly identical in other warming experiments.

All-cause mortality

We calculated the population-weighted mean change in mean daily temperature for 2002-2018 and for additional future global warming of 1, 1·5, and 2°C for Berau by overlaying our estimated daily mean temperature change with LandScan 2017 data,[15] which provides spatially explicit population data at 1x1 km resolution (appendix p 14). We then used estimated relationships of heat and all-cause (Philippines) and non-external (Vietnam) heat-attributable excess mortality reported in Lee et al.[16] for the Philippines and Vietnam to construct estimates of changes in heat-related excess mortality for Berau. We selected Vietnam and the Philippines as sources of country-specific heat-related excess mortality curves for Berau because annual mean temperatures are similar to Berau (appendix p 16, 18) and no such curve exists for Indonesia nor can it be estimated given lack of daily mortality data,[17–19] and because these countries are similar to Berau in key drivers of heat-related mortality (appendix p 16).[16,20] Lee et al.'s[16] heat-mortality slopes represent the estimated percentage point (%p) increase in heat-attributable excess mortality (heat-attributable mortality divided by non-heat-attributable mortality) per °C increase in mean daily temperature. While Lee et al.'s[16] relationships are predominantly estimated from data for urban areas, there is no evidence that suggests that the excess risk (as measured by an increase in relative risk [RR]) for heat-attributable all-cause and cardiovascular mortality is smaller in rural settings than in urban ones.[21]

Mortality data for East Kalimantan were obtained from the Global Burden of Disease (GBD) cause-of-death data[22] for 2017, which is the most recently available data. We used GBD mortality data for East Kalimantan because these province-level data are the highest-resolution GBD data available for Indonesia and because they provide both the all-cause and the non-external mortality rates needed for applying Lee et al.'s heat-mortality slopes for the Philippines and Vietnam. Berau publishes only all-cause mortality data, which show an all-cause mortality rate comparable to East Kalimantan's overall mortality rate (appendix p 19). In addition to having comparable all-cause mortality rates, Berau Regency and the East Kalimantan Province overall also show very similar occupational compositions of their populations, and are comparable in key variables that affect heat-related excess mortality, including percent population below the poverty line, percent population aged 65 years or older, and health services availability and utilization rates (appendix p 19). They also have similar average per-capita expenditures (food and non-food) and Human Development Index (HDI) scores, suggesting similar population-level heat exposure, susceptibility and adaptive capacity. We used rates of all-cause (596 per 100,000 people) and non-external mortality (552 per 100,000 people) in 2017 for East Kalimantan after confirming that the year is not an outlier. Note that external causes of death comprise those due to injury or poisoning or other external causes (ICD-10 cause-of-death codes beginning with S, T, V, X or Y).

Unsafe work conditions: lost safe work time

We used an implementation of the American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Value (TLV), intended for computing time-weighted average exposure levels and adapted for use with the Heat Index assuming sun exposure,[23] to compute the amount of time considered unsafe ('lost safe work time') in each hour (work/recovery cycle). Guidance for heat exposure, such as from the World Health Organization and the ACGIH, is based on maintaining the core body temperature within a safe range (e.g., within 1ºC of normal [37 ºC]).[24] The development of recommended exposure levels, such as the ACGIH TLV for heat stress, considered findings from human laboratory studies that examined the effect of exposure to different ambient temperature and humidity on the rise in core body temperatures under different physical activity and clothing scenarios.[25] As defined in the ACGIH TLV,[25] we assumed acclimatization, recovery/rest in the shade, regular single-layer work clothes, and 415 W metabolic rate work, based on literature for heavy physical work in agriculture or construction.[25,26] We compared lost safe work time in each day in 2002 and 2018, and after applying 1, 1·5, and 2ºC of global warming relative to present conditions. In the analysis of future lost safe work time, we assumed no further deforestation or population changes and used the shape of the diurnal cycles of heat index derived from the MODIS observations.

<u>Analyses</u>

<u>*Relationship between deforestation and heat exposure*</u>

We computed 1x1 km pixel-level changes in temperature between 2002 and 2018, composited by geographic locations in Berau that experienced forest loss and maintained forest cover. These high-resolution data illustrate spatial relationships between the amount of forest cover and annual mean maximum daily land surface temperature in 2002 and 2018, and the difference between these years. We created histograms of mean daily maximum temperature differences between 2002 and 2018 for areas that kept and lost cover and computed the percent of pixels with various degrees of warming that were co-located with pixels experiencing forest loss.

Effects of deforestation and climate change on all-cause mortality due to heat exposure

Lee et al.[16] estimated heat-mortality slopes for the Philippines (9·15%p/°C) and Vietnam (11·82%p/°C) using all-cause and non-external mortality data, respectively. We multiplied these slopes by the 2002-2018 change in population-weighted mean annual temperature in Berau to estimate the %p change in heat-attributable excess mortality due to the 2002-2018 temperature change. We multiplied the GBD all-cause and non-external mortality rates in 2017 for East Kalimantan by Berau's 2018 population[27] from the Berau Census Bureau to estimate Berau's 2018 all-cause and non-external mortality, respectively (details on mortality and population data in the SI). Because the 2018 mortality numbers already reflect the mortality impact from the 2002-2018 temperature change, we calculate corrected, counterfactual (i.e., without the 2002-2018 temperature change) mortality numbers for Berau, as follows:

$$Actual\ mortality/(1 + \%p\ increase_{Mortality}),$$

where $\%p\ increase_{Mortality}$ is equal to the product of the heat-mortality slope and the observed mean population-weighted temperature change in Berau during 2002 and 2018. We then obtained the estimated 2018 mortality attributable to the change in mean daily temperature during 2002-2018, as the difference between Berau's 2018 counterfactual all-cause and non-external mortality, respectively. Future all-cause mortality from an additional 1, 1·5, and 2ºC of global warming was calculated by applying the local warming multiplier to estimate future population-weighted temperature changes in Berau. This was then used to estimate future changes in all-cause mortality.

Impact of changes in lost safe work time due to heat exposure from deforestation and climate change

We estimated the total population affected by lost safe work time due to increases in heat exposure by overlaying estimates of lost work time with LandScan 2017 data.[15] We define the affected population as those living within any pixel where there has been increases in exposure to higher heat indices due to deforestation and climate change. Because we are estimating changes for 1x1 km pixels, our estimate assumes people largely work and live within these areas. This assumption is supported by data from a study that described the adaptations to rising temperatures in the same study region.[28]

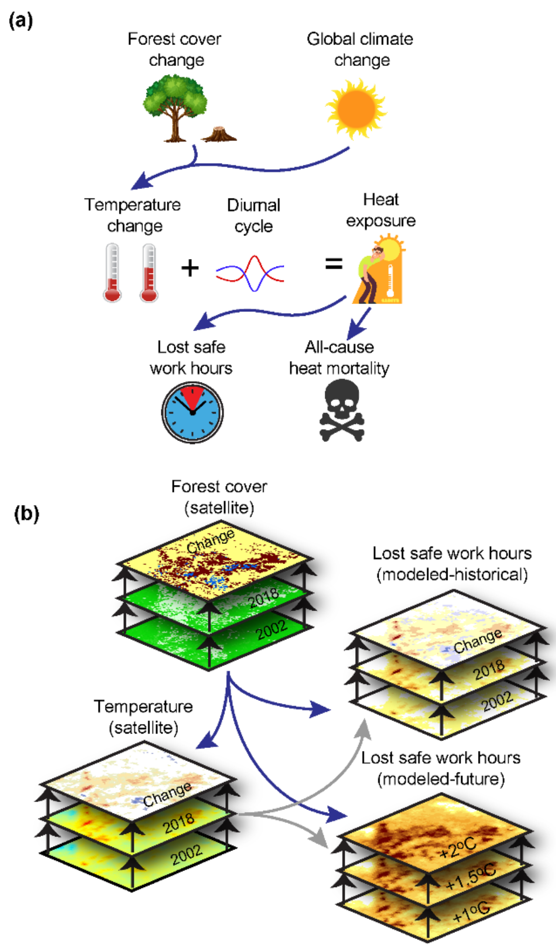

Figure S1. (a) Schematic of the study design and (b) the primary study components from spatially explicit data. Our goal was to quantify the impacts of deforestation, global warming and their interaction on present (2018) and future temperatures, lost work hours and all-cause mortality. To do this, we used satellite observations to estimate spatially explicit forest cover and temperature changes between 2002 and 2018. For future scenarios, we applied 1°, 1·5°, and 2°C of global warming to present temperature conditions and assumed no more deforestation after 2018. Mean Berau diurnal cycles of temperature and humidity were estimated from a data product that integrates models and observations. These hourly data, combined with satellite observations of temperature, allowed us to calculate spatially explicit hourly heat index values (heat exposure) using Rothfusz's modification of Steadman's work[13]. Finally, we estimated the hours per day deemed unsafe by established occupational health guidelines for heat stress (gray lines in b). Changes in all-cause mortality was estimated using changes in population-weighted mean temperature values and applying it to Lee et al.'s[16] heat-mortality slopes. Comparisons of forested versus deforested pixels with corresponding temperature and lost safe work hours pixels, allowed us to estimate both the role of deforestation on aggravating, and the role of forests at mitigating, heat stress impacts (blue lines in b). Symbols (a) are from Vecteezy.com and Shutterstock.com.

Study context

The Berau Regency, Indonesia is an area that has experienced significant land use change in the past decade, with mean annual rate of forest loss between 2000-2010 being 60% higher than the pantropical mean.[9,29] Forest loss has been driven by significant land use pressures from the expansion of mining, oil palm, fiber plantations, agriculture, and logging.[29] Unspecified agricultural was the primary driver of forest conversation (43% of forest conversion between 2000-2010). Land use pressures threatening forests remains high, with approximately 47% of the remaining forests currently zoned for conversion. Despite these recent forest losses, 85% of the Berau Regency's original forest is still standing.

Berau's population in 2018 was 232,528, and outside of the capitol the population density is approximately 17 people per square kilometer. The population skews young, with approximately 50% of the population under the age of 30. The primary economic activities for Berau are the production of oil palm, agriculture, logging, and mining.[30] Berau has a dry and rainy season, although there is little temperature variation throughout the year, and agriculture is a year-round activity. Daylight hours also vary little throughout the year (maximum 30 minutes).

Heat exposure: historical (daily temperature and hourly heat index)

Diurnal cycles of temperature and humidity

The National Oceanic and Atmospheric Administration uses heat index, 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, we needed higher temporal resolution temperature and humidity data to estimate work hours lost. We used the fifth generation of the European Centre for Medium-Range Weather Forecast atmospheric reanalysis data product (ERA5) to obtain the diurnal (24-hour) cycle of land surface temperature ('skt' variable) and relative humidity over Berau Regency in the years 2002 and 2018. For each grid point over land (N=78) in Berau Regency (1°N-3°N, 116°E-119°E), we calculated the average hourly temperature and relative humidity for the whole year, then averaged all the diurnal cycles for all 78 grid points in this region to create one regional mean diurnal cycle. We used this regionally averaged diurnal cycle to approximate the periodicity of the daily sinusoidal cycle and the linear decrease in temperature between sunset and the following sunrise. The diurnal cycle can vary slightly from month to month but given the proximity of Berau Regency to the equator, these monthly changes in mean diurnal cycle are minimal. Figure S2 shows the average monthly diurnal cycle (light dotted lines) and annual average (colored dark solid lines) over Berau Regency.

We combined the shape of this average diurnal cycle of temperature with the MODIS observations to estimate the hourly temperature for each day in 2002 and 2018; we used the daily MODIS observations to define the maximum and minimum values of the sinusoidal cycle, then we created continuous diurnal cycles for each day based on the two temperatures observed by the MODIS satellite. The solid grey line in Figure S2 shows an example diurnal cycle that combines the satellite-derived maximum and minimum temperatures (grey dots) for a given day with the shape of the reanalysis-derived diurnal cycle (colored lines).

In addition to our continuous temperature cycles described above, we needed a continuous estimate of relative humidity to calculate diurnal cycles of heat index. Hourly observations of relative humidity are not available at 1km resolution, so we assumed that the amount of water vapor in the atmosphere was constant over the Berau Regency and calculated relative humidity accordingly. This assumption, combined with our diurnal cycles of land surface temperature discussed above, generated a relative humidity diurnal cycle that closely matched the diurnal cycle in Berau Regency in ERA5 data (Figure S2). Thus, with just the two values for daytime and nighttime temperatures obtained from MODIS data, we were able to generate hourly estimates of heat indices using Rothfusz's modification of Steadman's work.

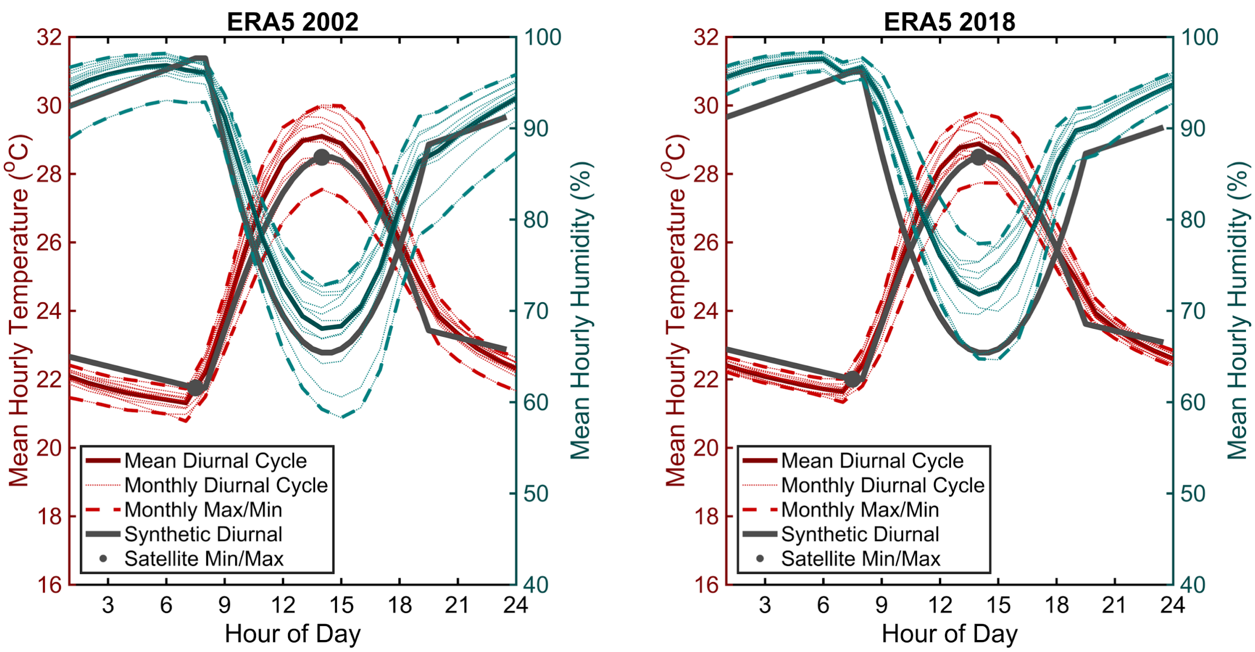

Figure S2. Average monthly diurnal cycle of land surface temperature (red) and relative humidity (teal) from the ERA5. Grey lines show an example sinusoidal diurnal cycle; the shape of this cycle was derived from the ERA5, and the maxima and minima (grey dots) were derived from the MODIS satellite observations of temperature. The grey line shown on top of the relative humidity diurnal cycle shows the hourly synthetic relative humidity diurnal cycle created using the satellite-derived daily maximum and minimum temperatures and assuming constant water vapor in the atmosphere over Berau Regency.

Heat index distributions

Diurnal heat index cycles were estimated from diurnal cycles of temperature and relative humidity. Heat indices were estimated using a refinement of Rothfusz's multiple linear regression analysis[13] of Steadman's complex, multi-parameter equations[31] (See https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml for the equations used). Rothfusz's primary contribution was to simplify Steadman's biometeorological equations, which included many difficult to measure physiological parameters, to a regression reliant on just temperature and relative humidity. The heat index value for the ACGIH Threshold Limit Value (TLV) for heat stress, based on existing literature for heavy physical work in agriculture or construction is 85 ^{o}F.

Given our temperature results, it was no surprise that heat indices were greater in 2018 than 2002 (Fig. S3a and S3b). Much of this difference between time periods can be explained by deforestation (Fig. S3c).

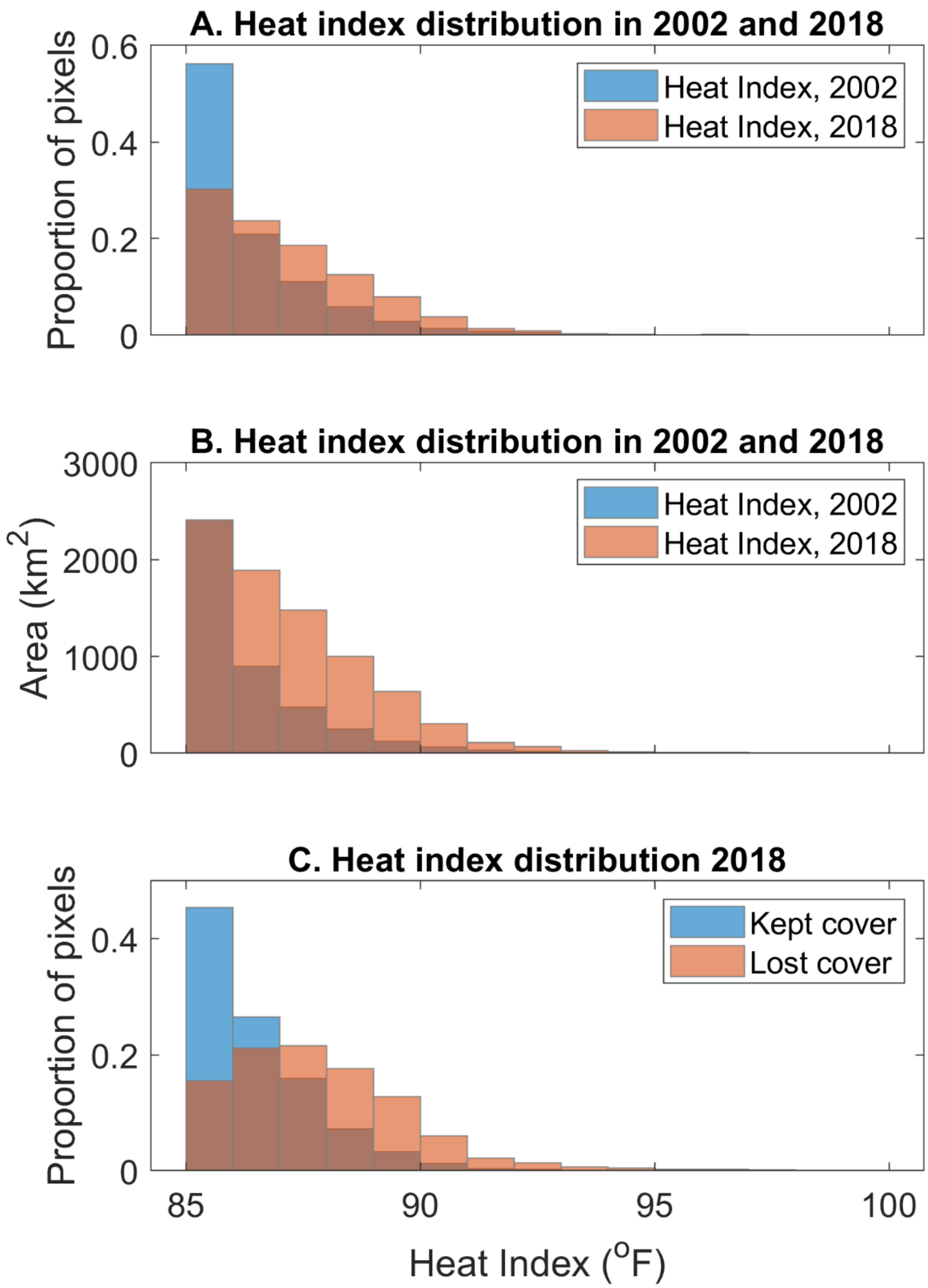

Figure S3. Mean maximum daily heat index distributions in 2002 and 2018 based on both proportion (a) and areal extent (b). Panel c compares the distribution of 2018 heat indices from pixels that kept forest cover with pixels that lost forest cover since 2002. Only pixels below 200 m are included. Only indices above the ACGIH Threshold Limit Value of 85 ^{o}F are shown.

Heat exposure: future

Climate Model Projections of Future Warming

Future global warming pathways are uncertain because future greenhouse gas emissions cannot be predicted. Therefore, where possible we do not rely on any specific warming scenario (e.g., Representative Concentration Pathway, or RCP, as used in the Intergovernmental Panel on Climate Change reports); instead we rely on robust relationships between global mean temperature change and local temperature change in Berau Regency. In this 'pattern scaling' approach[32], we regress global mean surface air temperatures (CMIP5 atmospheric surface temperature, or 'ts' variable) against local air temperatures in future global warming scenarios; we find that global mean temperature change is a good predictor of local change over Berau Regency. Specifically, climate models show that global mean temperature changes explain an average of 96% (N=39 models, SD 0.03%) of local temperature variance in Berau, with local temperature changing an average of 0.94ºC (N=39 models, SD 0.12ºC) per degree of global mean temperature change. We have tested the consistency of these results using the 2-m air temperature ('tas') CMIP5 variable and find no meaningful difference in our local warming per degree of global warming results.

We use CMIP5 RCP8.5 simulations to derive the relationships between global and local warming in Berau Regency in the 21st century. However, the RCP8.5 simulations can include factors influencing warming other than increasing atmospheric greenhouse gas concentrations, so we tested this global to local warming relationship in idealized CMIP5 simulations in which atmospheric concentrations of CO_2 increase by 1% per year and found minimal changes in our results (0.92ºC, N=33 models, years 1-140 of the idealized 1%CO_2 experiments).

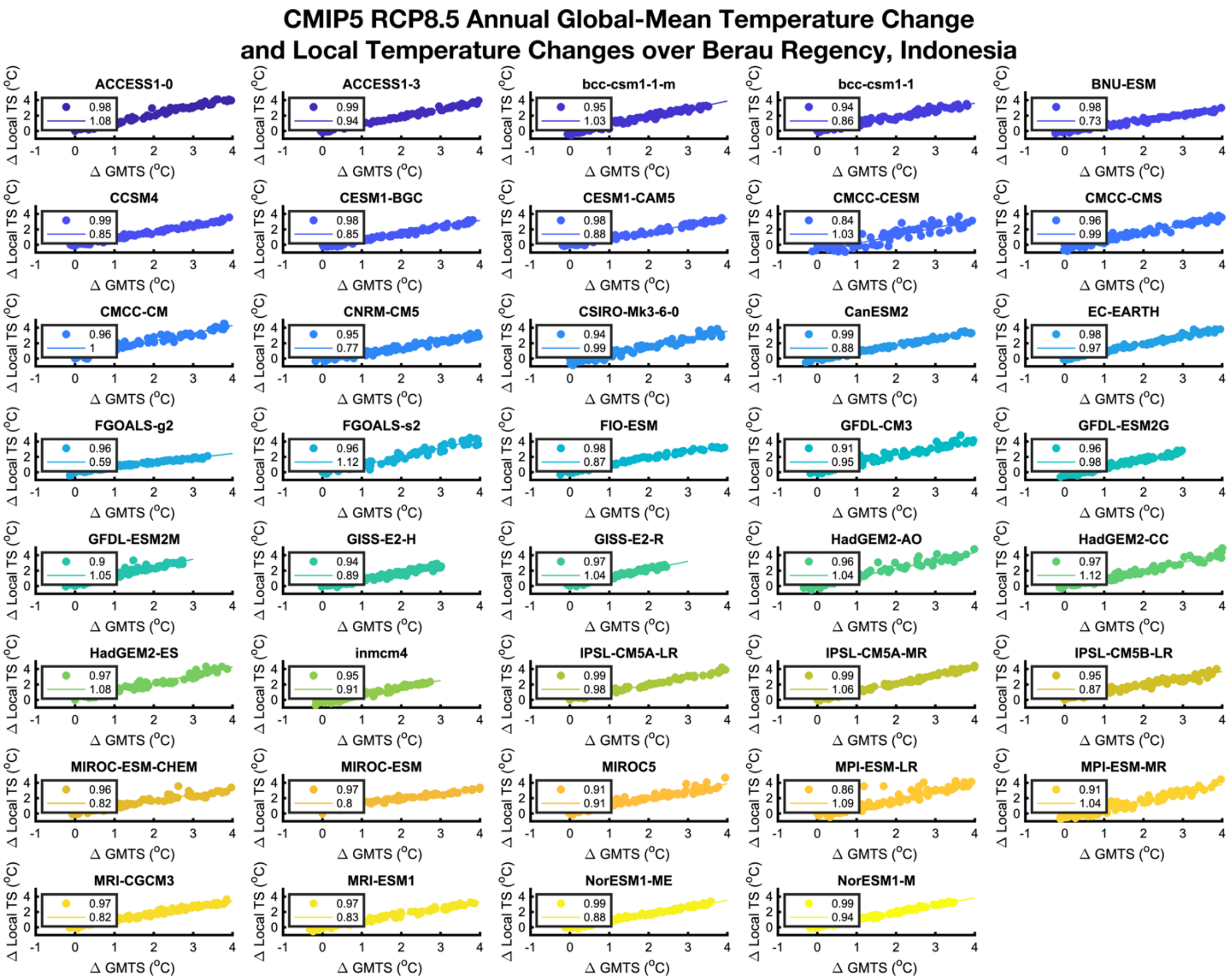

Figure S4. Regressions of global mean (GM) against local surface air temperatures over Berau Regency, Indonesia in 39 CMIP5 models. In each panel, the top number in the legend shows the r-squared statistic relating global to local temperatures, and the bottom number in the legend shows the regression coefficient. CMIP5 simulations are from the high emissions scenario, known as Representative Concentration Pathway (RCP) 8.5, but these global vs local regressions are robust regardless of modeling experiment (e.g., idealized 1%CO_2 or other RCP simulations).

We use average temperatures 2008-2027 in CMIP5 RCP8.5 simulations as a nominal 2018 baseline to compare to future temperature changes (Figure S5). Relative to the 2008-2027 baseline, CMIP5 models project global temperature increase of 1ºC in 2047 (2038-2057), 1.5 ºC in 2056 (2048-2074), and 2ºC by 2066 (2057-2089) under a high emissions scenario. These global mean changes are the equivalent of 0.94ºC, 1.41ºC, and 1.88ºC warming over Berau Regency (see Figure S4 for global vs local temperature relationships in these 39 CMIP5 models). Because warming patterns are robust regardless of emissions pathway with nearly identical warming patterns in idealized 1% CO2, RCP 8.5, and RCP. 4.5 experiments, we also show results for CMIP5 RCP4.5 simulations (Figure S5).

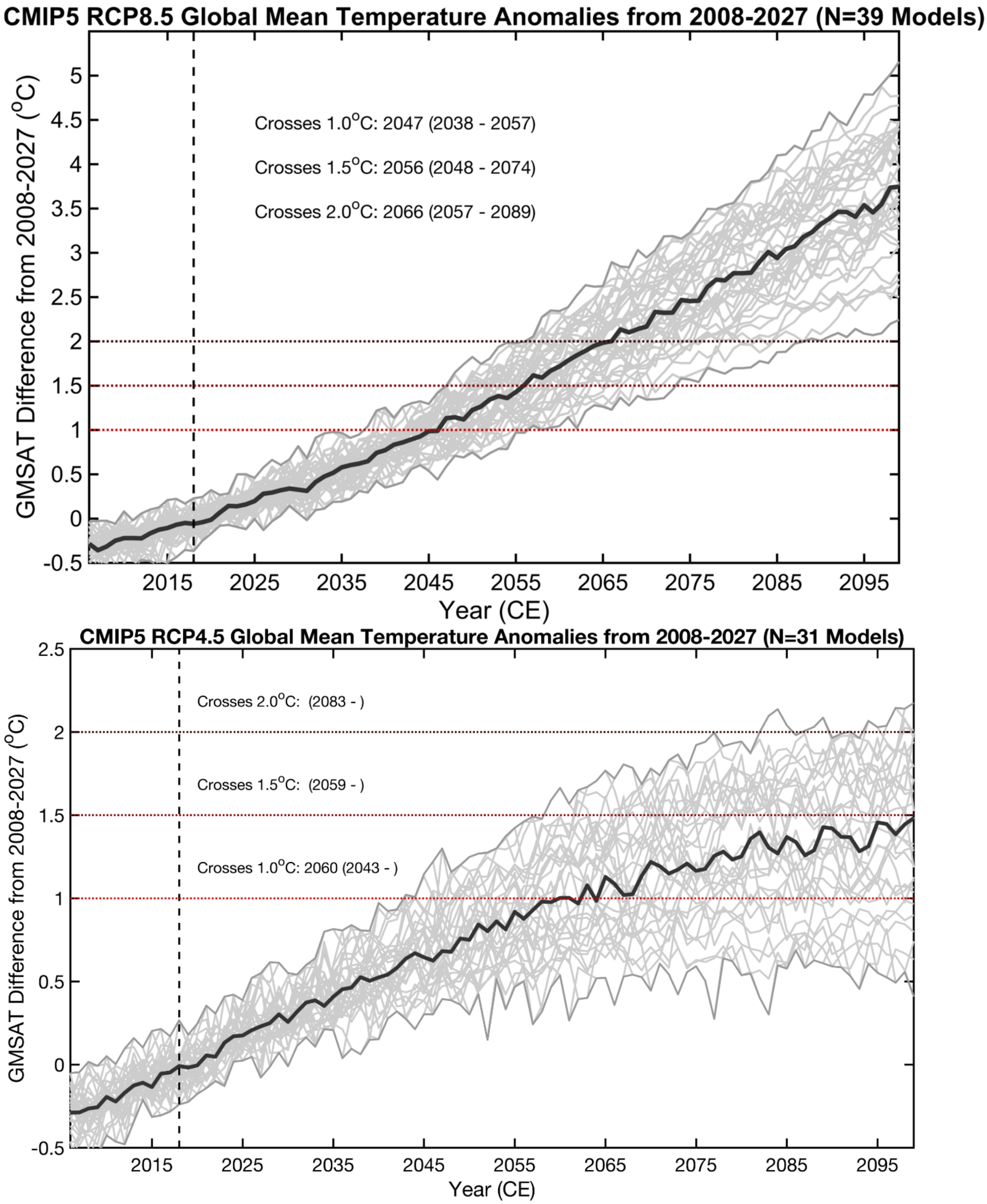

Figure S5. Global mean surface air temperature changes in CMIP5 models using the high emissions scenario, RCP 8.5 (39 models) and intermediate emission stabilization scenario, RCP

4.5 (31 models). Temperatures are normalized to each model's estimate of global mean temperatures in 2018. Dashed horizontal lines show 1, 1.5, and 2ºC temperature thresholds relative to ~2018 (2008 – 2027). Black line shows the multi-model median, and grey lines shows the spread across the individual CMIP5 models.

Spatially explicit population estimates

LandScan 2017 (*LandScan 2017™, Oak Ridge National Laboratory, UT-Battelle, LLC;* https://landscan.ornl.gov/)[15,33], which represents 2017 population estimates at approximately 1 km^2 (30″ X 30″) spatial resolution, was re-gridded to match the grid of the 1 km^2 MODIS temperature data used in this study (Fig. S6). LandScan is a community standard for global population distribution data and represents an ambient population (average over 24 hours) distribution. LandScan is developed using best available demographic (Census) and geographic data, remote sensing imagery analysis techniques and statistical modeling.

Berau Regency is very rural with a mean density of 7.1 people per km^2, considerably lower than the Indonesia average of 148 people km^{-2} (https://data.worldbank.org/indicator/EN.POP.DNST). Only 78 km^2, approximately 0.3% of the land area, has a density greater than 100 people km^{-2}. According to LandScan, over 83% of the Regency is devoid of people (Fig. S6). However, LandScan data likely underrepresents the amount of Berau land that is used by people. For example, some of the landscape classified as being devoid of people has been deforested.

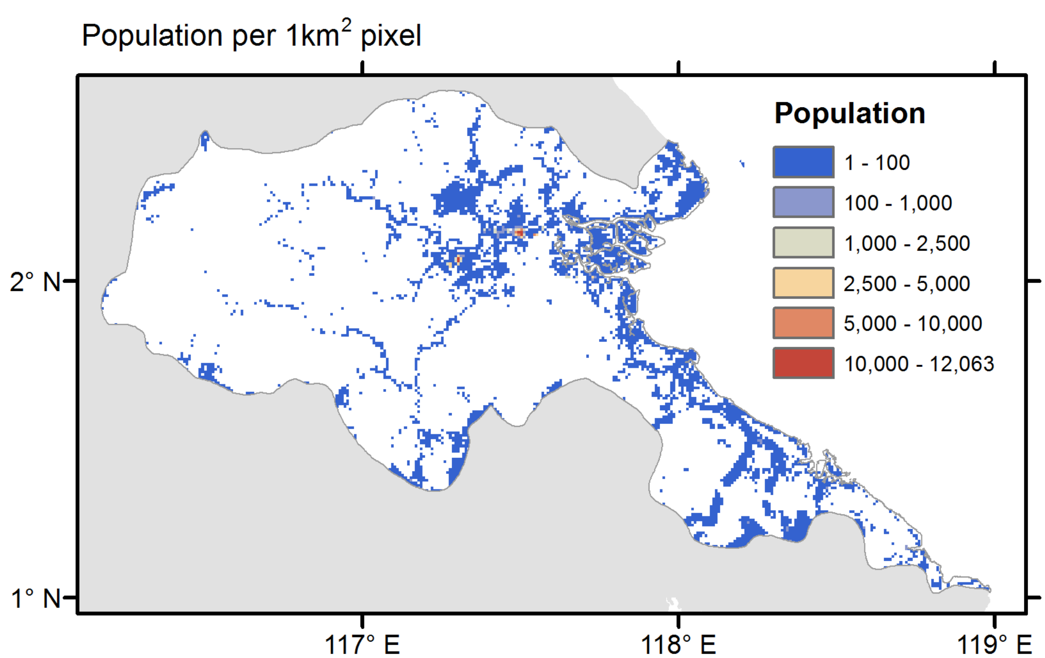

Figure S6. Spatially explicit population estimates for Berau Regency in 2017.
This product was made utilizing the LandScan 2017™ High Resolution Global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under

Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set.

Elevation data

Version 4.1 of the CGIAR-CSI SRTM dataset (http://srtm.csi.cgiar.org) was used to delineate regions of Berau Regency that were below 200 m for our analysis. The CGIAR-CSI SRTM dataset are derived from USGS/NASA SRTM data which are further processed to provide seamless continuous topography surfaces at an approximate resolution of 30 m.[34] These data were re-gridded to match the grid of the 1 km^2 MODIS temperature data used in this study (Fig. S6).

A threshold of below 200 m was used for comparing lost work hours per day in pixels that maintained forest cover with pixels that lost forest cover between 2002 and 2018. This threshold was used to minimize elevation effects on temperature (and thus Heat Index and lost work hours) and because most of the population (97.8%) lives in these lower elevations. Further, 89.3% of the 2002 to 2018 deforestation occurred below 200 m. Between 2002 and 2018, 3,905 km^2 of land below 200 m was deforested and 9,759 km^2 maintained forest cover.

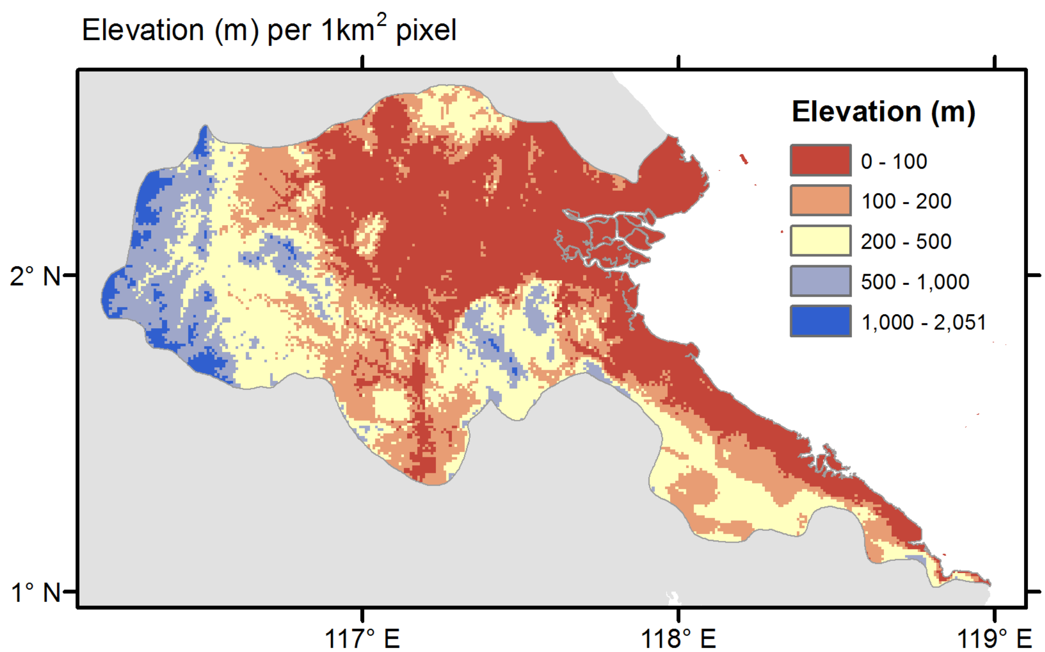

Figure S7. Elevation using version 4.1 of the CGIAR-CSI SRTM dataset (http://srtm.csi.cgiar.org). Data have been re-gridded from 90 $m^2$to 1km^2 resolution.

Heat vulnerability curves

We select Vietnam and the Philippines as sources of country-specific heat vulnerability curves for the Berau Regency because these countries are similar to the Regency in key drivers of heat-related mortality[16,20] (Table S1): per-capita health expenditure; percent of population aged 65 or over; percent of population below poverty line; percent of population with obesity; and mean daily temperature. Of these, percent population below the poverty line and mean daily temperature have the smallest effect on heat vulnerability, with the effect of the other three variables being roughly similar.[16] We analyzed background mean annual temperatures over the Regency, the Philippines, and southern Vietnam using three temperature data products and found mean annual temperatures are largely similar over the last decade.

Table S1 presents data for Berau (Indonesia), the Philippines and Vietnam on key drivers of heat-related mortality[16,35]: per-capita health expenditure; percent of population aged 65 or over; percent of population below poverty line; percent of population with obesity; and mean daily temperature.

Table S1. Comparative data for five key drivers of heat-related mortality for Indonesia (Berau), Philippines and Vietnam

	Indonesia	Philippines	Vietnam
Health expenditure per capita, 2016 US$, PPP [a]	363	342	356
Population below poverty line, %			
at PPP $1.90/day (2011) [b]	5.7	6.1	2.0
at PPP $3.20/day (2011) [b]	27	26	8.0
Population aged ≥65 y (2018), % [b]	6.0	5.0	7.0
Population obese (2016), %[c]	6.9	6.4	2.1
Mean daily near-surface air temperature, °C			
2010-2017 UDel [e]	26.4 (Berau)	25.3	26.5
2010-2018 GHCN CAMS [f]	26.0 (Berau)	25.5	26.9
2010-2018 ERA5 [g]	26.2 (Berau)	26.1	26.9

[a] WHO Global Health Expenditure Database (http://apps.who.int/nha/database/ViewData/Indicators/en) – current health expenditure per capita (in 2016 $ PPP).
[b] https://data.worldbank.org
[c] Prevalence of obesity among adults, BMI ≥ 30, age-standardized Estimates by country. Source: NCD Risk Factor Collaboration.[36]
[d] Lee et al.[16] Table S2 for Philippines and Vietnam.
[e] University of Delaware Air Temperature v5.01.[37] See text for calculations.
[f] Global Historical Climatology Network (GHCN) Climate Anomaly Monitoring System (CAMS).[38] See text for calculations.
[g] European Centre for Medium-Range Weather Forecast atmospheric reanalysis data product (ERA5), 2-m air temperature.[12]

Comparison of mean daily temperatures for the Berau Regency, the Philippines, and southern Vietnam

To compare background mean annual temperatures over Berau Regency (1.5ºN-2.5ºN, 116.5ºE-118ºE), the Philippines (5ºN-17ºN, 116ºE-127ºE), and southern Vietnam (10ºN-15ºN, 103ºE-

109ºE), we use three temperature data products: the European Centre for Medium-Range Weather Forecast atmospheric reanalysis data product (ERA5), the Global Historical Climatology Network (GHCN) Climate Anomaly Monitoring System (CAMS), and the University of Delaware (UDel) v5.01 product. ERA5 combines historical in-situ and satellite-based climate observations using data assimilation and modeling to provide hourly estimates of temperature on a 30km grid.[12] The GHCN CAMS data provide monthly time series (1948-2018) of gridded surface air temperature derived from homogenized station data combined with interpolation methods, such as spatially-temporally varying temperature lapse rates from reanalysis data.[38] The UDel land-only temperature data provide monthly time series (1900-2017) of gridded surface air temperature derived from the GHCN2 network and the Global Surface Summary of Day archive.[37] We compare mean annual temperatures over land for 2010-2018 (GHCN CAMS and ERA5) or 2010-2017 (UDel). The mean annual temperatures in southern Vietnam and Berau Regency are quite similar over the last decade (mean difference ~0.85ºC in the GHCN CAMS data, ~0.12ºC in the UDel data, and ~0.71ºC in the ERA5 data); the mean annual temperatures in the Philippines and Berau Regency are also quite similar over the last decade (mean difference ~0.47ºC in the GHCN CAMS data and ~1.06ºC in the UDel data, and ~0.11ºC in the ERA5 data), with Berau's mean temperature exceeding that of the Philippines but lower than Vietnam's (Fig. S8).

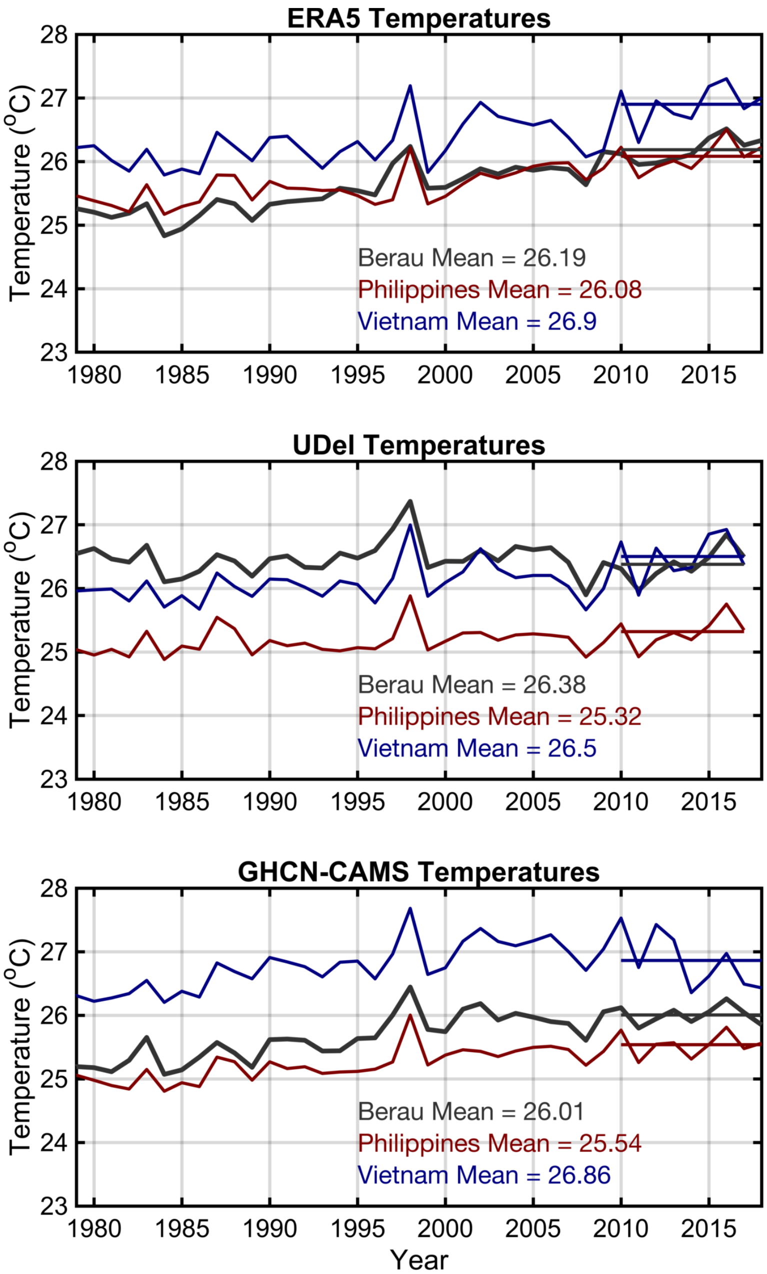

Figure S8. Near-surface air temperature time series over land for Berau Regency (1.5ºN-2.5ºN, 116.5ºE-118ºE), Southern Vietnam (~10ºN-15ºN, ~103ºE-109ºE) and Philippines (5Nº-17ºN, 116ºE-127ºE). Data from European Centre for Medium-Range Weather Forecast atmospheric reanalysis (ERA5), Global Historical Climatology Network (GHCN) Climate Anomaly Monitoring System (CAMS), and University of Delaware (UDel) Air Temperature data set v5.01. Country means and horizontal lines indicate average temperatures during 2010-2018 (GHCN-CAMS, ERA5) or 2010-2017 (UDel). Solid horizontal line in graphs marks the average temperature s in each region over these time periods.

Mortality and population data

Mortality

As stated in the text, we use East Kalimantan Province's mortality rates to estimate excess heat-related mortality from temperature increases because we need both all-cause and non-external mortality rates to apply Lee et al.'s[16] temperature-excess mortality slopes, and the latest published mortality rate for Berau Regency we were able to obtain was for 2012, and only for all-cause mortality. In 2012, the Regency's all-cause mortality rate (627 per 100,000 people) was slightly higher than that of East Kalimantan as a whole (597 per 100,000 people). All else equal, applying East Kalimantan's all-cause mortality rate to Berau thus would result in a downward bias in our mortality estimates for Berau. To further assess how representative East Kalimantan may be of Berau in terms of exposure, susceptibility and adaptive capacity to heat, in addition to their all-cause mortality rates, we compared the two using indicators for demographic, socio-economic, and health drivers of heat-related mortality and for population-level heat exposure.

Comparability of drivers of heat-related mortality

Lee et al. [16] identify four demographic, socio-economic and health drivers of heat-related mortality (see Table S1): health expenditure per capita, percent population below the poverty line, percent population aged 65 years or older, and percent of population obese. In addition to Berau and East Kalimantan having a similar all-cause mortality rate (see main text), comparable performance of the two geographies with respect to these drivers would support the assumption of comparable susceptibility and adaptive capacity to heat-related mortality. Table S2 shows data on these drivers for Berau and East Kalimantan, except for *percent obese population* and *health expenditures per capita*, data for which are available only at the Province level. We provide data on additional metrics as surrogate indicators in lieu of health expenditure per capita: *number of people per hospital bed*, *number of people per public health center*, *number of people per doctor*, and *standardized prevalence rate of healthcare utilization*. As Table S2 shows, Berau and East Kalimantan perform very similarly on these indicators.

Table S2: Data on key drivers of heat-related mortality, Berau Regency and East Kalimantan Province

	Berau	East Kalimantan
Share of population aged 65+y, % (2018)	3.1 [1]	3.4 [2]
Prevalence of obesity, % (2018)	n/a	35.6 [3]
Population below poverty line, % (2019)	5.0 [4]	5.9 [4]
No. of people per:		
Hospital (2015)	214,828 [5]	76,114 [5]
Hospital bed (2015)	1,432 [5]	704 [5]
Public health center (2015)	1,935 [5]	4,029 [5]
Doctor (2015)	2,066 [6]	1,738 [6]
Standardized prevalence rate of healthcare utilization, % (2013)		

Outpatient care	8.9 [7]	9.8 [7]
Inpatient care	2.5 [7]	2.6 [7]

Notes: *Percent population below poverty line*, *percent population aged 65 years or older*, and *percent population obese* are identified as key drivers of heat-related mortality in Lee et al. (2019). Other drivers shown in the Table are presented as substitute indicators for *health expenditure per capita*, another driver of heat-related mortality identified in Lee at al. (2019) for which no data are available for Berau. n/a – no data available; [1]Badan Pusat Statistik Kabubaten Berau [Central Bureau of Statistics Berau Regency], *Age Group Based on Gender, 2015-2018*, https://beraukab.bps.go.id/indicator/12/45/1/kelompok-umur-berdasarkan-jenis-kelamin.html (Accessed 30 March 2021). [2]Badan Pusat Statistik Provinski Kalimantan Timur [Central Bureau of Statistics East Kalimantan Province], *Population Projection by Age Group and Gender, 2018-2020*, https://kaltim.bps.go.id/indicator/12/100/1/-sp2010-proyeksi-penduduk-menurut-kelompok-umur-perempuan-laki-laki-.html (Accessed 30 March 2021). [3]Adisasmito et al.[39] [4]Badan Pusat Statistik [Central Bureau of Statistics Indonesia], *Percentage of Poor Population by Regency/City (2019-2020)*, https://www.bps.go.id/indicator/23/621/1/persentase-penduduk-miskin-menurut-kabupaten-kota.html (Accessed 02 March 2021). [5]Badan Pusat Statistik Provinski Kalimantan Timur [Central Bureau of Statistics East Kalimantan Province], *Number of Public Health Centres, Subsidary Public Health Centre and Doctor by Regency/Municipality, 2015*, https://kaltim.bps.go.id/statictable/2015/03/17/296/banyaknya-puskesmas-puskesmas-pembantu-dan-dokter-puskesmas-menurut-kabupaten-kota-2015.html (Accessed 30 March 2021). [6]Badan Pusat Statistik Provinski Kalimantan Timur [Central Bureau of Statistics East Kalimantan Province], *Number of Doctors by Regency/Municipality, 2015*, https://kaltim.bps.go.id/statictable/2015/03/17/289/banyaknya-dokter-menurut-kabupaten-kota-2015-.html (Accessed 30 March 2021). [7]Mulyanto et al.[40]

The indicators shown in Table S2 relate to susceptibility and adaptive capacity to heat. Additional factors such as wealth affect adaptive capacity to heat, and here we use surrogate metrics for income or level of development, such as average per-capita expenditures on food and non-food items, or Human Development Index (HDI). These vrairables are similar for Berau and East Kalimantan. In 2019, adjusted average annual per-capita expenditure (comprising food and non-food categories) was 12.7 million Rupiah in Berau and a comparable 12.4 million Rupiah in East Kalimantan.[1] In 2017, the Human Development Index (HDI), a composite index of three subindices that measure health (assessed by life expectancy at birth), education (measured by mean of years of schooling for adults aged 25 years and more and expected years of schooling for children of school entering age), and standard of living (measured by gross national income per capita), was 73.6 for Berau compared to 75.1 for East Kalimantan as a whole.[2]

[1] Badan Pusat Statistik [Central Bureau of Statistics Indonesia], *Adjusted Per Capita Expenditure (Thousand Rupiah / Person / Year), 2019-2020*. https://www.bps.go.id/indicator/26/416/1/-metode-baru-pengeluaran-per-kapita-disesuaikan.html (Accessed 01 March 2021).

[2] Badan Pusat Statistik [Central Bureau of Statistics Indonesia], *Human Development Index 2019-202*0. https://www.bps.go.id/indicator/26/413/1/-metode-baru-indeks-pembangunan-manusia.html (Accessed 02 March 2021).

Comparability of population-level exposure to heat

The occupational composition of Berau and East Kalimantan can serve as a proxy indicator for potential population-level exposure (Table S3).

Table S3: Percent of population by occupation, East Kalimantan Province and Berau Regency, 2020

	East Kalimantan	Berau Regency
Occupational distribution		
Not working	30.00%	30.88%
Homemaker	21.03%	21.05%
Student	17.12%	17.12%
Govt., Armed forces, Police	2.36%	2.58%
Agriculture (incl. plantations)	4.81%	8.86%
Fisheries	0.84%	2.67%
Industry, construction	0.12%	0.40%
Transportation	0.03%	0.05%
General employees	11.59%	8.29%
Govt enterprises	0.31%	0.22%
Contract employees	0.92%	0.90%
Freelance	1.70%	2.70%
Business owner	6.39%	1.78%
Teacher	0.57%	0.51%
Health providers	0.26%	0.21%
Others	1.94%	1.78%
TOTAL	100.00%	100.00%

Notes: Calculated from East Kalimantan Department of Population, Women's Empowerment, and Child Protection, *Total Population by Occupation, 2020*. https://dkp3a.kaltimprov.go.id/ (Accessed 01 March 2021)

Given that exposure to high ambient temperatures is related to type of work and workplace setting (especially, indoors vs outdoors), a similar occupational composition is expected to lead to similar heat exposure, all else equal. Table S3 shows that in 2020, Berau and the larger East Kalimantan Province had very similar distributions of their respective populations across the reported occupational categories. The most notable differences were a higher proportion of people working in agriculture and plantations (+4 percentage points [%p]) and a lower share of business owners (-4.6%p) in Berau Regency compared to the larger East Kalimantan Province. This suggests that, on average, Berau's population may be *more* likely to be exposed to excessive heat, all else equal. Importantly, a detailed comparison of the distribution of occupations between Berau and East Kalimantan underscores our argument that our mortality estimates are likely a lower bound estimate of true impacts in Berau.

Our comparison of key factors affecting susceptibility, exposure and adaptive capacity to heat suggests that East Kalimantan Province provides a strong and relevant proxy for Berau Regency in terms of key metrics that impact population heat exposure and adaptive capacity. Furthermore, given this comparison, our estimates of increases in heat-related mortality in Berau are likely biased low.

Population data

We used Berau Census Bureau data in this case because it is the most recent information and did not require spatially explicit information which is the primary benefit of LandScan 2017. Note that the total Berau population estimates are different across these two data sets: 177,385 according to LandScan 2017 and 232,528 according to Berau Census Bureau from 2018. However, LandScan 2017[15] utilizes census counts, along with data on roads, landcover, and other spatially explicit factors when generating their dataset. Their population distribution model estimates a "likelihood" coefficient, which is then applied to each cell to provide spatially explicit population data, and thus provides an average a day/night population count. The Landscan 2017 data provide rigorous spatially explicit population distribution information, which is then used to estimate the population weighted temperature change.

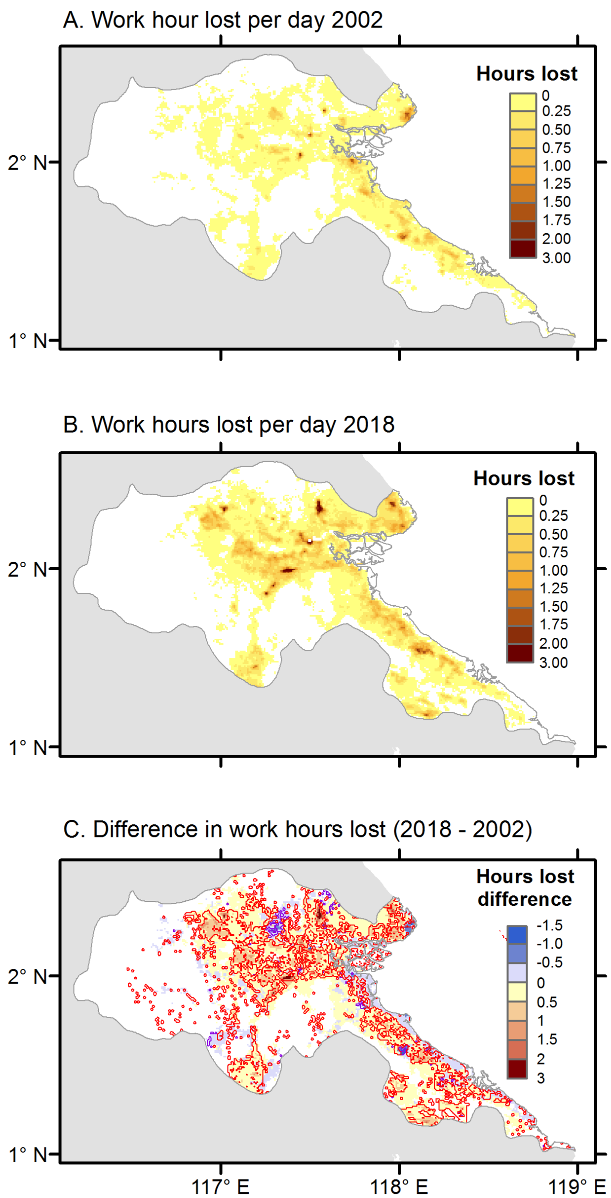

Figure S9. Estimates of average work hours lost per day at each pixel in 2002 (a) and 2018 (b). Panel (c) shows the difference between 2018 and 2002 indicating how many extra hours per day have been lost or gained between the two years. Red contours delineate forest lost since and blue contours delineate forest gain since 2002. Note, only differences greater than 0.5 and less than -0.5 hours are shown. Differences greater than 2 hours are shown in dark red.

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