Heat Stress, Pollution Risk, and Population Exposure: Evidence from Selected Asian Countries

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ERDI Seminar, Aug 2025

Background and Motivation

Heat stress and air pollution risks in Asia

Stratification of exposure to environment

Interaction between these climate factors

Heat stress and air pollution risks in Asia

- Asia is a global **hotspot for climate change**, facing disproportionately high and escalating climate-related risks, from extreme heat and air pollution, with risks unevenly distributed (IPCC's Sixth Assessment Report, 2023)

- **Cities** such as Dhaka, Karachi, and Manila are climate hotspots due to high population density and large vulnerable groups, including slum dwellers and outdoor workers (Mishra et al. 2017, Jacobs 2019, Debnath et al. 2023)

- **South Asia**: Population exposed to extreme heat increased by 17 million/year (Kyaw et al. 2023, Lakhoo et al. 2025). Urban populations are regularly exposed to elevated concentrations of PM2.5 (Maharjan 2022)

- **Southeast Asia**: Population exposure to heat stress and air pollution increases substantially (Zander et al. 2018, Reddington 2021, Sun et al. 2022)

Stratification of environmental exposure

Environmental stratification conceptual framework (Bullard 1990, IPCC 2022)

1. Exposure stratification: Who is more exposed to heat stress and air pollution risks? → Focus of this paper

- Residential location, occupational roles, daily activity patterns, and built environment characteristics contribute to environmental stratification
- Certain groups experience significantly greater cumulative exposure to harmful environmental conditions (Bell & Ebisu 2012, Tessum 2021)

2. Sensitivity stratification: Who suffers more, given same exposure, and what can mitigate harm?

Interactions between these climate factors

- Evidence on joint effects remain mixed between air quality, extreme heat, and health outcomes (Chowdhury et al. 2024)

1. South Asia is particularly vulnerable to heatwaves and air pollution combination (Xu et al. 2020, Hasan et al. 2023)

2. **Interaction between high temperature and air pollution increases mortality rates** (Qin et al. 2017, Lee et al. 2019, Zhou et al. 2023) **and human health** (Piracha and Chaudhary 2022, De Vita et al. 2024)

3. **Direction and magnitude of interactions remain uncertain**
    - High temperature increases harmful air pollutant levels (Chowdhury et al. 2024)
    - When air pollution levels are lower, temperature increases (He et al. 2023)
    - Temperature inversions may exacerbate pollution accumulation (Hou 2024)

Study Overview

Research questions and design

Spatial and temporal coverage

Contribution to literature

Research questions and design

- *How are heat stress and air pollution risks distributed?*

- We use district-month observations to document seasonality and correlation between heat stress and air pollution risk

- *Who are more exposed to heat stress and air pollution risks?*

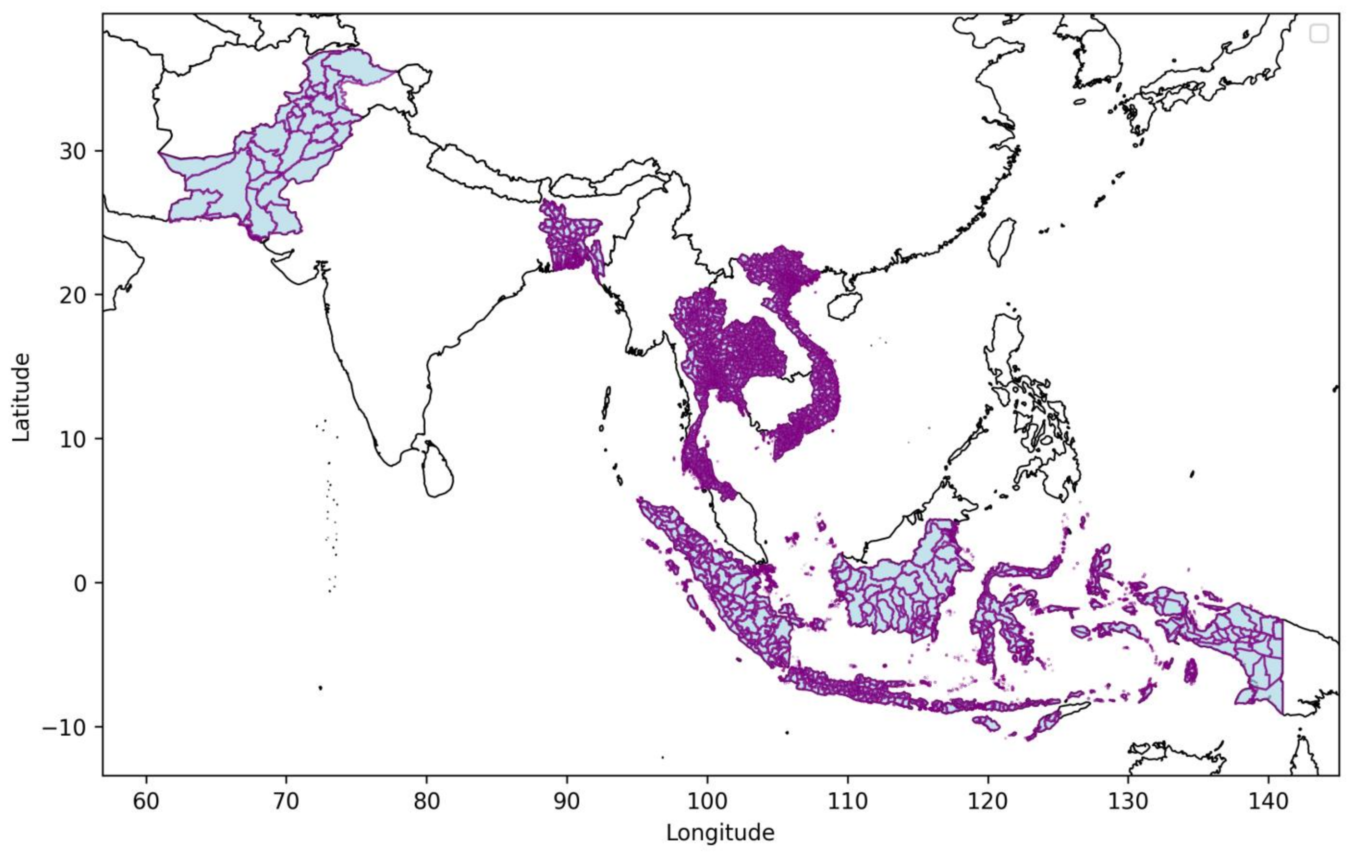
- We apply a *double-dual-distribution framework* to analyze both duration and intensity of exposure among population groups (Feng et al. 2024)

- We investigate if certain population groups are exposed more to both risks considering gender, age, and employment status

Spatial and temporal coverage

- Countries: Bangladesh, Pakistan, Thailand, Vietnam, Indonesia

- For each country, district-level analysis and exposure over time is explored using publicly available data



Contribution to literature

- Most "population exposure" work emphasizes income/urbanicity; demographics and work status are underexplored (Tuholske et al. 2021, Rentschler & Leonova 2023, Xu et al. 2023)

→ We quantify exposure by **gender, age,** and **employment status** (demographic–occupational stratification)

- Evidence is often global or single-country and time-narrow (Han et al. 2017, Liu et al. 2017, Xu et al. 2023)

→ We deliver a **harmonized multi-country analysis** with consistent definitions, thresholds, and spatial units; compare change over time with two benchmarks (≈1990 vs. most recent year) to track distributional shifts

Data and Spatial Integration

Heat stress (temperature, UTCI)

Air pollution (PM2.5 level)

Population distribution and demographic groups

Data for heat stress

- **Universal Thermal Climate Index (UTCI)** from the ERA5-HEAT (Human thErmAl comforT) dataset, derived from the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses

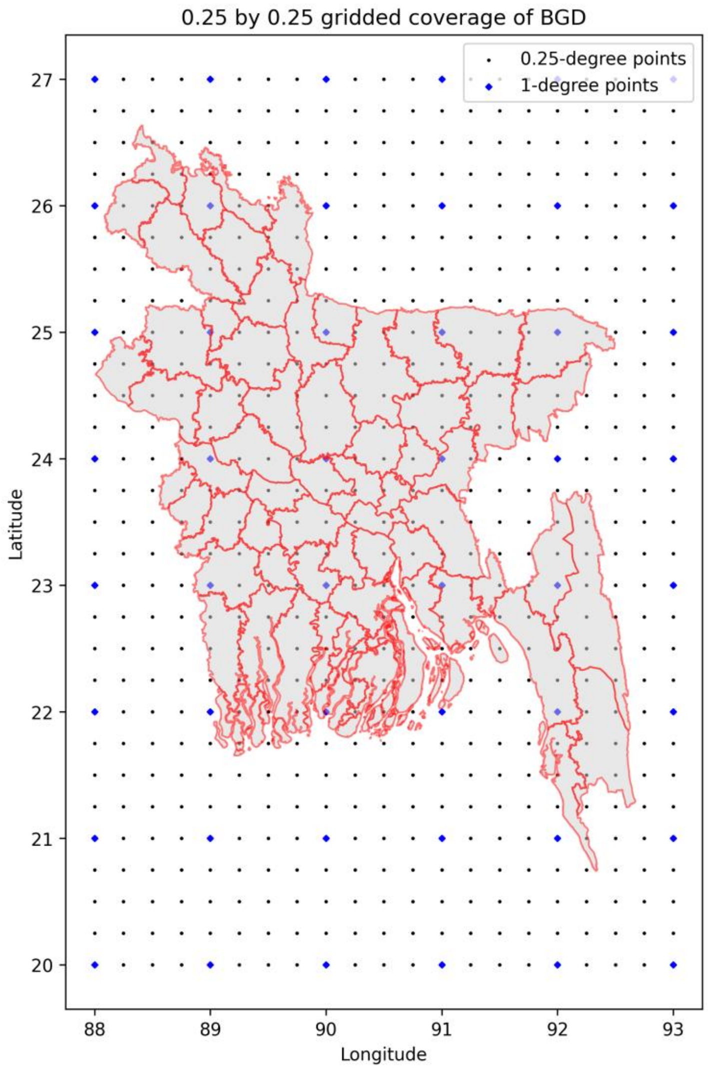
- Describe how human body experiences atmospheric conditions, specifically air temperature, humidity, ventilation, and radiation

Format:
- **Hourly**
- **Gridded data, 0.25X0.25 resolution**
- **1940 to present**

Spatial merging for UTCI

- Map for Bangladesh
- Each dot is one coordinate
- Boundaries show districts

- **District-level hourly UTCI**: take average of UTCI at each merged coordinates

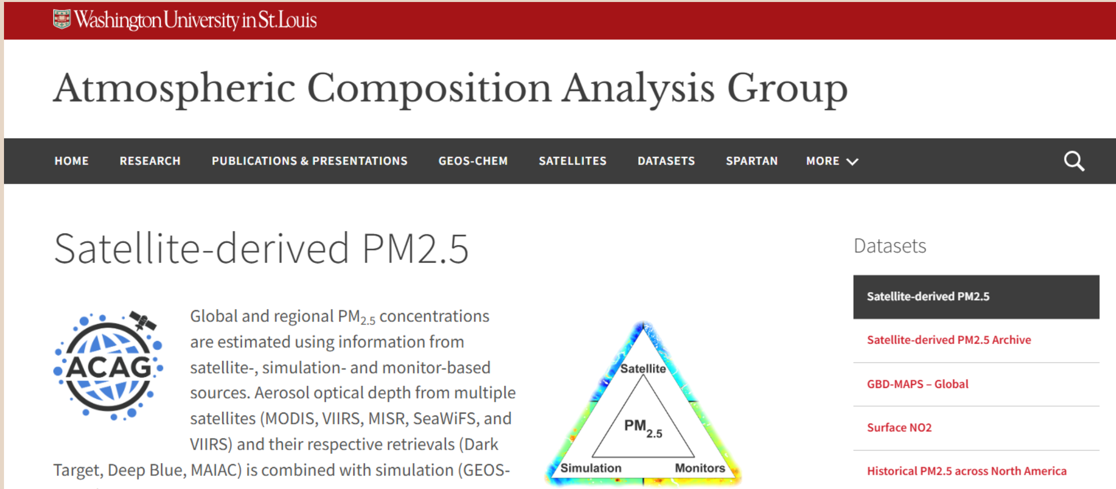


Data for air pollution

- Global **PM2.5 data** estimated by Washington University in St. Louis, which integrates satellite, simulation, and monitor-based sources

- Provide geophysical estimates that explain most of the variance in ground-based PM2.5 measurements

Format:
- **Monthly mean PM2.5**
- **Gridded, 0.01X0.01 resolution**
- **1998 to present**



Data for population

- **Census** data
- Approximately 1990 and the most recent available year for each country
- Geo-location is available at province (admin 1) and district (admin 2) level
- **Totally, there are 2 X 3 X 4 = 24 groups**
    - Gender: male, female
    - Age range: children (0-14), working-age (15-59), elderly (60+)
    - Employment status: employed, unemployed, inactive, housework

Country	Year	Year
Bangladesh	1991	2011
Indonesia	1990	2010
Thailand	1990	2000
Vietnam	1989	2019

- *Pakistan Census is only available for 1973, 1981, 1998, and does not contain employment status information

Climate Shocks Distributions

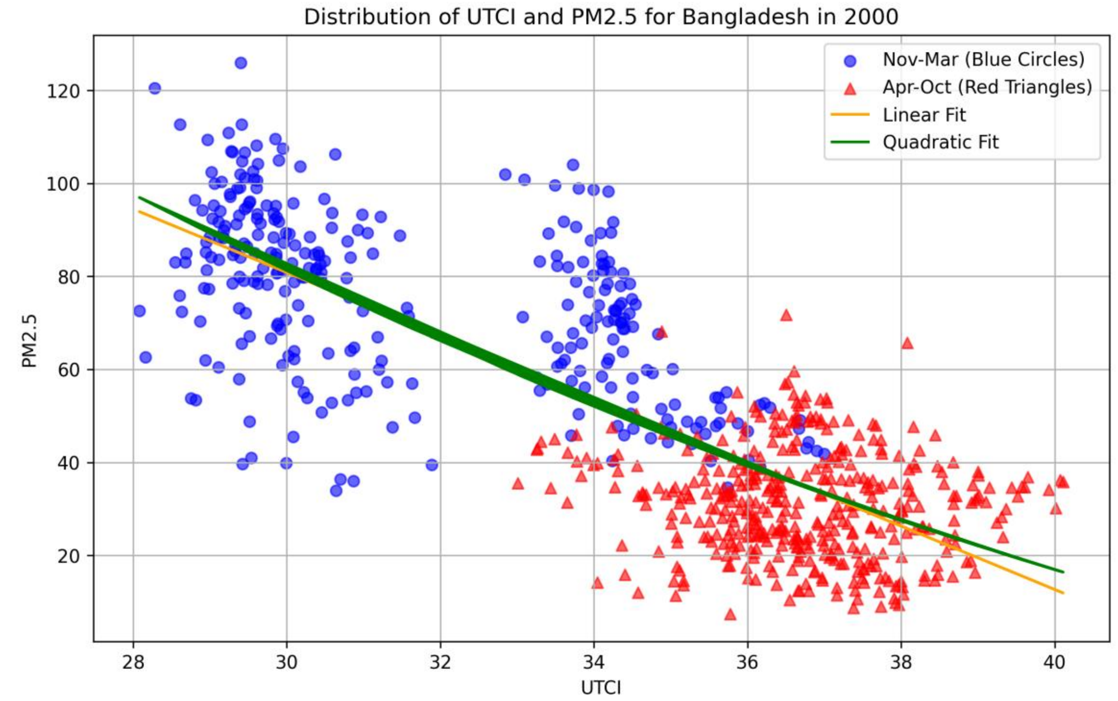
Measures and methodology

Correlation between air pollution and heat stress

Correlation between UTCI & PM2.5

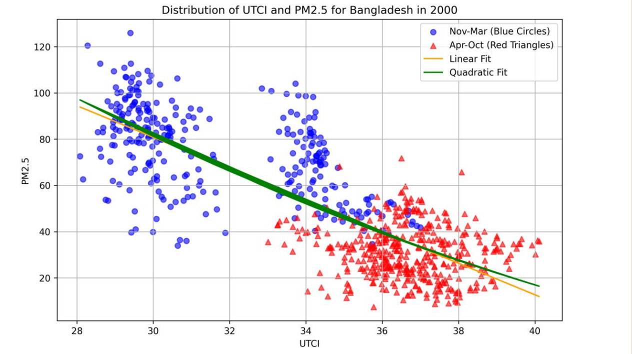
- For each country-year, we illustrate correlation between UTCI and PM2.5 level
- x axis: UTCI, y axis: PM2.5, dots: district-month

- Blue circles – cold months
- Red triangles – hot months
- Linear and quadratic fit lines
- Pearson correlation coefficient



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Bangladesh in 2000 is -0.80.

UTCI & PM2.5: Bangladesh



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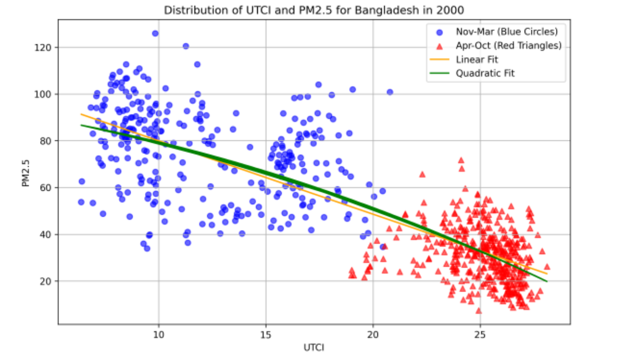
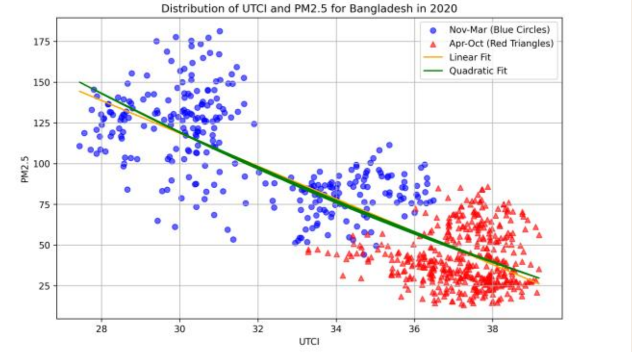
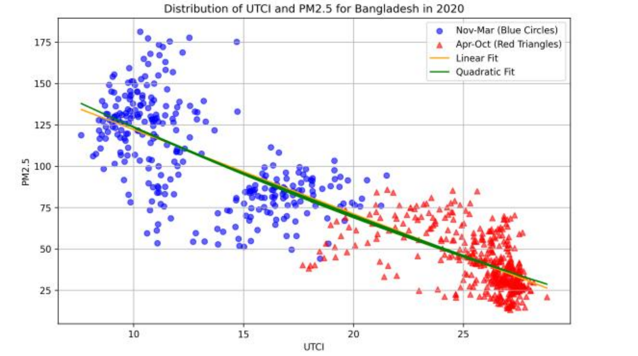


Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Bangladesh in 2000 is -0.82.



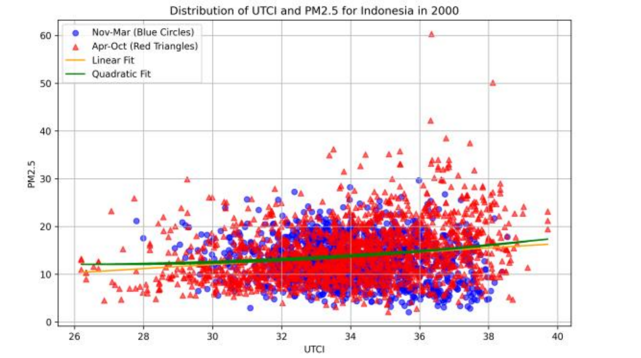
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Bangladesh in 2020 is -0.83.



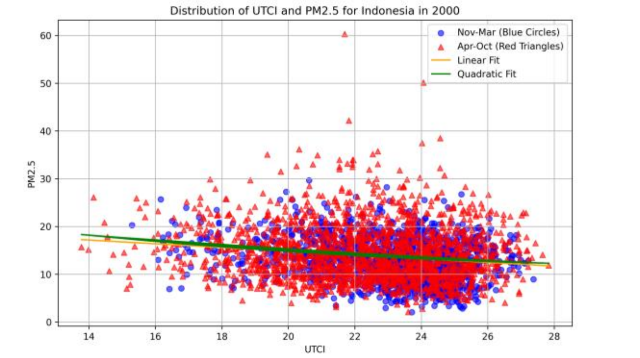
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Bangladesh in 2020 is -0.88.

- Notable increase in PM2.5 levels over time
- Lowest PM2.5 level remains around 10 $\mu g/m^3$, but maximum level rises significantly from 120 to over 175
- Strong negative correlation
- Seasonal patterns: air pollution is notably higher during the colder months

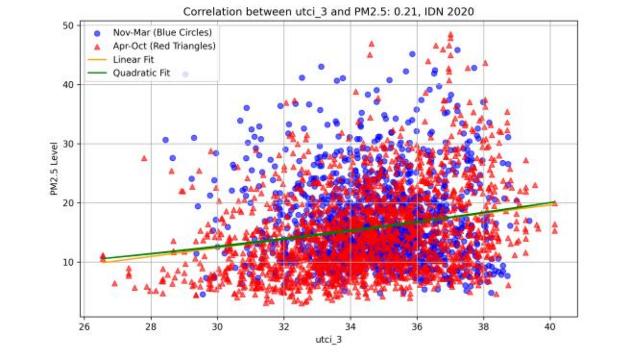
UTCI & PM2.5: Indonesia

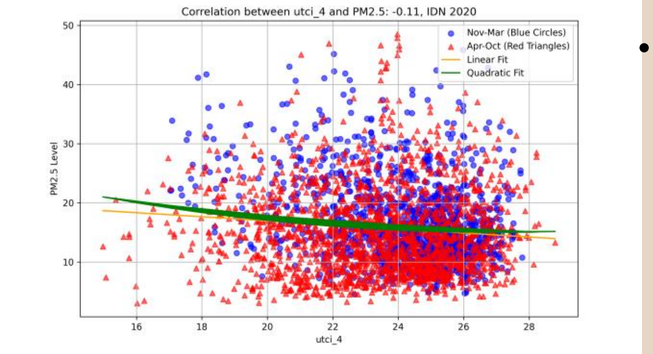


Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Indonesia in 2000 is 0.18.



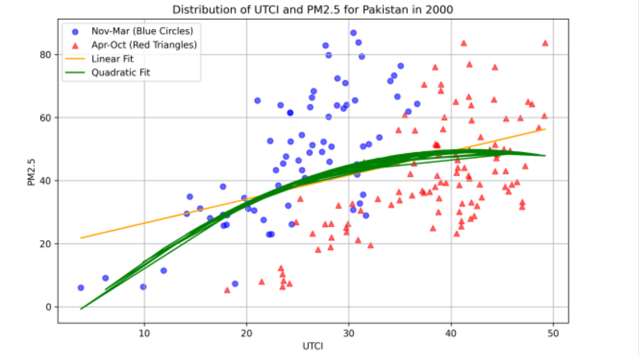
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Indonesia in 2000 is -0.17.



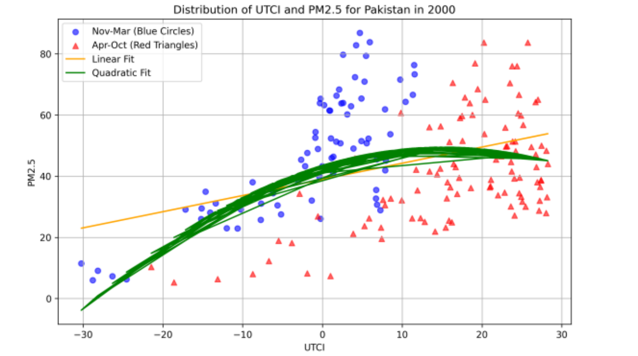


- PM2.5 levels show smaller change over the two decades
- Correlation between temperature and PM2.5 concentration is weak
- No evident seasonality in PM2.5 levels across different months

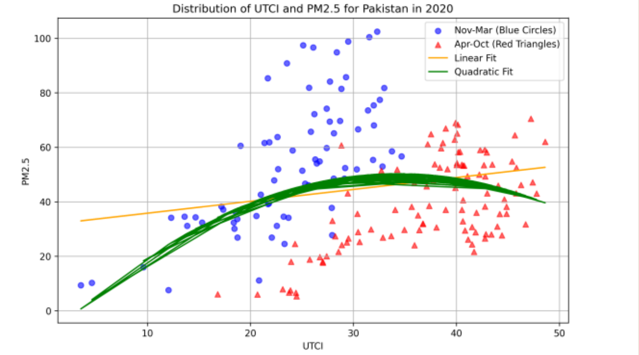
UTCI & PM2.5: Pakistan



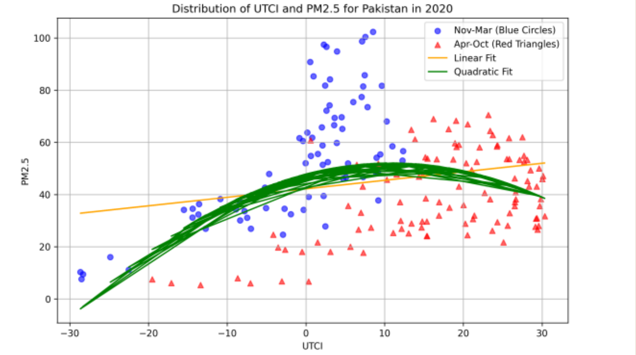
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Pakistan in 2000 is 0.39.



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Pakistan in 2000 is 0.39.



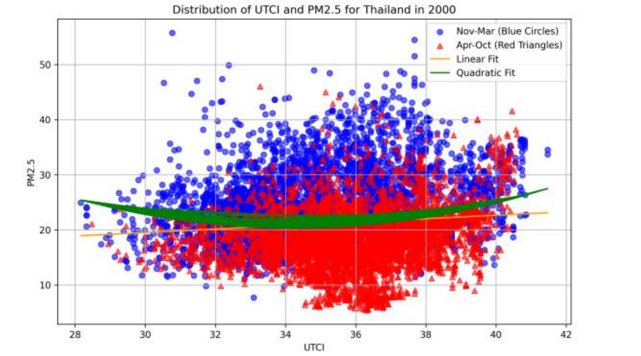
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Pakistan in 2020 is 0.20.



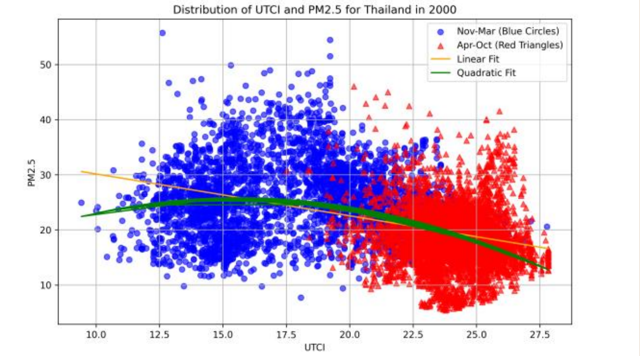
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Pakistan in 2020 is 0.21.

- PM2.5 levels in Pakistan exhibit great variation, similar to Bangladesh
- Distributional shift in PM2.5 levels: increase in the extreme values of the distribution; central or lower part toward lower values
- Positive correlation across years

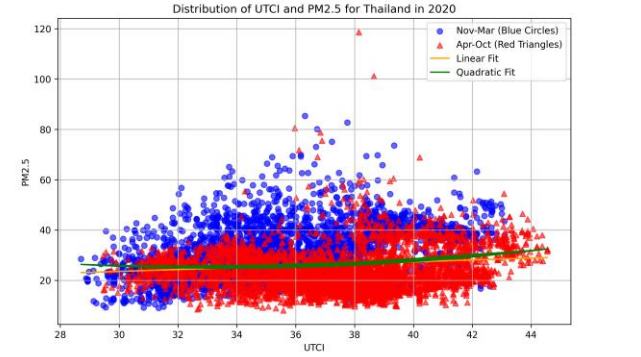
UTCI & PM2.5: Thailand



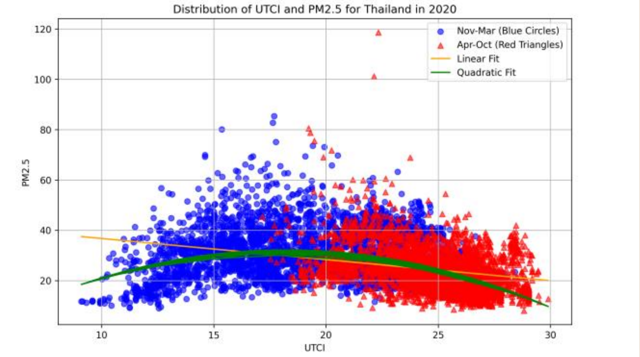
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Thailand in 2000 is 0.10.



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Thailand in 2000 is -0.42.



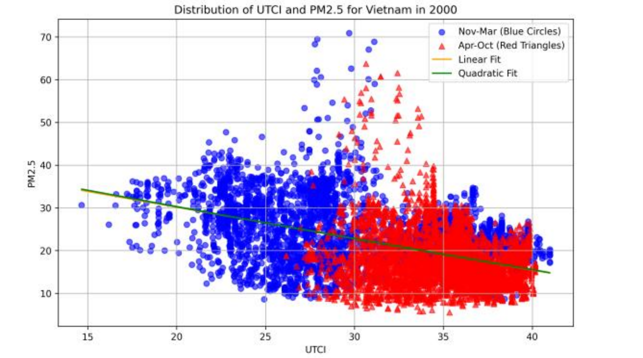
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Thailand in 2020 is 0.12.



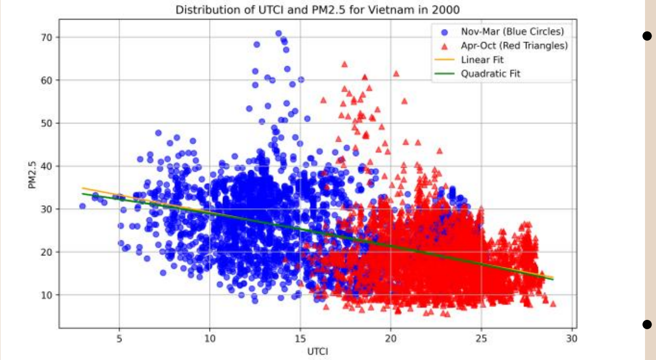
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Thailand in 2020 is -0.36.

- PM2.5 levels show moderate increase over two decades
- Correlation changes depending on measure used: + using max, - using min daily temperature
- Strong negative correlation
- No clear seasonality in PM2.5 levels

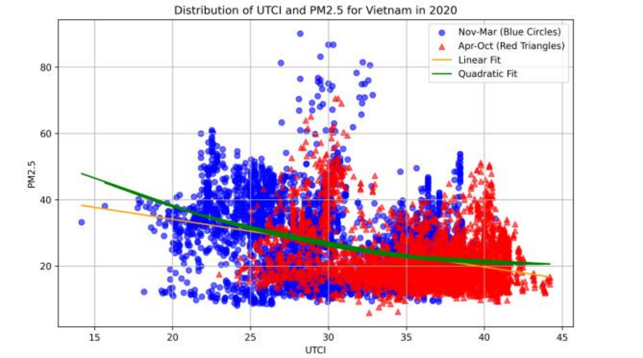
UTCI & PM2.5: Vietnam



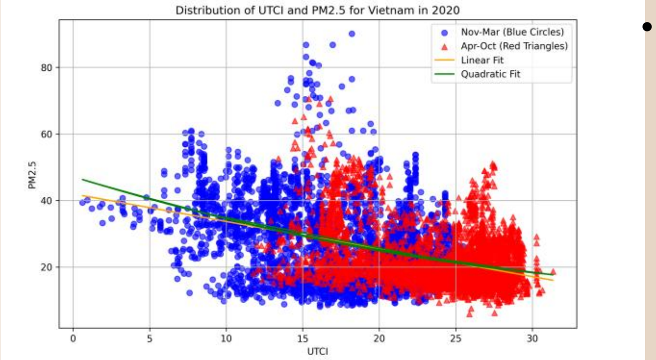
Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Vietnam in 2000 is -0.45.



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Vietnam in 2000 is -0.52.



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily maximum UTCI values. The correlation between monthly UTCI and PM2.5 for Vietnam in 2020 is -0.37.



Notes: Each observation is a district-month in certain country. The monthly UTCI measure is average of daily minimum UTCI values. The correlation between monthly UTCI and PM2.5 for Vietnam in 2020 is -0.44.

- Clear and unique pattern: highest PM2.5 levels are concentrated within the temperature [27, 35]
- Negative correlation
- Over time, while PM2.5 levels do not increase dramatically, there is slight upward shift in extreme values, particularly in right tail of distribution

Population exposure

Measures and methodology

Within country across demographic groups distribution

Measure 1. STAC

Share of **T**ime the **A**verage individual in a **C**ategory exposed to heat stress

1. For each district d, obtain share of people in category m relative to the total population of that category across the entire country

$$Population\ share_{d,m} = \frac{Population\ of\ m\ in\ d}{Total\ population\ of\ m\ in\ the\ country}$$

2. For each district, calculate total hours above a threshold over a period

$$Share\ of\ time\ exposed_d = \frac{Hours\ with\ temperature > threshold}{Total\ hours\ in\ time\ period}$$

3. Calculate population-weighted STAC at national-level

$$STAC_m = \sum_{d=district1}^{district\ n} (Population\ share_{d,m} \times Share\ of\ time\ exposed_d)$$

Results from STAC: BGD 2011 as example

Category	Gender	Age	Employment	> 28° C	> 36° C
1	Male	Children	Employed	50.9%	11.3%
2	Male	Children	Unemployed	50.9%	10.5%
3	Male	Children	Inactive	51.2%	11.3%
4	Male	Children	Housework	50.4%	10.6%
5	Male	Working Age	Employed	51.3%	11.7%
6	Male	Working Age	Unemployed	51.3%	11.0%
7	Male	Working Age	Inactive	51.4%	11.5%
8	Male	Working Age	Housework	50.9%	10.8%
9	Male	Elderly	Employed	51.5%	11.6%
10	Male	Elderly	Unemployed	51.0%	10.6%
11	Male	Elderly	Inactive	51.8%	11.3%
12	Male	Elderly	Housework	51.1%	10.6%
13	Female	Children	Employed	50.5%	11.2%
14	Female	Children	Unemployed	50.4%	10.4%
15	Female	Children	Inactive	51.2%	11.3%
16	Female	Children	Housework	50.8%	10.8%
17	Female	Working Age	Employed	50.9%	11.5%
18	Female	Working Age	Unemployed	51.5%	11.4%
19	Female	Working Age	Inactive	51.4%	11.3%
20	Female	Working Age	Housework	51.4%	11.6%
21	Female	Elderly	Employed	50.9%	11.5%
22	Female	Elderly	Unemployed	51.2%	11.3%
23	Female	Elderly	Inactive	51.7%	11.5%
24	Female	Elderly	Housework	51.4%	11.6%

- Col “> 28°C”: on average for certain category, share of time exposed to heat > 28 degree in one year
- Compare STAC at the same threshold across categories
- For heat > 28 degree, elderly inactive population are more exposed
- For heat > 36 degree, male employed are heavily exposed

Measure 2. SEIDT

Share of population in one category **E**xposed to heat stress by various **I**ntensity and **D**urations **T**hresholds

1. Set up thresholds:

$$I = temperature,\ H = share\ of\ time\ within\ a\ period$$

2. For each district d, calculate duration of time exposed to heat

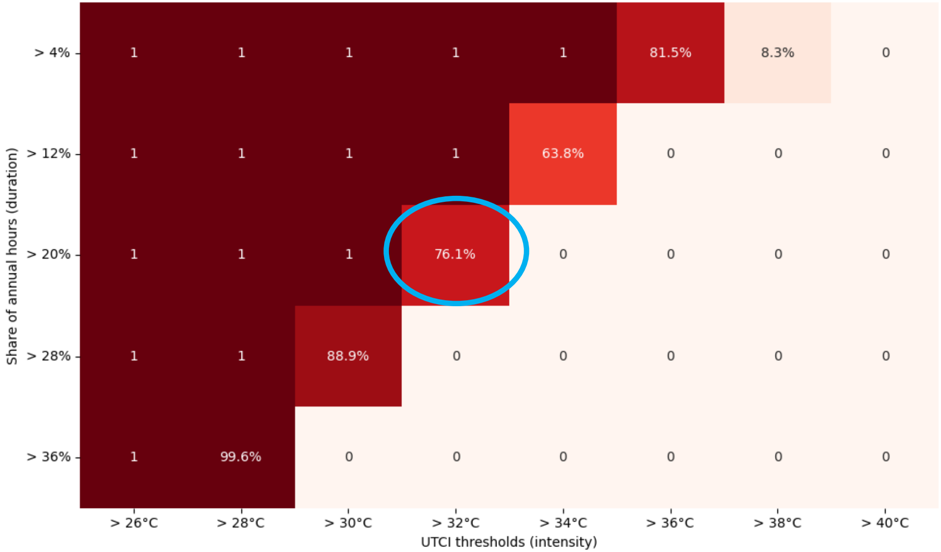
$$H_d = \frac{\#\ of\ hours\ where\ temperature\ exceeding\ I}{Total\ hours\ in\ period}$$

3. Sum the share of population for category m in districts where exposure time exceeds duration threshold

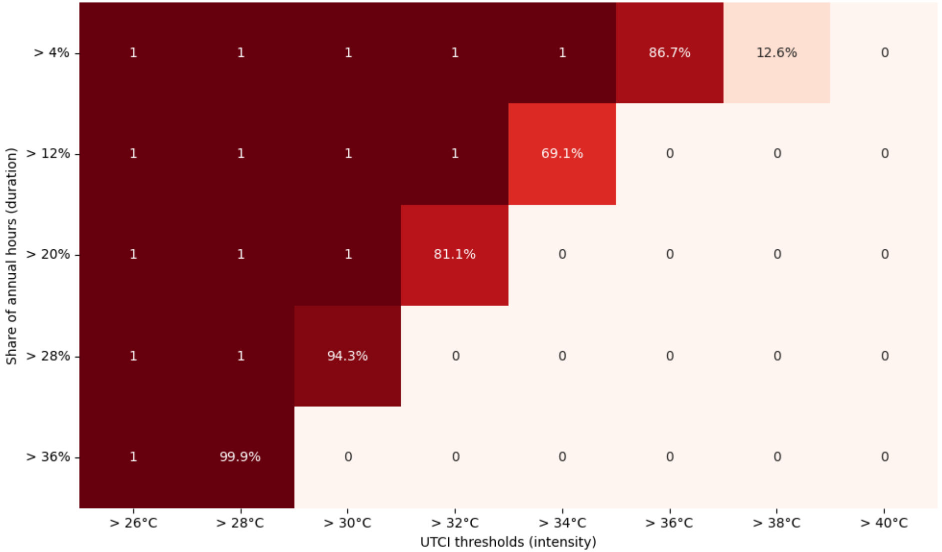
$$SEIDT_m = \sum_{d\ \in \{d: H_d > H\}} Population\ share_{d,m}$$

Results from SEIDT: BGD 1991 as example

Less exposed:
female, working-age, unemployed



More exposed:
female, elderly, housework



76.1% of unemployed working-age females experienced strong or very strong heat stress for over 20% of the year—equivalent to more than 10 weeks

Results: population exposure to heat stress

- Bangladesh 1991: The elderly are exposed more to heat stress; this pattern still exists in 2011
- Indonesia 1990: Unemployed population are more exposed; this changes as in 2010, the employed population STAC increases substantially
- Thailand 1990: Overall employed population are more exposed, and female are exposed for longer time of heat than male; In Thailand 2000, unemployed population are heavily exposed to heat stress and heterogeneity across gender still exists
- Vietnam 2019: For the employed, female are exposed to heat stress for longer time than male

Results: population exposure to pollution risk

- Bangladesh 2011: Children and the elderly are more exposed to air pollution than working age. Within the people who are employed, more female are exposed to extreme PM2.5 level (above 50 $\mu g/m^3$) for long duration (almost all the months in one year)

- Indonesia 2010: The employed is not exposed to higher pollution risk than unemployed or inactive population

- Thailand 2000: Children who are employed and male elderly population are more exposed to pollution risks

- Vietnam 2019: In general, higher proportion of female are exposed to higher pollution risk than the male

Conclusions and Discussions

Exposure patterns vary significantly across countries and demographic groups

There is an urgent need for targeted policies to mitigate the compounded effects of climate and pollution hazards on vulnerable populations

Next steps

- Collaborating with Emily Hannum and Jere R. Behrman, we will quantify how heat stress and PM2.5 affect young children's health and human capital, stratified by socio-economic status, using rich household surveys
- Studies have examined the health effects of future heat exposure or air pollution exposure, but there has been little work to evaluate effects of both heat and air pollution exposure under the same scenarios (Shindell 2024)
- **Short-run cognitive performance and health** can be impaired by elevated temperatures (Park et al. 2021, Hu and Li 2019)
- Pollution exposure negatively affects **educational outcomes, labor productivity, and health** (Brabhukumr et al. 2020, Gakidou et al. 2017)