# Extreme Heat: The Economic & Social Consequences for Global Cities

## Methodology

Prepared for the Adrienne Arsht-Rockefeller Foundation Resilience Center at the Atlantic Council

July 2022

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# Contents

# List of Tables



# List of Figures



# List of Boxes

# 1 Introduction

**This methodology document accompanies the July 2022 report "Extreme Heat: The Economic & Social Consequences for Global Cities," prepared for the Adrienne Arsht-Rockefeller Foundation Resilience Center at the Atlantic Council.** The methodology document provides additional detail into the assumptions of the main report and the sources relied on to support and develop those assumptions. The contribution of the main report is to quantify some of the likely economic and social effects of heat in a selection of global cities under current and possible future conditions. It provides new, quantitative evidence on the economic importance of heat for policymakers and investors and shows how they are disaggregated across sectors of the economy. The paper considers only a subset of the ways in which extreme heat can impact a city's economy and society and appraises impacts only in 'normal' – as opposed to unusually warm – years, meaning it provides a conservative view of the overall significance of the issue.

**This methodology proceeds as follows:**

- **Section 2:** Description of the underlying climate modelling used to produce the heat data for all subsequent analyses: indoor and outdoor simplified Wet Bulb Globe Temperature (WBGT) and local relative heat days, and explanation of the "workability" model which relates indoor and outdoor WBGT to effective labor losses due to heat stress.
- **Section 3:** Outline of the economic production model used to estimate lost value added due to reduced worker productivity from WBGT-related heat stress, and core assumptions on sectoral exposure to heat stress.
- **Section 4:** Explanation of the Urban Heat Island (UHI) effect modelling for 2020 and projections to 2050.
- **Section 5:** Description of the model that relates local excess mortality increases to increases in local relative heat days.
- **Section 6:** Bibliography of references and sources to support the methodology.

# 2 Heat Stress Modelling

**This work advances previous analysis on the impacts of heat in the United States**[1] **by adopting the most current generation of climate models.** Climate models are complex computational models based on physics that simulate the atmosphere, ocean, land, biosphere, and cryosphere down to resolutions of roughly 100km-by-100km. This analysis draws from an ensemble of around 100 climate models known as general circulation models (GCMs) or earth system models; they are developed, owned, and operated independently by 48 leading scientific research institutions across the world.[2] The World Climate Research Programme brought these models together to run standardized experiments to determine the likely outcome of various rates of carbon emissions in an undertaking known as CMIP6: Coupled Model Intercomparison Project 6. The results of the CMIP project are the most widely used source of climate projections in climate research today.

The analysis also draws on projections from an ensemble of statistically downscaled and bias-corrected climate models to obtain a finer resolution from the simulations. This allows scientists to more accurately investigate future climates in regions with complex terrain and ensure adequate representation of the historical observations. These climate data are produced using the CMIP6 SSP3-7.0 scenarios and the ERA5-Land reanalysis dataset for the historical input data. All model results are downscaled to $9km^2$.

**We selected four well-performing models for use in this analysis to reflect the variation and uncertainty across CMIP6 models.** We relied on the multimodel ensemble mean or median projection as the central projection to feed into the impact modelling to avoid the bias of any individual model. In line with IPCC guidance, we averaged models across consistent degrees of warming rather than time horizons to allow for the models to warm at their own rate yet be consistent with our ensemble mean. Our ensemble selection was chosen for each individual model's independence and varying sensitivity to capture a well-rounded ensemble result. As we focused on SSP3-7.0 and outcomes to 2050 in this analysis, we modelled the different measures of heat at approximately 2°C global mean temperature increase, which is consistent with that scenario and time horizon. SSP3-7.0 consists of rising emissions and temperatures with $CO_2$ concentrations nearly doubling by 2100 compared to current levels. This pathway is considered a medium to high end future forcing pathway, where countries become more competitive with each other for things such as securing their own food sources.[3] This climate scenario selection provides a view of how large relative losses might be without large abatement and adaptation, while the

[1] Adrienne Arsht – Rockefeller Foundation Resilience Center (2021). Extreme heat: The economic and social consequences for the United States. 31 August 2021. Available at: https://www.atlanticcouncil.org/in-depth-research-reports/report/extreme-heat-the-economic-and-social-consequences-for-the-united-states/

[2] Zeke Hausfather for CarbonBrief (2019). CMIP6: the next generation of climate models explained. 2 December 2019. Available at: https://www.carbonbrief.org/cmip6-the-next-generation-of-climate-models-explained/ Full list of participating modelling groups available at: https://wcrp-cmip.github.io/CMIP6_CVs/docs/CMIP6_institution_id.html

[3] Zeke Hausfather for CarbonBrief (2018). Explainer: How 'Shared Socioeconomic Pathways' explore future climate change. 19 April 2018. Available at: https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change/

economic scenario results in moderate expectations of the absolute dollar value associated with future losses, due to the smaller expected sizes of economies.

**Projections from climate models are the key input driving the results of the analysis.** The modelling uses two different measures of heat as inputs:

- **Wet Bulb Globe Temperature (WBGT).** WBGT is a type of apparent temperature which usually takes into account the effect of temperature, humidity, wind speed, and visible and infrared radiation – these factors mediate the impact of temperatures on the human body. WBGT projections feed into the workability calculation. The simple WBGT was calculated daily using average temperature, maximum temperature and relative humidity based on Stull et al. (2011)[4] and Parsons (1995)[5] for each model over the twenty-year period surrounding each model's appropriate degree of warming time. The mean, mid and max WBGT each represented four working hours for a total of a 12-hour working day in which losses were calculated. The daily average WBGT was then calculated.
- **Days above the local 90$^{th}$ and 97.5$^{th}$ percentile air temperatures.** Local relative extreme heat is an important determinant of health outcomes, as bodies and behaviors adapt to some degree to local conditions. Over the twenty-year period baseline period of 1986-2005, the local 90$^{th}$ and 97.5$^{th}$ percentile of average and maximum air temperature was computed. The number of days above this historical threshold were calculated for the twenty-year periods surrounding each model's appropriate degree of warming time. The model ensemble was computed for the average number of days per year in a 2°C world above the historical extreme percentiles.

**The workability analysis captures how labor productivity declines as workers are subjected to greater human heat stress.** The effect of heat stress on work comes through two channels: the need to take breaks to rest, hydrate, or seek cooling in a less exposed environment, and a natural self-limiting response of an overheated body reducing effort to maintain function. There is a well-established literature and experimental body of evidence relating productivity loss to the WBGT.

**Three different damage functions were applied to the WBGT daily averages to calculate the workability at that temperature.** The functions represent indoor work (indoor or outdoor in shade[6], outdoor work (Dunne et al. (2013))[7] and sedentary work (Pilcher et al. (2002))[8]. We also introduced adaptive outdoor workability. For any day where the maximum WBGT was above 31°C, the mid-point WBGT (the average between the mean and max WBGT) was applied instead. This

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[4] R. Stull, 'Wet-bulb Temperature from Relative Humidity and Air Temperature," Journal of Applied Meteorology and Climatology, November 2011, Volume 50, pp. 2267–69.

[5] Parsons, K.C., 'International heat stress standards: a review', Ergonomics 38 (1), 6-22

[6] McKinsey Global Institute, 'Climate risk and response: physical hazards and socioeconomic impacts', January 2020

[7] John P. Dunne et al., "Reductions in labour capacity from heat stress under climate warming," Nature Climate Change, February 2013, Volume 3, pp. 563–66; Josh Foster et al., "A new paradigm to quantify reduction of physical work capacity in the heat," Medicine and Science in Sports and Exercise, 2019, Volume 51, Number 6, p. 15.

[8] Pilcher JJ, Nadler E, Busch C. Effects of hot and cold temperature exposure on performance: a meta-analytic review. Ergonomics. 2002 Aug 15;45(10)

method was introduced to mimic hour shifting to avoid the hottest parts of the working day and work under cooler temperatures.

# 3 GVA losses

## 3.1 Exposure to heat

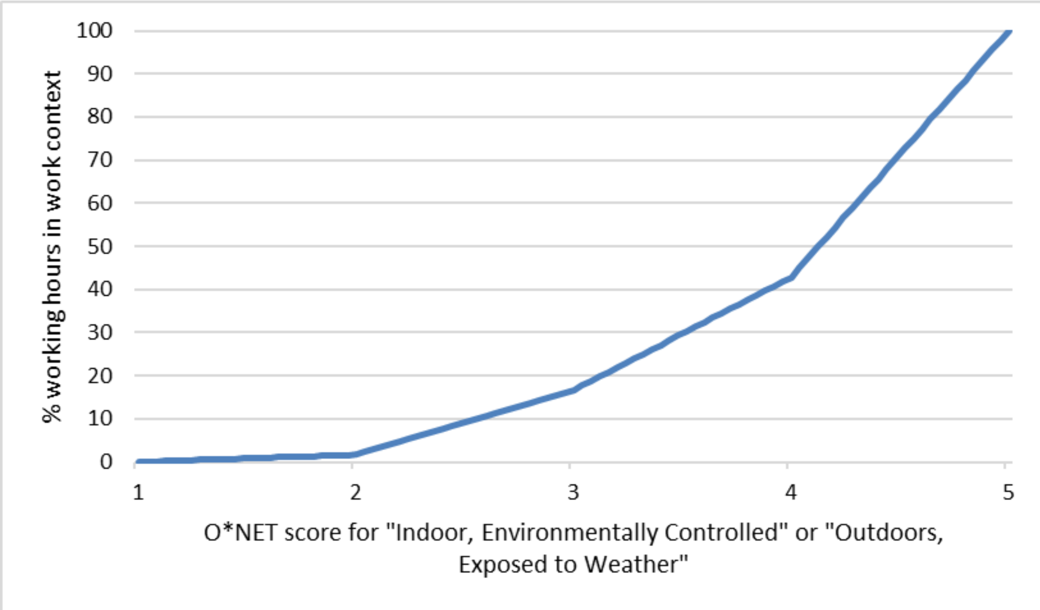
### 3.1.1 Outdoor and climate controlled work

**Heat stress affects labor productivity only when workers are exposed to the heat.** Workers who enjoy fully air-conditioned commutes and workplaces will not experience any loss of productivity. Modelling the effects of human heat stress on labor productivity requires determining how much work in each sector is done outdoors or in non-climate-controlled buildings. A city where all work is done in climate-controlled environments would have zero workability loss regardless of the incidence of heat stress in that geography. However, there are no direct sources of data on the exposure of different sectors to heat, so expert judgment determines the levels of exposure applied based on the best data available.

**O*NET Database informs the estimation of economic activity's exposure to indoor and outdoor heat stress.** O*NET Database is a resource developed by the US Department of Labor to catalogue the working conditions and skill requirements of detailed occupations.[9] The data report how frequently work is done outdoors, inside in non-climate-controlled buildings, and inside in climate-controlled buildings. Data is additionally provided on the frequency of time spent sitting and standing for each occupation. **O*NET scores report frequency of exposure to a range of work contexts, which must be converted into percentages of time exposed.** The percentages of time spent with air conditioning ("AC") and outdoors for given jobs are based on the "Indoor, Environmentally Controlled" and "Outdoors, Exposed to Weather" variables from the O*NET® 26.2 Database 'Work Context' file, respectively. The formula relating O*NET scores to percentage exposure is as follows: a score of 2 corresponds to being exposed to the given work context one day every other month ("Once a year or more but not every month"), 3 to being exposed two months in a year ("Once a month or more but not every week"), 4 to being exposed 3 times per week ("Once a week or more but not every day"), and 5 to being exposed every day. Linear interpolation completes the mapping of O*NET scores to percentage exposure between these inflection points. Figure 1 illustrates the function relating the O*NET score from 1-5 to a percentage from 0-100.

[9] Outdoor work: (O*NET OnLine, 2021c), Indoor, not environmentally controlled work: (O*NET OnLine, 2021b), Indoor, environmentally controlled work: (O*NET OnLine, 2021a)

Figure 1: Mapping O*NET score to percent of working hours in work context




Source: Vivid Economics, O*NET

### 3.1.2 Downscaling US AC estimates to global cities

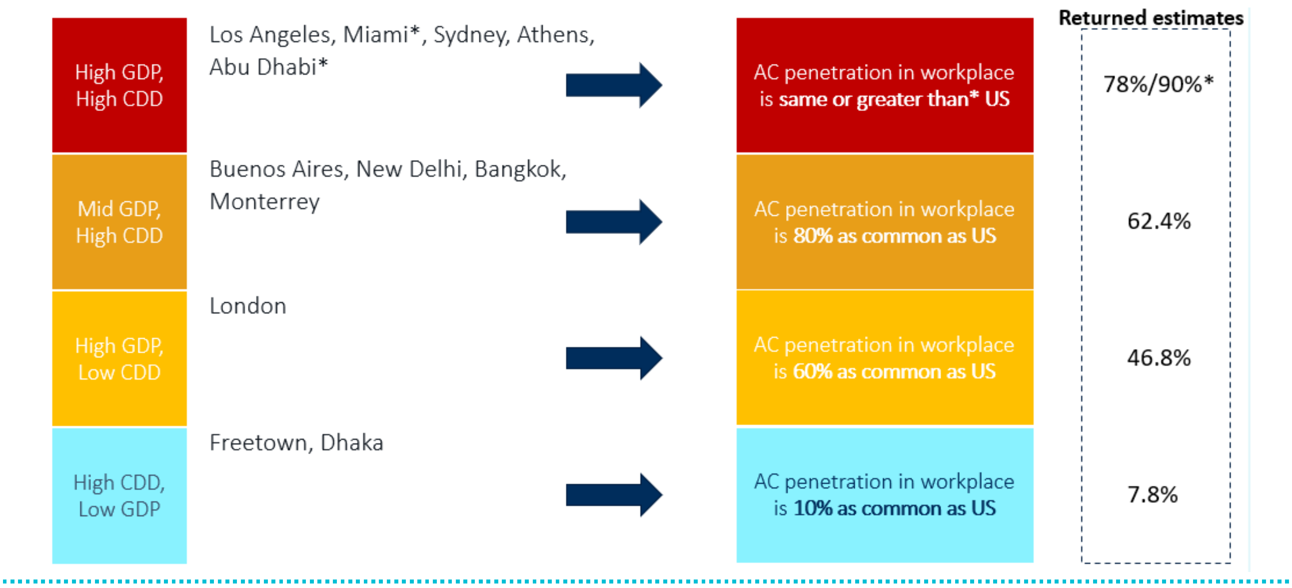
**Providing accurate city-level estimates of heat exposure requires adjusting estimates of working conditions in that city.** O*NET provides data on US nationwide working conditions. We assume that across global cities, occupations are treated identically and share the same share of time spent outdoors versus indoors in active or sedentary work. This is a strong assumption given potential variability of occupations within a sector, but likely a conservative one as US occupations in a given major sector are potentially more indoor and sedentary on average than occupations in the same major sectors in other, particularly developing, cities. However, cities are estimated to have different availability of AC within the workplace.

**Where data on air conditioning coverage is not available, we estimate workplace availability of AC using income per capita and the local need for cooling.** Where data on AC workplace coverage is available at the city or national level, we use this as our primary data source. However, where this data is not available, we follow published academic literature (McNeil and Letschert, 2008; Davis et al., 2021) in estimating AC availability according to two-dimensional framework: the income level (GDP per capita) and climate (number of cooling degree days, or CDDs). By examining EU27 service sector data (European Commission, 2018) and global household data on AC availability (McNeil and Letschert, 2008), we developed an income threshold of \$2,500 (\$2,000 USD, in PPP) and a climate threshold of 500 CDDs. We then categorized cities according to these criteria, using data from the World Bank[10] and local climate data.[11] This allowed us to develop four categories for scaling US AC data, set out in Figure 2, which are calibrated to available data.

[10] International Comparison Program, World Bank | World Development Indicators database, World Bank | Eurostat-OECD PPP Programme. https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD

[11] Cooling degree days is the product of the number of days multiplied by the temperature difference above 18˚C in a year, measured as a 5-year average from a centrally-located weather station. Degree Days.net, www.degreedays.net

Figure 2: A framework for estimating national air conditioning penetration




Note: Cities marked with an asterisk are assumed to have AC penetration 15% higher than the US average, yielding an average penetration rate in the workplace of 90%.

Source: McNeil and Letschert, 2008; Davis et al., 2021

### 3.1.3 Active and sedentary indoor work

**To incorporate workability curves which consider both active and sedentary indoor productivity impacts, we use O*NET scores for time spent standing and sitting.** As discussed in Section 3, we draw on workability curves representing losses from both active and sedentary indoor work. We first calculate the 'indoor' share of working hours from the residual after accounting for time exposed to AC and time spent outdoors.[12] To estimate the split between active and sedentary indoor work, we convert O*NET scores for time spent standing and sitting into percentages, and then calculate their relative shares of indoor time. Indoor work multiplied by time standing's share gives the work hours percentage exposure for active indoor work, while indoor work multiplied by time sitting's share gives the work hours percentage exposure for sedentary indoor work.

**Table 1 below shows estimates for time spent indoors in an air-conditioned environment, time spent indoors in a non-air-conditioned environment in both sedentary and active work, and time spent outdoors in an unshaded environment for the list of NAICS sectors.**

[12] If time exposed to AC and time spent outdoors account for 100% of working hours, then indoor exposure is equal to zero.

Table 1: Heat exposure data from O*NETS inform our understanding of working conditions – example data for Los Angeles

| **Major sector for analysis** | **NAICS sector** | **NAICS code** | **Time indoors with AC** | **Time indoors and sedentary without AC** | **Time indoors and active without AC** | **Time outdoors** |
|---|---|---|---|---|---|---|
| Agriculture | Agriculture, Forestry, Fishing and Hunting | 11 | 29% | 5% | 6% | 59% |
| Construction and other outdoor occupations | Mining, Quarrying, and Oil and Gas Extraction | 21 | 15% | 16% | 27% | 42% |
| Construction and other outdoor occupations | Utilities | 22 | 39% | 3% | 6% | 52% |
| Construction and other outdoor occupations | Construction | 23 | 14% | 2% | 16% | 69% |
| Manufacturing | Manufacturing | 31-33 | 39% | 19% | 41% | 1% |
| Logistics | Wholesale trade | 42 | 72% | 12% | 9% | 6% |
| Logistics | Retail trade | 44-45 | 49% | 11% | 34% | 5% |
| Logistics | Transportation and warehousing | 48-49 | 24% | 11% | 7% | 57% |
| Business administration | Information | 51 | 77% | 15% | 2% | 7% |
| Business administration | Finance and insurance | 52 | 75% | 23% | 2% | 1% |
| Business administration | Real estate and rental and leasing | 53 | 55% | 12% | 2% | 31% |

| Major sector for analysis | NAICS sector | NAICS code | Time indoors with AC | Time indoors and sedentary without AC | Time indoors and active without AC | Time outdoors |
|---|---|---|---|---|---|---|
| Business administration | Professional scientific and technical services | 54 | 75% | 16% | 2% | 7% |
| Business administration | Management of companies and enterprises | 55 | 65% | 29% | 3% | 3% |
| Other services | Administrative support and waste management | 56 | 58% | 24% | 15% | 2% |
| Public services | Educational services | 61 | 75% | 15% | 10% | 1% |
| Public services | Healthcare and social assistance | 62 | 88% | 5% | 5% | 2% |
| Leisure | Arts entertainment and recreation | 71 | 67% | 11% | 18% | 5% |
| Leisure | Accommodation and food services | 72 | 49% | 2% | 48% | 2% |
| Other services | Other services (except public administration) | 81 | 80% | 11% | 9% | 0% |
| Public services | Government and government enterprises | 92 | 52% | 12% | 5% | 31% |

Note: Percentages may not sum to 100% due to rounding.

Source: O*NET, Vivid Economics

## 3.2 Output losses – production function

**The analysis uses a simple economic model to estimate the impact of worker heat stress on economic production.** Production within each sector follows a Cobb-Douglas production function with constant returns to scale, where $Y$ represents output, $A$ total factor productivity, $L$ labor input, K capital input, and β is the labor share in production. Exposure to extreme heat reduces the productivity of labor, reducing the effective size of the labor force. We do not model second order capital substitution effects from reduced labor productivity.

$$Y = AL^{\beta}K^{(1-\beta)}$$

$$Marginal\ product\ of\ labor\ (MPL):\ \frac{\partial Y}{\partial L} = \beta\frac{Y}{L}$$

Given the nature of the production function, estimating economic losses associated with extreme heat for the baseline and 2050 require three inputs:

- the labor share in production (β), which the analysis assumes remains constant over time;
- sector output at the city level, which is projected forward to 2050;
- effective reduced labor supply due to heat stress (from outdoor, indoor active, and indoor sedentary shares of working time), which is modelled historically and for 2050.

**Output losses are translated to economic losses expressed in dollar terms by multiplying the sector's loss in output by the value of the sector.** Exposure to heat leads to a negative labor supply shock and a corresponding reduction in sectoral output, which is transformed into an economic loss according to the total size of the sector. Economic losses depend on the total value of the sector, the overall exposure to heat and the share of labor in the production function.

**The analysis assumes that losses are already embedded in reported GDP data and forecasts**. That is, if reported GDP in a city in 2020 is $95mn, and the workability-related losses are 5%, the gross GDP without exposure to heat stress would have been $100mn.

### 3.2.1 Labor share in production

**The component β can be approximated by the relative earnings to labor for each sector.**[13] The analysis assumes that β is sector specific and varies across countries but not over time. The sectoral share of labor in the production function is estimated from the Global Trade Analysis Project (GTAP) 2014 Social Accounting Matrix (SAM) for each country. The relative earnings are calculated as:

$$\frac{Rent\ paid\ to\ labor}{Rent\ paid\ to\ physical\ capital + \ Rent\ paid\ to\ natural\ capital + \ Rent\ paid\ to\ labor}.$$

### 3.2.2 City-level sector output

**The gross value added (GVA) for each sector and city is extracted from regional economic accounts[14] and projected forward to 2050.** Projections use Murakami and Yamagata's (2019)

[13] This relies on the assumption of perfect competition in the economy. Under perfect competition, profit-maximizing behavior means that the factors of production are paid a return equal to their respective marginal products.

[14] Major economic sectors of analysis for regional employment and GVA accounts are mapped to NAICS codes, as set out in table 2. Where regional accounts are available for a smaller or larger economic geography, estimates are downscaled using regional GDP as a scaling factor and sector allocations are adjusted to reflect the composition of the city's economy based on additional research. We generally adopt 2019 as the baseline year to avoid capturing the effects of Covid-19 and instead reflect economic activity in a 'typical' year.

gridded geospatial projections of GDP and population growth under different development scenarios. The analysis takes the GDP forecast for the SSP3 scenario (our central scenario across all analyses) and assumes that sectoral GVA grows proportionally with the city's GDP growth. This assumes there is no structural economic transformation, which is discussed in Box 1.

### 3.2.3 City-sector labor supply

**Regional economic accounts provide the baseline number of jobs in each sector and each city, which is projected forward using SSP3-aligned population forecasts from Murakami and Yamagata (2019).** By using NAICS level employment data, we are able to build weighted average heat exposure profiles for major economic sectors in each city. Once again, the analysis assumes that sectoral employment shares are unchanged, but that total employment grows proportionally with overall population growth. This assumes there is no structural transformation nor demographic impacts on overall employment rates.

Box 1: Structural economic transformation in the model

**In this analysis, the structure and spatial distribution of economic activity in 2050 does not change from 2020.** Key features of the economy remain fixed within each city at baseline levels:

- sectoral composition of economic activity
- the share of capital and labor in each sector
- sectoral and overall employment rates

These are inherently unrealistic assumptions, as the economy should undergo some adaptation to the extreme heat modelled in the future:

- Heavily exposed areas should reduce their economic activity in outdoor work (sectoral shift)
- Heavily exposed sectors should increase their capital intensity (capital/labor shift)
- Employment rates may change due to transition effects (exposed occupations shrinking and requiring a smaller workforce)

However, they are useful assumptions to illustrate the effect of climate change without adaptation. Likewise, the emissions pathway under SSP3-7.0 contains certain assumptions on economic activity that may be inconsistent with any adaptation pathway modelled as a response to extreme heat. As such, the results indicate how the impact of extreme heat will evolve if current ways and places of living and working are maintained.

In addition, while we do not model structural adaptations to heat, where clearly relevant we do consider the impact of hours-shifting on reducing exposure to outdoor heat. This adjusted outdoor workability is applied Abu Dhabi, where regulations limiting exposure to heat are already in place.

### 3.2.4 Effective reduction in labor supply due to heat stress

**The effective reduction in labor supply due to heat stress is a combination of the workability data (Section** Error! Reference source not found.**) and the exposure analysis (sections 3.1. and REF _Ref100593527 \r \h 3.1.3).** For example, if the workability modelling estimates a 20% loss in outdoor workability in a given city, and workers in sector 1 have 100% outdoor heat exposure, the effective reduction in labor supply is 20%. In contrast, workers in sector 2 have 50% heat exposure, the effective reduction in their labor supply is 10%.

# 4 Urban Heat Island (UHI) Effect

## 4.1 Baseline UHI effect

**Baseline UHI effect is calculated as the difference between urban land surface temperatures and the average of a sample of rural areas around the urban core in the baseline scenario.** The sample of rural points is selected at random using geospatial statistical software within the bounding box of the raster tile of the city. Land surface temperatures (LST) are measured using satellite products from Landsat 8, which provide LST at a 30m$^2$ resolution.[15] Within each 30-meter square cell we calculate the average of the last 10 years of summer month land surface temperatures and then process the data to clear clouds and address data errors or issues. To assess the UHI effect in each cell, we then subtract a similar 10-year summer month average LST for the sample of rural comparator cells.

**Modelled UHI effect in 2050 captures both climate change and development related intensification.** Future air temperature projections developed as discussed in Section 2 are applied to calculate land surface temperature in 2050. To calculate land surface temperature in 2050, we use future air temperature projections in 2050 and calculate the average difference between air temperatures in the baseline and 2050 per cell. We then apply the difference to the baseline land surface temperature to calculate the temperature in each cell in 2050. This approach assumes that the relationship between air temperatures and LST remains constant over time. The analysis also considers the impact of UHI from urban form in the future and uses Huang et al. (2019)'s models to project the future UHI due to urban land expansion.[16] Future UHI is calculated as the difference in land surface temperature in 2050 in the urban area and an average of a sample of rural points around the urban area in the baseline.

[15] Landsat-8 Collection 2 Level 2 dataset courtesy of the U.S. Geological Survey

[16] Huang, Kangning, et al, ' Projecting global urban land expansion and heat island intensification through 2050', 2019 Environ. Res. Lett. 14 114037

# 5 Mortality

**The mortality analysis draws on C40 Cities' Heat Resilient Cities Tool's mortality modelling.** Each city's population is broken down into Infants (0-1 years), Adults (2-64 years) and Elderly (65 years +), with country- and age group-specific values for all-cause daily mortality drawn from WHO Life Tables. The model then provides climate-specific percentages of all-cause mortality which is attributable to temperature in each Köppen Climate Zone, corresponding to temperatures between the $90^{th}$ and $97.5^{th}$ percentiles and above the $97.5^{th}$ percentile for a given Climate Zone.[17] Population growth rates are taken from Murakami and Yamagata (2019)'s global SSP3 projections, downscaled to city level, and demographic changes are modelled using UN World Population Prospects (WPP) projections.[18] The additional deaths due to extreme heat are calculated by multiplying these age-specific changes in mortality rates (due to additional days above temperature thresholds) by the local population in each city, producing a multiplier for heat-related deaths in 2050 relative to the baseline climate.

[17] Supplementary research was used to identify Köppen Climate Zones for Abu Dhabi and Monterrey, which are not included in the C40 Cities' Heat Resilient Cities Tool.

[18] Murakami and Yamagata, Estimation of Gridded Population and GDP Scenarios with Spatially Explicit Statistical Downscaling, 2019

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