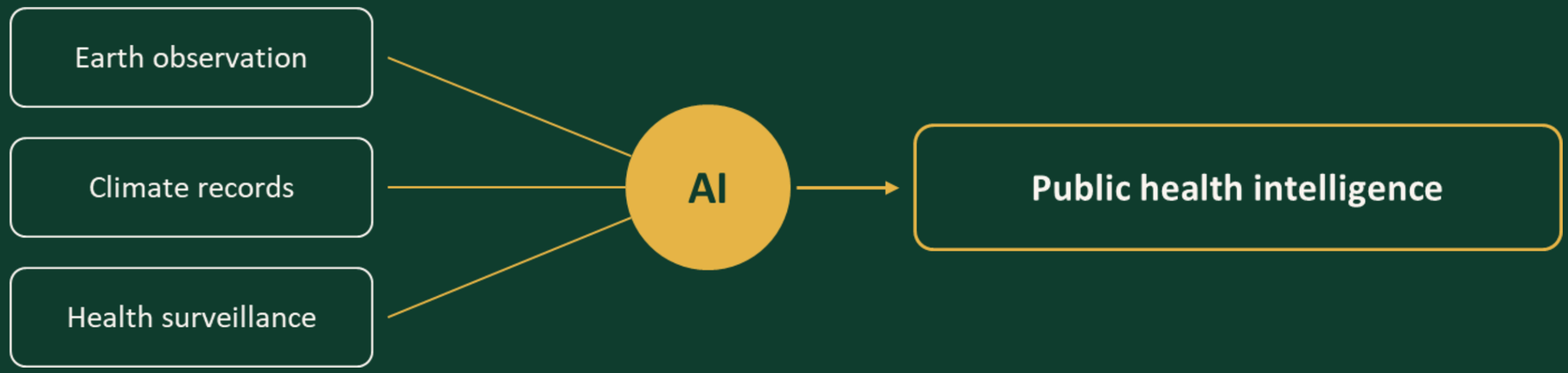
AI for Public Health

Usman Nazir, Sara Khalid (PI)

Planetary Health Informatics (PHI) Lab
University of Oxford



Modelling the climate signal in measuring disease burden

Climate sensitive diseases (Malaria, ARI, Child wasting, MSK Injury)

Live poll 1 of 8

Which three areas are most interconnected in climate-sensitive public health?

A Climate, food and health

B Climate, transport and finance

C Food, education and technology

D Health, finance and energy

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Scan or type to vote

The Climate–Food–Health Triangle

Three crises, one interconnected system



- Global warming reduces food production.
- Food contributes 25–30% of GHG emissions.

- Climate change increases the risk of new disease emergence (zoonoses, vector-borne).
- Healthcare system contributes 4-5% emissions.

- *Food is needed for nutrition & good health.*
- *Protein deficiency is a global problem.*

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● Live poll 2 of 8

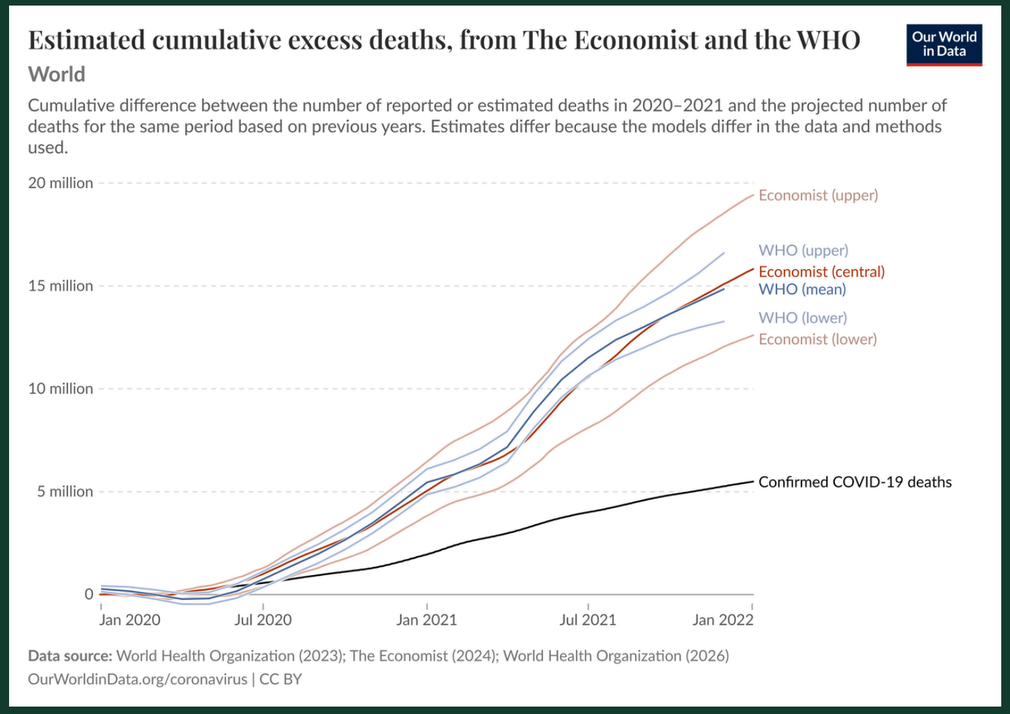
Which climate-sensitive health problem contributes the largest share of WHO's projected deaths?

A Malaria

B Childhood undernutrition

C Heat exposure

D Diarrhoeal disease

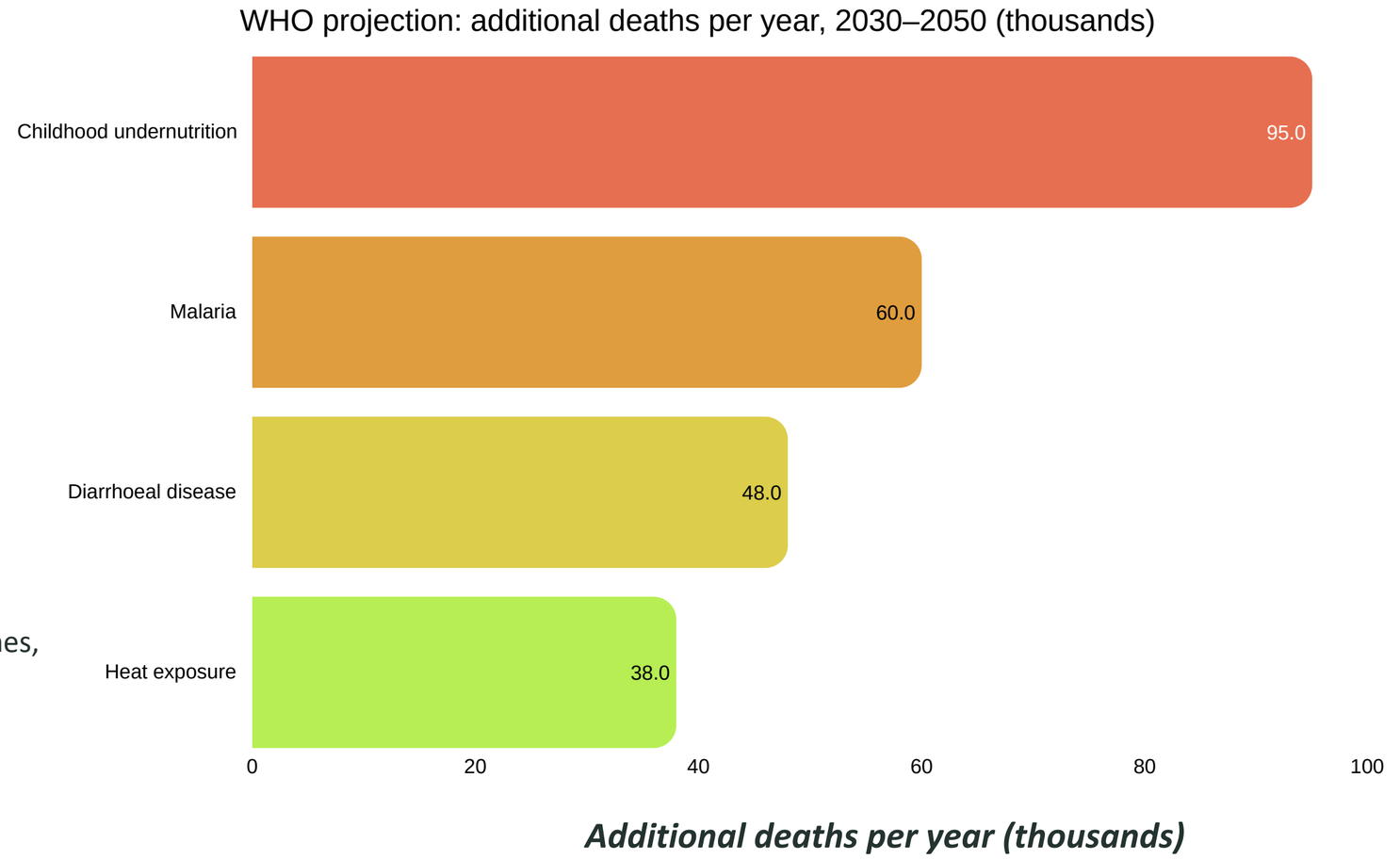


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Scan or type to vote

Why Climate-Sensitive Diseases?

- WHO projects **~250,000 additional deaths per year, 2030–2050** from climate change — a deliberately conservative estimate covering only selected pathways.
  - **Childhood undernutrition is the single largest component** of that projection, ahead of malaria, diarrhoea and heat.
- Lancet Countdown 2024: **10 of 15 health-hazard indicators at record highs**; vector suitability is already expanding.
  - Climate-health is not simply a story about heatwaves.



Three diseases, three pathways

Malaria — vector ecology — temperature, rainfall, humidity

Acute respiratory infection — air quality, temperature extremes, wildfires

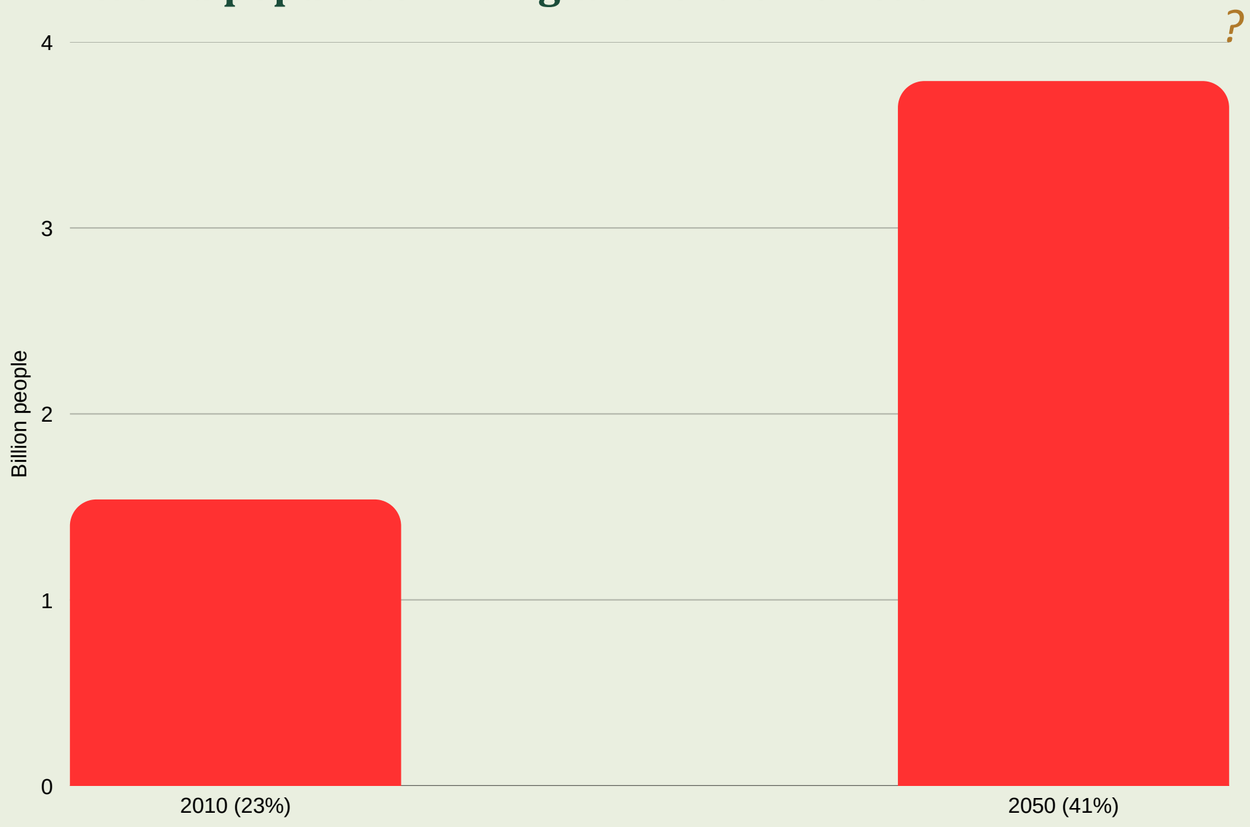
Child wasting — food systems — drought, floods, crop failure

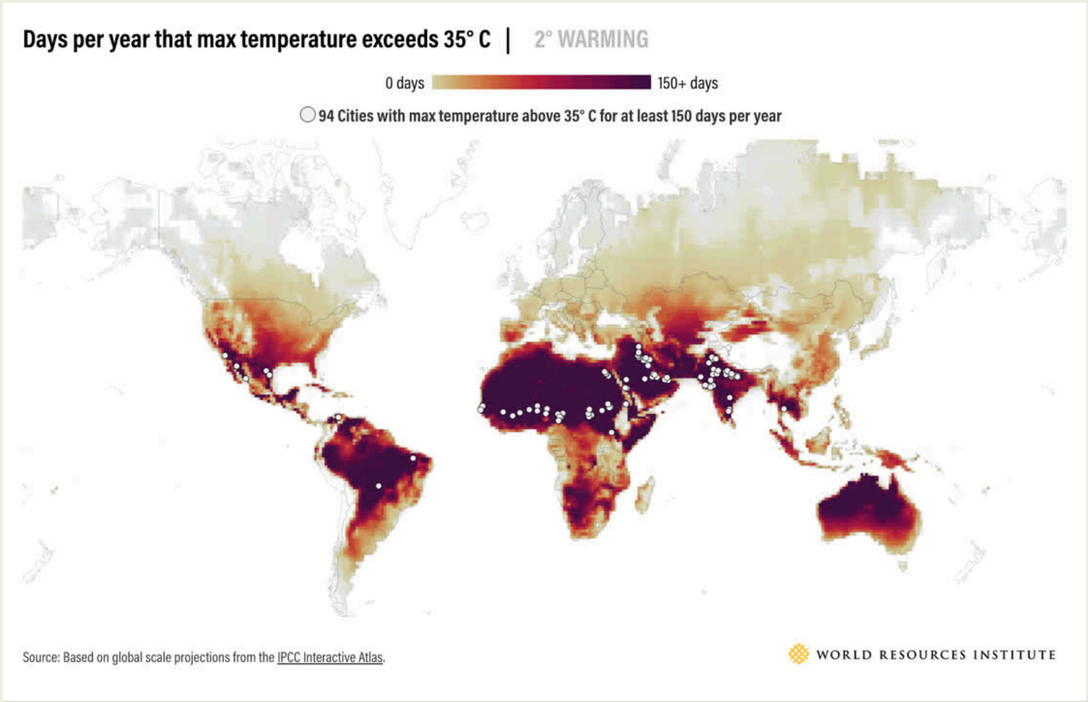
Sources: *WHO (2014) Quantitative risk assessment of climate change effects on selected causes of death · Romanello et al. (2024) The Lancet 404:1847–96.*

Why global populations?

where should we study climate-related health impacts

World population living with extreme heat





Where the burden concentrates

- Largest affected populations: India, Nigeria, Indonesia, Bangladesh, Pakistan and the Philippines.
- These are low- and middle-income countries in the tropics — exactly where standardized health-survey data (DHS, MICS, DHIS2) makes this analysis possible.
- Exposure is rising fastest where health systems are least resourced to respond.

Sources: Oxford / Nature Sustainability (2026) — 3.79bn (41%) exposed by 2050 at 2°C, up from 1.54bn (23%) in 2010; WHO Climate & Health.

Live poll 3 of 8

Which is harder: predicting disease from climate data, or determining how much disease climate actually caused?

A Prediction

B Attribution

C They are the same problem

D Neither is harder



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Scan or type to vote

Questions



What is Climate telling us?

Questions



What is Climate telling us?

How much of the disease burden can we attribute to climate?

Questions



What is Climate telling us?

How much of the disease burden can we attribute to climate?

How can the Global Goals guide our response to the climate challenge?

A Stewardship Lens on Mitigation and Adaptation

“Sustainable development meets the needs of the present without compromising the ability of future generations to meet their own.”

— Brundtland Commission, 1987

Before the analytics, I want to set the lens.
Two words run through everything!

MITIGATION

SDG 13 · Climate Action

Stopping the problem from getting worse — cutting CO_2, switching to clean energy, protecting forests.

ADAPTATION

SDG 10 · Reduced Inequalities

Managing the problem we can no longer avoid — preparing for heatwaves, floods, droughts and sea-level rise.

An SDG Lens on Climate & Health

The Global Goals each study speaks to – and the lens through which we read the analytics

Common language: goals.









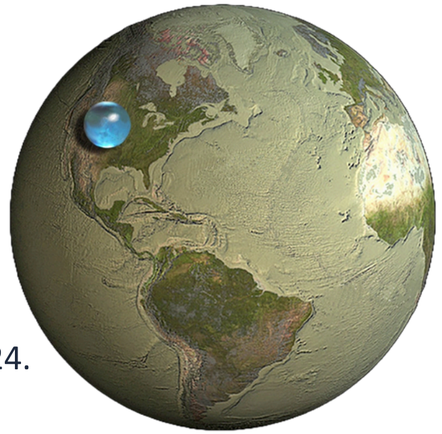




Each study → a goal.

Selected work

Over the last few years, our work has explored **AI for Public Health** from several directions:



- "Learned Geospatial Priors for Malaria Forecasting," NeurIPS 2026 (submitted).
- "KilnBench: Benchmarking Deep Learning for Brick Kiln Detection in Satellite Imagery," NeurIPS 2026 (submitted).
- "Weakly-supervised Multimodal Flood Nowcasting under Asynchronous EO Streams," NeurIPS 2026 (submitted).
- "Foundation Models for Mapping Emission Sources and ARI Hotspots," NeurIPS Workshop 2025.
- "Predicting Malaria Outbreaks Using EO and Spatio-temporal Deep Learning: A South Asian Case Study (2000–2017)," The Lancet Planetary Health 2024.
- "Humanitarian Costs of Climate Change: Mapping Extreme Floods on Displacement, Education and Health via EO and Data Fusion," PHAM 2024.
- "Predicting Malaria Outbreaks Using EO and Spatio-temporal Deep Learning: A South Asia Case Study (2000–2017)," PHAM 2024.
- "Towards a Spatio-temporal Deep Learning Approach to Predict Malaria Outbreaks in South Asia," NeurIPS TCCML Workshop 2023.
- "Spatio-temporal Graph Neural Networks with Block Adjacency Matrix (STAG-NN-BA)," AAAI Climate Change Symposium 2023.
- "Mitigating Climate and Health Impact of Small-scale Kiln Industry Using Multi-spectral Classifier and Deep Learning," ICLR TCCML Workshop 2023.



The Climate → Health Analytics Pipeline

How we connect a climate signal to a disease outcome



Climate inputs

ERA5 · CHIRPS · MODIS



Earth observation

Sentinel · Landsat · AlphaEarth



Health outcomes

Big Data



Models

ML · DL



Inference

R^2 ↑ RMSE ↓ attribution

Four case studies — same pipeline, four different outcomes

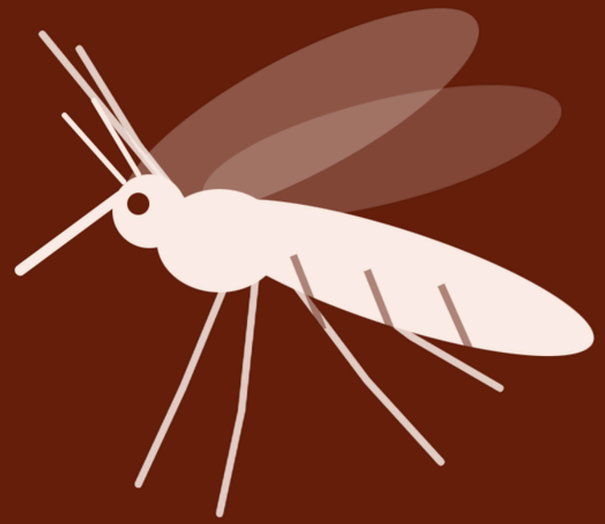
① Malaria · ② Acute respiratory infection · ③ Child wasting · ④ MSK Injury

CLIMATE-SENSITIVE DISEASE SERIES

CASE STUDY 01

Malaria

Warming widens mosquito breeding zones



282M

malaria cases worldwide each year

ASIA & AFRICA

Source: Our World in Data (WHO)

MALARIA · ARI · CHILD WASTING

● Live poll 4 of 8

As temperature rises continuously, what happens to malaria transmission?

A It always increases

B It always decreases

C It rises to an optimum, then falls

D Temperature has no effect

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Scan or type to vote

Warming Redistributes Malaria Risk

263M
cases worldwide, 2023

597k
deaths, 2023

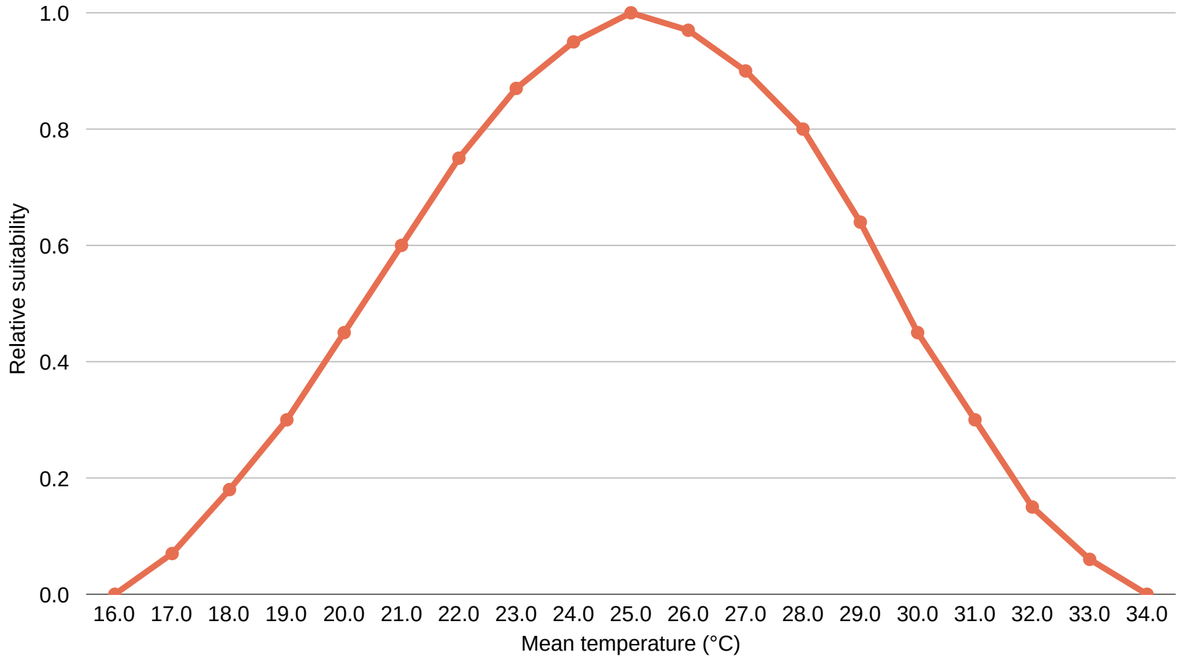
94%
of cases in WHO African Region

~3/4
of African deaths in under-5s

- **Temperature** governs mosquito development, biting rate and parasite sporogony — optimum **25 °C**, with transmission collapsing above ~28 °C (Mordecai et al. 2013).
- **Rainfall** creates breeding sites (~80 mm/month threshold in MARA-type models); extreme rain can flush larvae out.
- **Warming shifts risk uphill:** East African highlands; Papua New Guinea altitude limit projected to rise ~263 m.
  - Climate warms, risk can move geographically.
  - Some cooler regions may become more suitable.
  - Some already-hot regions may become less suitable.
- Up to **4.7 billion additional people** in areas climatically suitable for malaria + dengue by 2100 under the highest-emission scenario (Colón-González et al. 2021).

More warming does not simply mean more malaria everywhere.

Transmission suitability vs temperature — stylized after Mordecai et al. (2013): peak ≈25 °C, sharp decline >28 °C



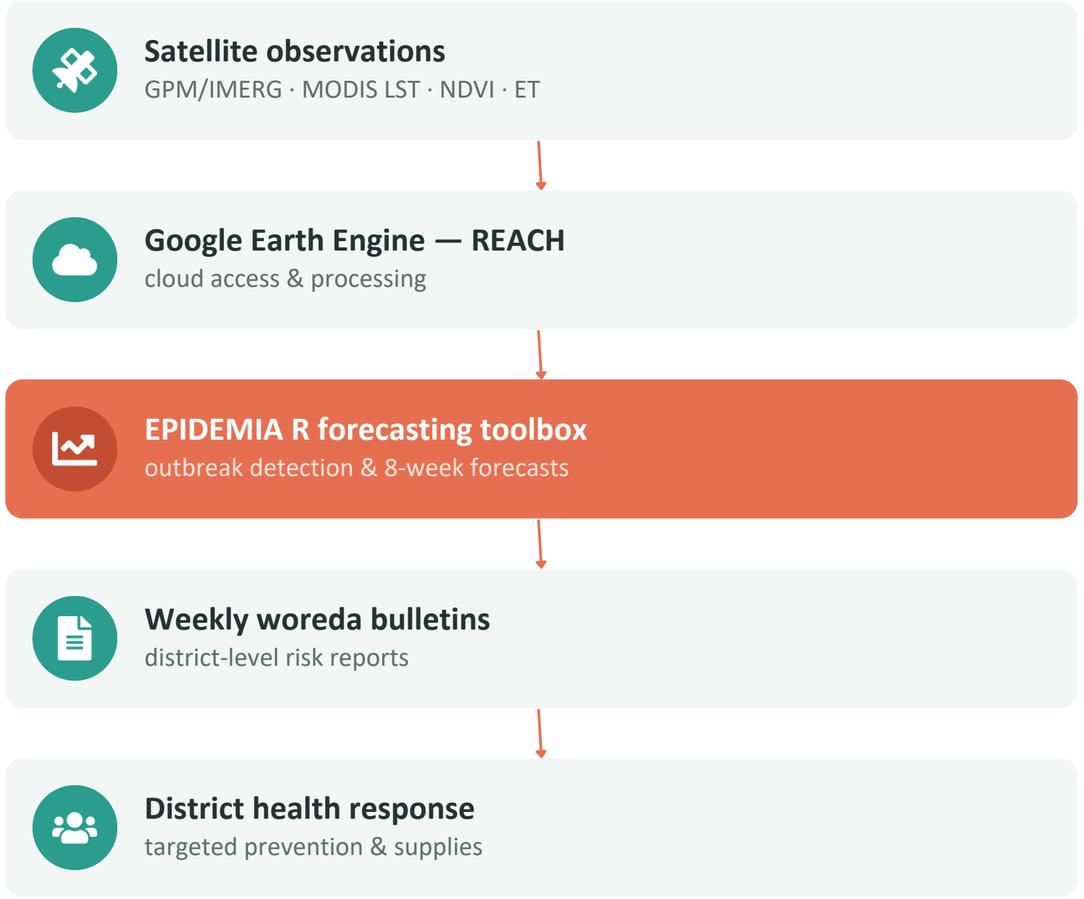
Sources: *WHO (2024) World Malaria Report · Mordecai et al. (2013) Ecology Letters 16:22–30 · Colón-González et al. (2021) Lancet Planetary Health 5:e404–14.*

CASE STUDY — ETHIOPIA

EPIDEMIA: Operational Malaria Early Warning

- **University of Oklahoma + Amhara Regional Health Bureau** — running for 10+ years, not a research prototype.
- Inputs: **GPM/IMERG rainfall, MODIS LST & NDVI, evapotranspiration** + weekly district (woreda) surveillance.
- Open-source R toolbox; cloud processing on **Google Earth Engine (REACH)**.
- Forecasts outbreaks **up to 8 weeks ahead**; USAID/PMI-supported roadmap toward national scale.

A critical point for AI in public health:
the best model is not necessarily the model with the highest benchmark score.



Why it survived a decade

- Open source
- Free satellite data
- Co-designed with local health authorities

Sources: *Merkord et al. (2017) Malaria Journal 16:89 · Davis et al. (2022) Scientific Data 9 (REACH) · Wimberly & Nekorchuk (2021).*

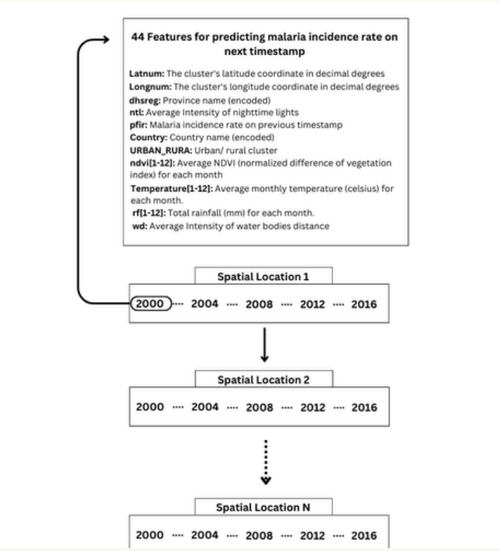
STUDY 1

Climate Indicators vs Malaria Outbreaks

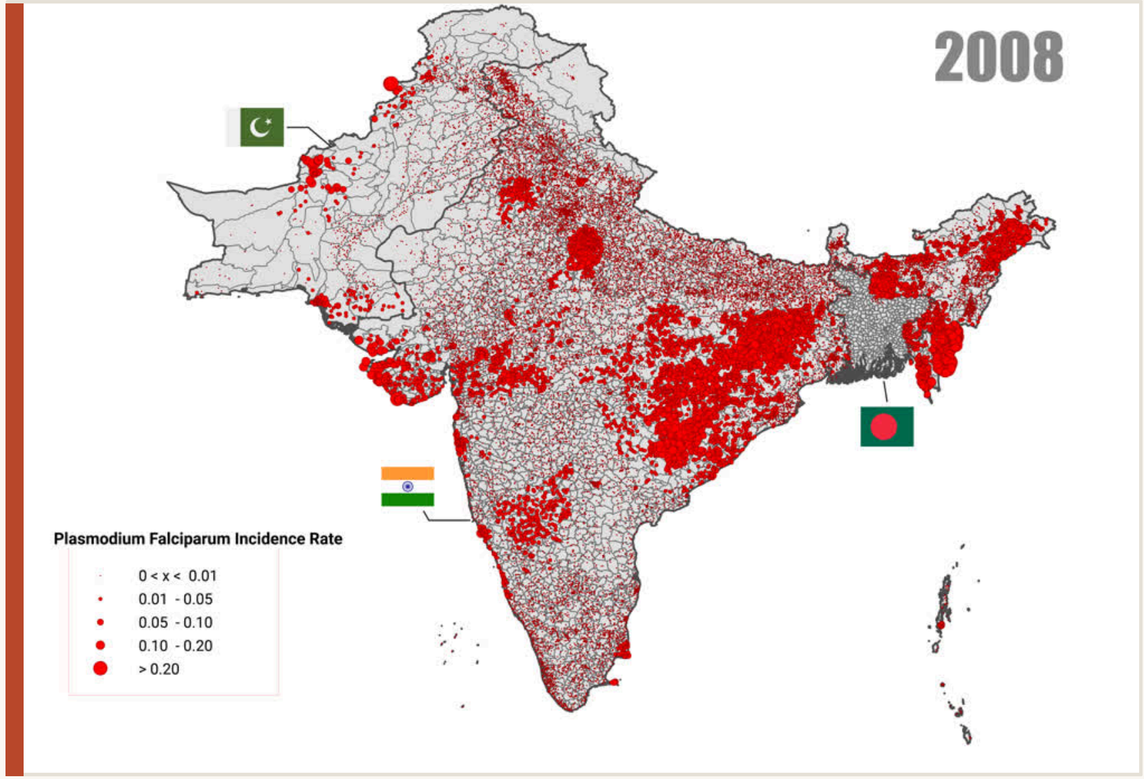
Detecting and predicting the climate signal in Plasmodium transmission

Climate indicators

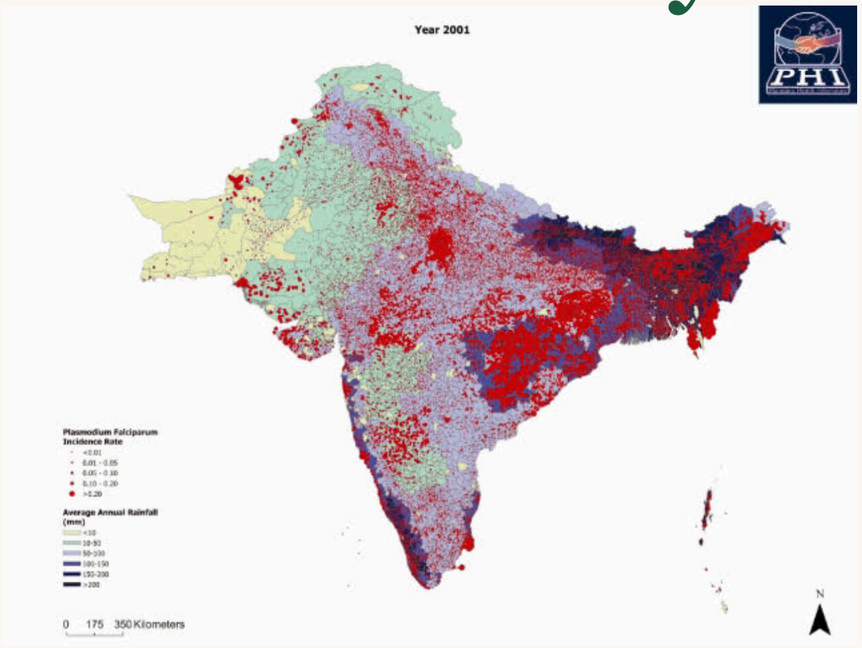
- Temperature (mean, min, max, anomaly)
- Rainfall — total, intensity, dry spells
- Relative humidity, NDVI greenness
- Surface water extent (flood / pooling)
- ...

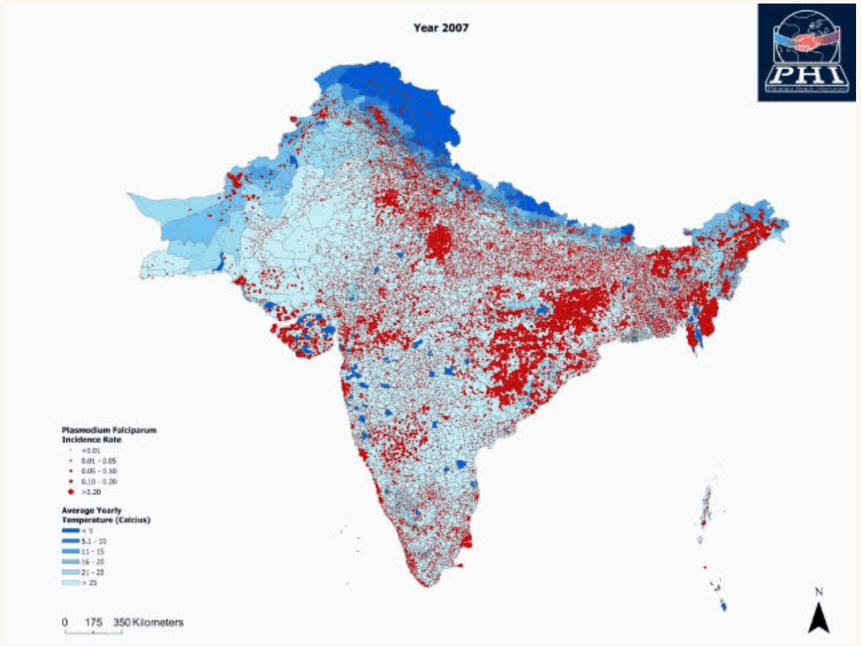


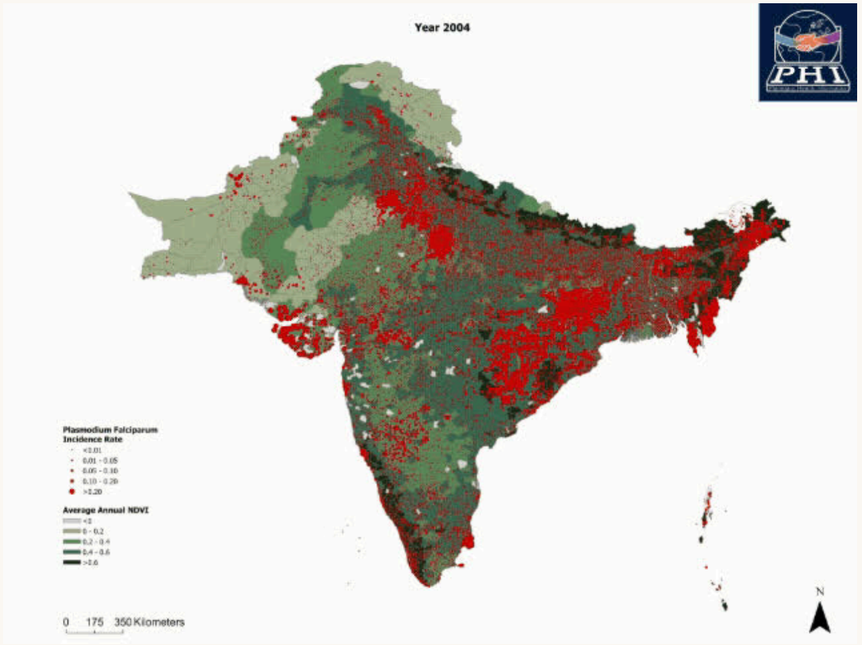
Malaria outbreak outcomes

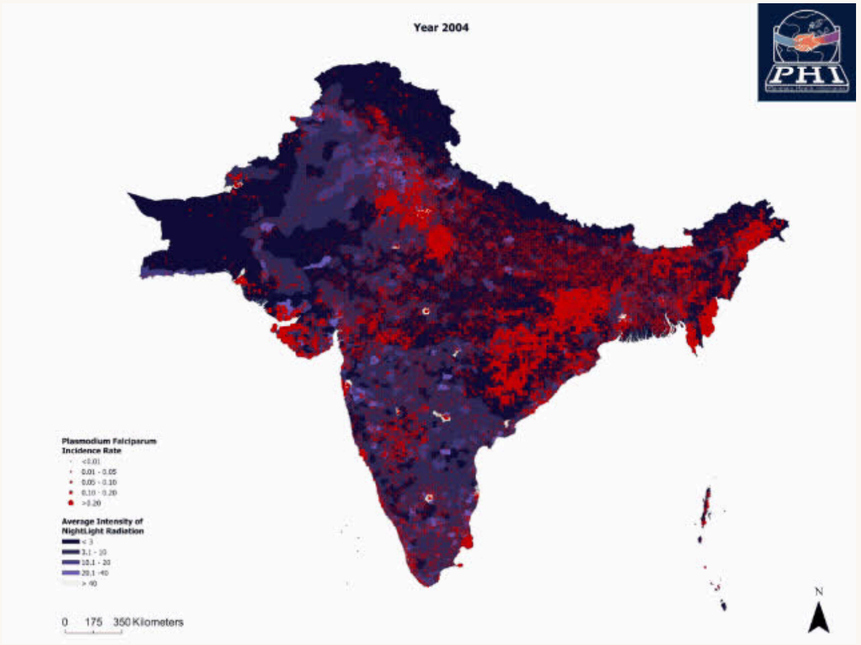


Key Outcomes



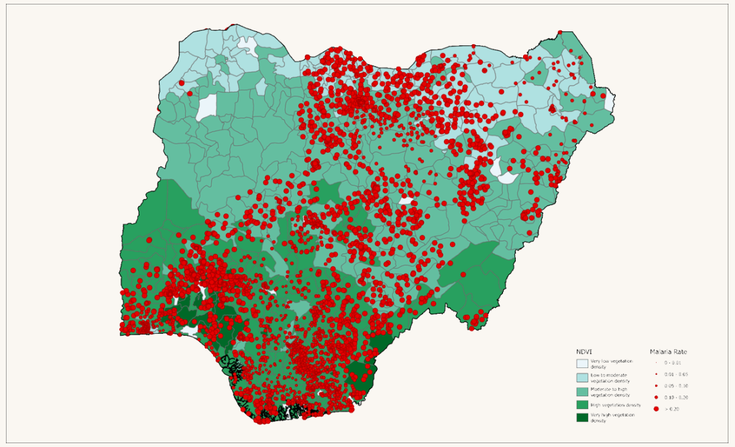


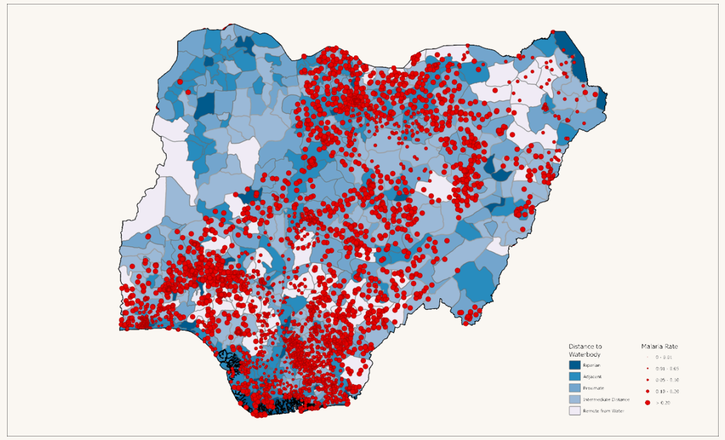


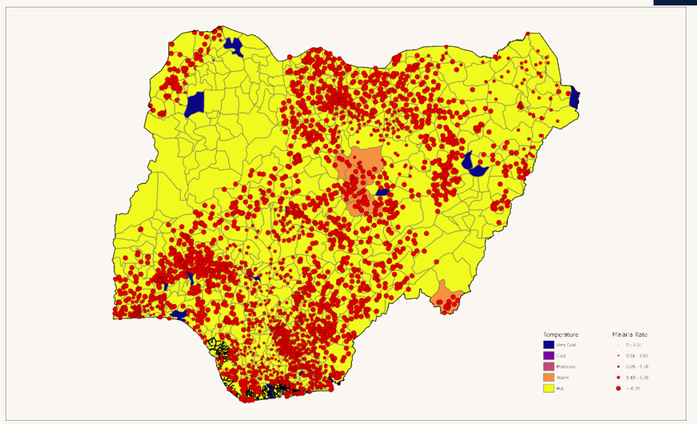


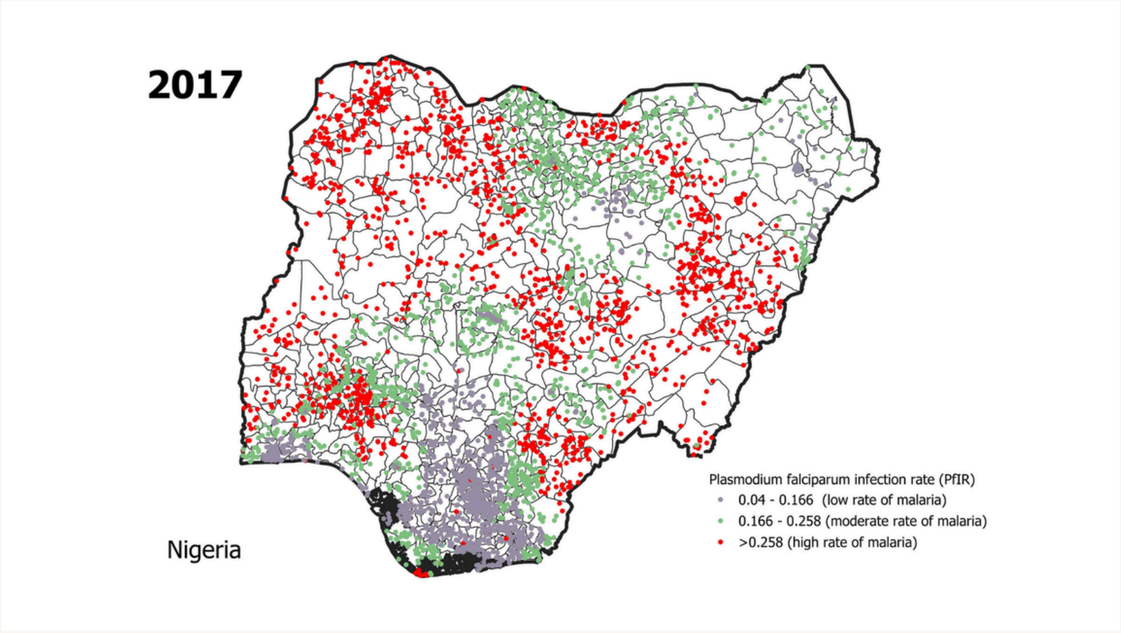
Usman Nazir et al. , “Predicting malaria outbreaks using earth observation measurements and spatiotemporal deep learning modelling: a South Asian case study from 2000 to 2017.” The Lancet Planetary Health, Volume 8, S17 (2024)

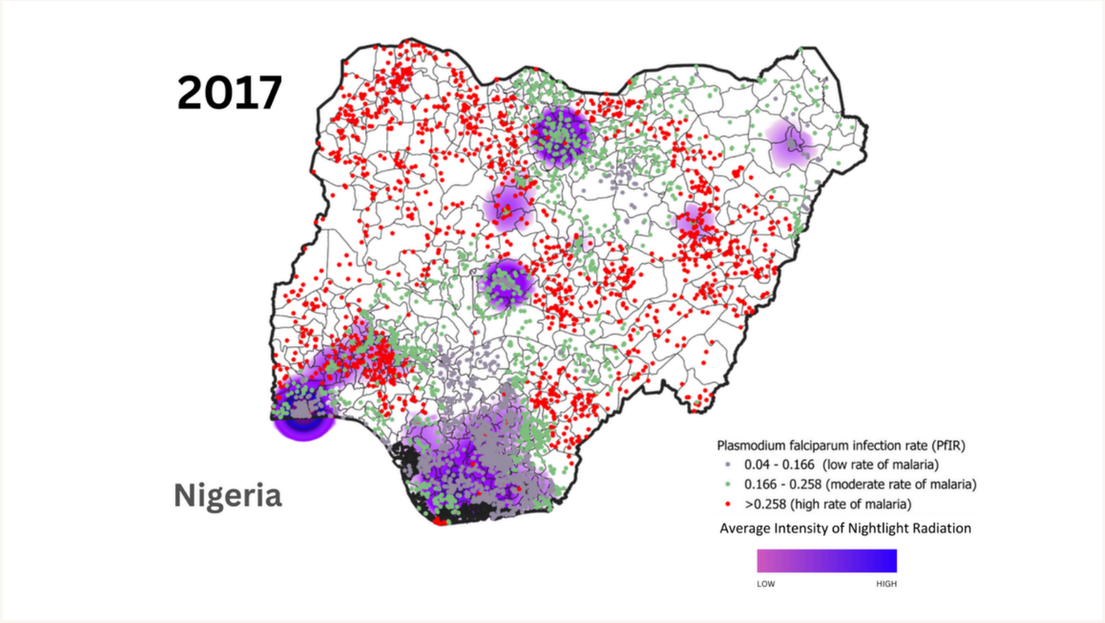
Key Outcomes









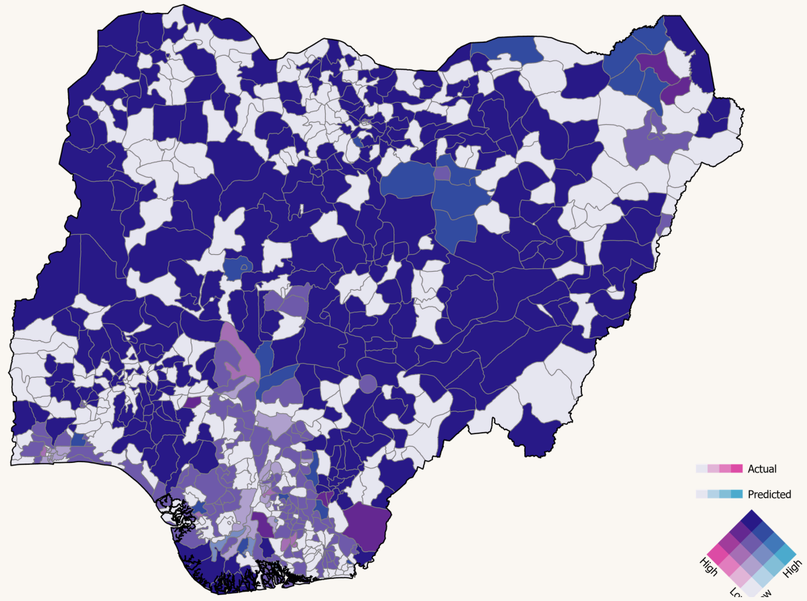


Usman Nazir, et al. "Data-Driven Prediction of Malaria Outbreaks in Nigeria." IEEE International Geoscience and Remote Sensing Symposium. IGARSS, 2025.

STUDY 1

Malaria — Results

- Developed a data-driven framework to predict malaria outbreaks in Asia and Africa.
- Integrated multi-modal Earth observation data (environmental, geospatial, urbanization).
- Strong spatial agreement supports model reliability for local planning.
- Demonstrates potential for supporting targeted public health interventions and climate-sensitive policies.
- Future work will explore additional environmental covariates and alternative models.



LSTM predicted malaria incidence rates.

Usman Nazir, et al. "Data-Driven Prediction of Malaria Outbreaks in Nigeria." IEEE International Geoscience and Remote Sensing Symposium. IGARSS, 2025.
Usman Nazir, Sara Khalid et al. , “Predicting malaria outbreaks using earth observation measurements and spatiotemporal deep learning modelling: a South Asian case study from 2000 to 2017.” The Lancet Planetary Health, Volume 8, S17 (2024)

CLIMATE-SENSITIVE DISEASE SERIES

CASE STUDY 02

Acute respiratory infection

Air pollution worsens respiratory illness



2.5M

lower-respiratory-infection deaths a year

Source: Our World in Data (IHME, GBD)

MALARIA · ARI · CHILD WASTING

Diffuse Pathways: Air, Heat & Smoke

2.5M

pneumonia deaths, 2023 (GBD)

610k

deaths in children under 5

#1

infectious cause of under-5 death

Ambient air pollution

PM2.5 and NO2 penetrate airways and impair mucosal defence and immunity; children inhale more per kg of body weight, with developing lungs.

- Directly affect the respiratory system

Household air pollution

Biomass and kerosene cooking fuels are linked to under-5 acute lower respiratory infection in low-resource settings.

Temperature extremes

Heatwaves raised paediatric ED visits for ARI (RR 1.05, ages 0–4, California); cold spells + high PM2.5 raise bronchiolitis and bronchitis incidence.

- Change respiratory risk

Extreme events & humidity

Wildfire smoke, dust storms and floods drive exposure spikes; humidity shifts alter pathogen transmission and seasonality.

- **Generate very large short-term exposure spikes.**

Sources: *GBD 2023 (IHME) · IJERPH (2020) 17:5344 · Frontiers in Public Health (2025) 13:1567206 · Pathogens (2025) bronchiolitis review.*

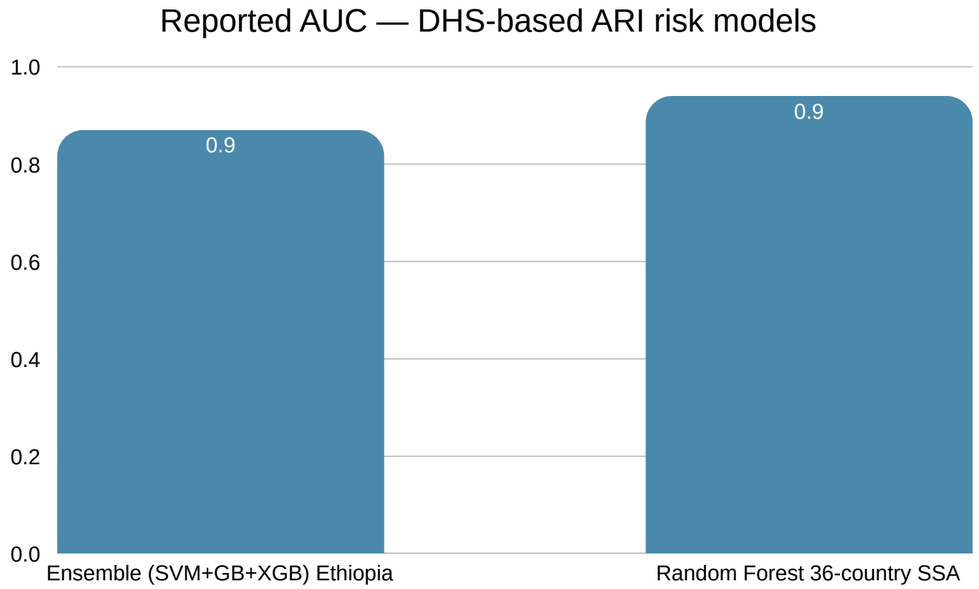
Two ML Modalities for ARI

1 · Tabular risk prediction (DHS surveys)

- Random Forest, XGBoost, SVM, 1D-CNN + SHAP interpretability.
- Best reported: **RF 96.4% accuracy, AUC 0.94** across 36 sub-Saharan countries (75,827 children).
- Deployed as Streamlit web + offline apps for screening.

2 · Imaging diagnostics (chest X-ray CNNs)

- **CheXNet**: 121-layer DenseNet trained on ChestX-ray14 (>100,000 images).
- **Exceeds average radiologist F1** on pneumonia detection — but requires imaging infrastructure.



Top predictors (via SHAP): breastfeeding · vaccination · cooking-fuel type · maternal education · recent diarrhoea

Sources: PMC11614669 (2024) 36-country SSA DHS study · Scientific Reports (2024) 10.1038/s41598-024-76847-3 · Rajpurkar et al. (2017) arXiv:1711.05225.

Live poll 5 of 8

What is most often missing from existing AI studies of acute respiratory infection?

A Health outcome data

B Machine learning methods

C Climate and air-quality covariates

D Demographic information

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Scan or type to vote

Key Studies — and the Climate Gap

- **Rajpurkar et al. 2017 · arXiv:1711.05225 (CheXNet)**
  121-layer DenseNet on >100,000 chest films; exceeds average radiologist F1 on pneumonia.

- **GBD 2023 · IHME**
  Pneumonia burden: 2.5M deaths in 2023, including 610,000 children under five.

- **36-country SSA DHS ML study · 2024**
  Random Forest best of the compared classifiers — AUC 0.94 on 75,827 children.

- **Amhara Region, Ethiopia · Scientific Reports 2024**
  Seven-model comparison with grid-search tuning for under-5 ARI prediction.

The gap

Very few ARI-ML studies integrate climate or air-quality covariates at all — most rely on socio-demographic survey variables alone.

The opportunity

CCAI-style fusion of pollution fields, weather and health surveillance — an open lane for climate-aware ARI prediction.

Few explicitly integrate climate or air-quality covariates.

Sources: *Rajpurkar et al. (2017) · GBD 2023 (IHME) · PMC11614669 (2024) · Scientific Reports (2024).*





- People are breathing this air.
- Children are going to school in it.
- Patients are arriving at hospitals from it.

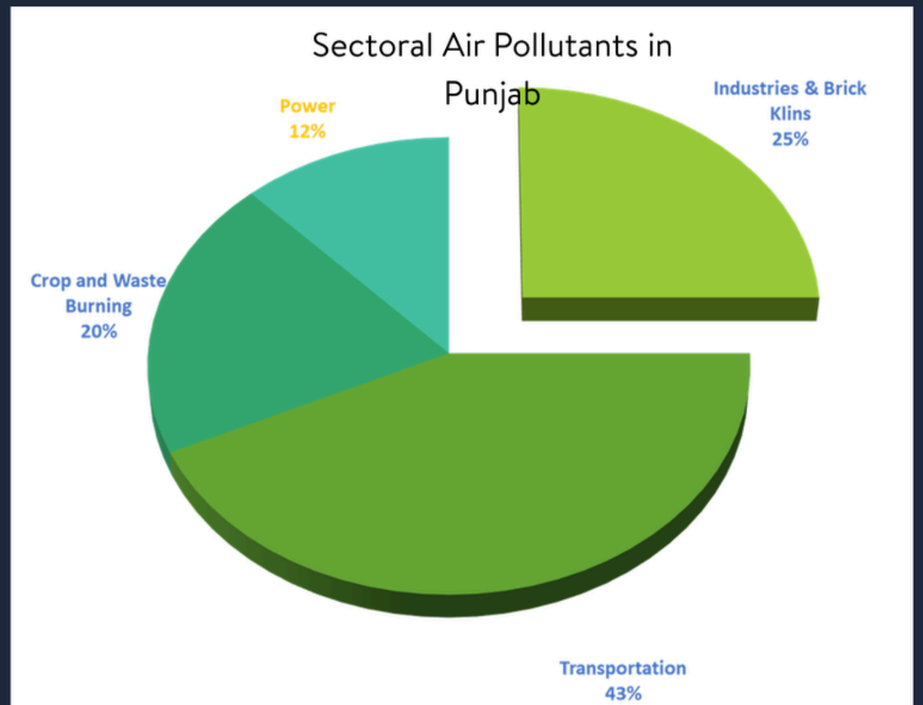




Photograph Credits: Reuters.

Smog, slavery, and the brick-kiln industry

- 40.3 million people are currently held in forced labour globally
- 24.3 million of these people are being forced to work at 55,000 brick kilns across Pakistan, India, Bangladesh, and Nepal
- UN SDG 8.7 specificies eradicating forced labour by 2025
- These brick kilns are also a major source of air pollution
- The research challenge for addressing this issue is the absence of spatially explicit data, the expense of conducting surveys in remote areas, and the challenges of scaling research



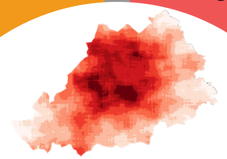


NDORMS
NUFFIELD DEPARTMENT OF ORTHOPAEDICS, RHEUMATOLOGY AND MUSCULOSKELETAL SCIENCES

PHI
Planetary Health Informatics

20–30%
hospital admissions for respiratory issues

15%
asthma cases among school children



Impact on Public Health in

Lahore

CM Punjab Smog Mitigation Plan 2024

50%
Pediatric patients due to respiratory issues

500
people were hospitalized in a single day in govt hospitals of Lahore



9%
Non – combustion Industrial Processes



24%
Industry



16%
Energy



39%
Transport



11%
Agriculture



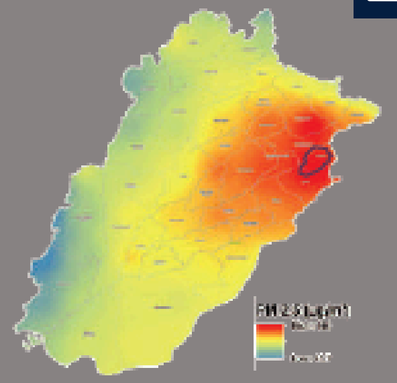
1%
Others

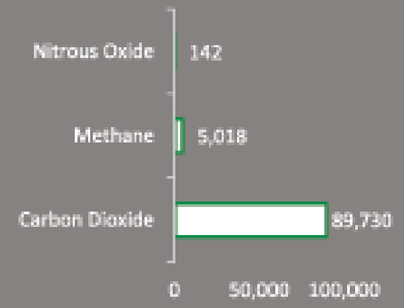
Emission Share

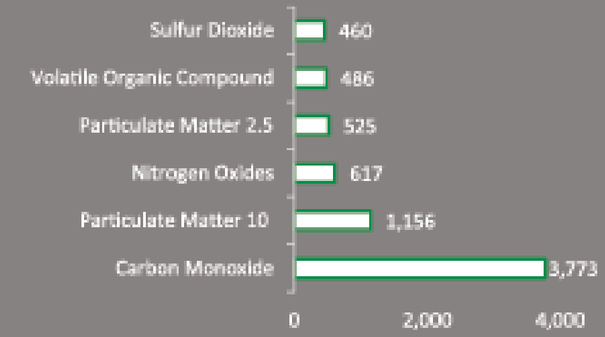
EMISSION SHARE OF PUNJAB

94,890 Kilotonnes/year (kt/y)
Total GHG Emissions
CO2, CH4 and N2O

7,017 Kilotonnes/year (kt/y)
Total Air Emissions
PM10, PM2.5, SO2, NOx, CO, VOC

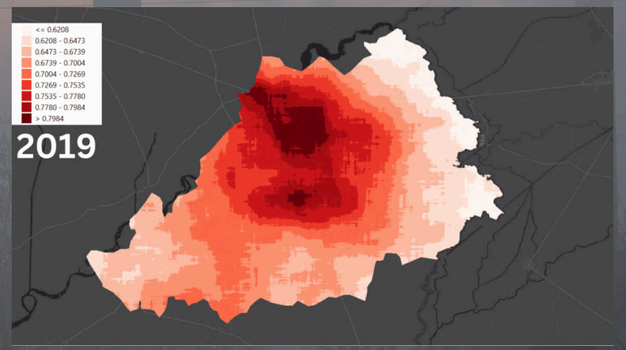






Source: Integrated Assessment of Air Pollution and Climate Change Mitigation in Pakistan 2022 (ccacoalition.org)

Source: Punjab Pollution Inventory, SUPARCO and Urban Unit 2023 https://urbanunit.gov.pk/Download/publications/Files/8/2023/Emission%20Inventory%20of%20Punjab%201990-2020_FD.pdf



STUDY 2

Emission Sources vs ARI Cases

Linking air-pollution emissions to acute respiratory infections





Emission sources

- **Brick kilns**
- $PM_{2.5}$ / PM_{10} — satellite-derived (MAIAC, CAMS)
- NO_2 column (Sentinel-5P TROPOMI)
- Traffic, crop-residue burning
- Household solid-fuel use (proxy from DHS)
- Meteorology — wind, mixing height, inversions

ARI outcomes

- **ARI cases in < 5s**
- Pneumonia & ARI cases in <5s
- Hospital admission rates
- Mortality from lower-respiratory disease
- Stratified by age (<5)
- Seasonal vs episodic exposure windows

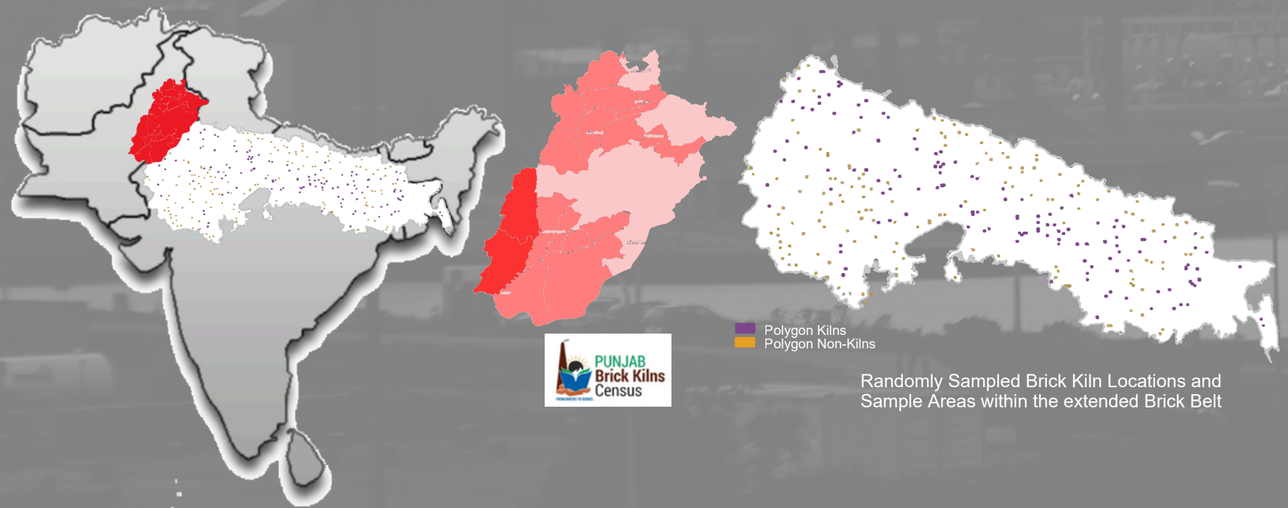
Challenges

- Bottleneck: Absence of spatially explicit data.
- Huge variations in satellite imagery.



Existing Strategies & Limitations

- Field surveys and manual localization are both tedious and lack scalability [2].
- Data obtained manually from satellite imagery is very sparse [3].

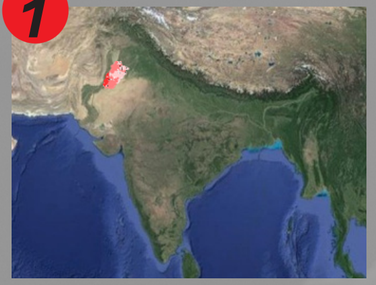


Randomly Sampled Brick Kiln Locations and
Sample Areas within the extended Brick Belt



Emission Sources Detection Framework

A classical machine-learning approach to localize brick kilns in remote-sensing imagery.

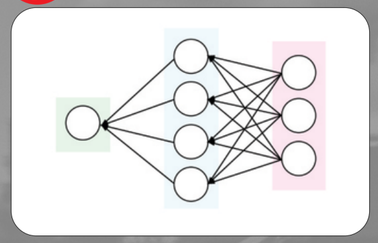
1

Region of Interest

2


Province Punjab, Pakistan

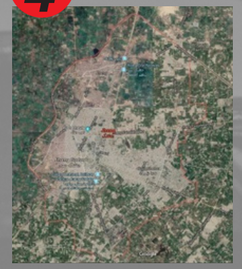
3

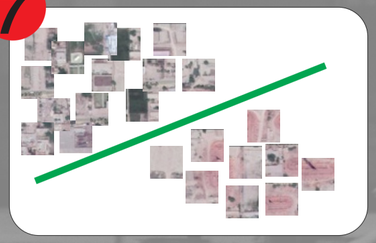

District Jhang, Punjab

6

Deep Neural Network

5

Slicing image patches

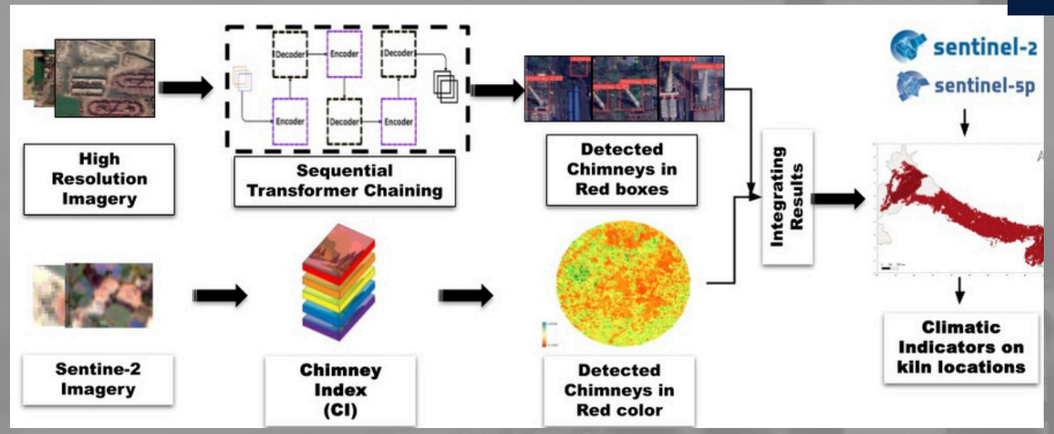
4

Satellite Imagery of the region

7

Classification of Kiln/Non-kiln patches

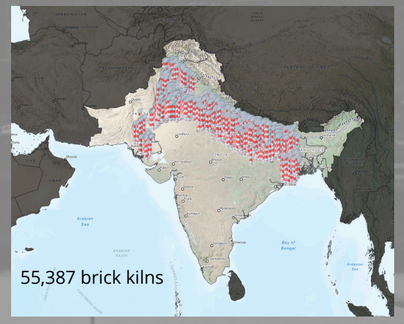
8

Locating possible Brick Kilns

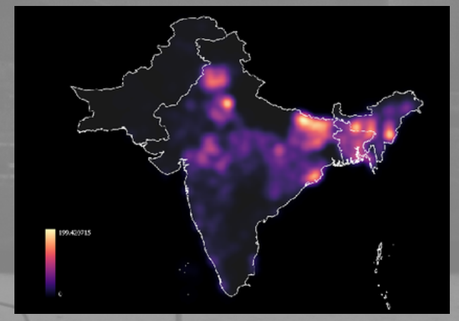
Proposed Architecture



Qualitative Results



Brick kiln Belt of South Asia


Acute Respiratory Infection cases

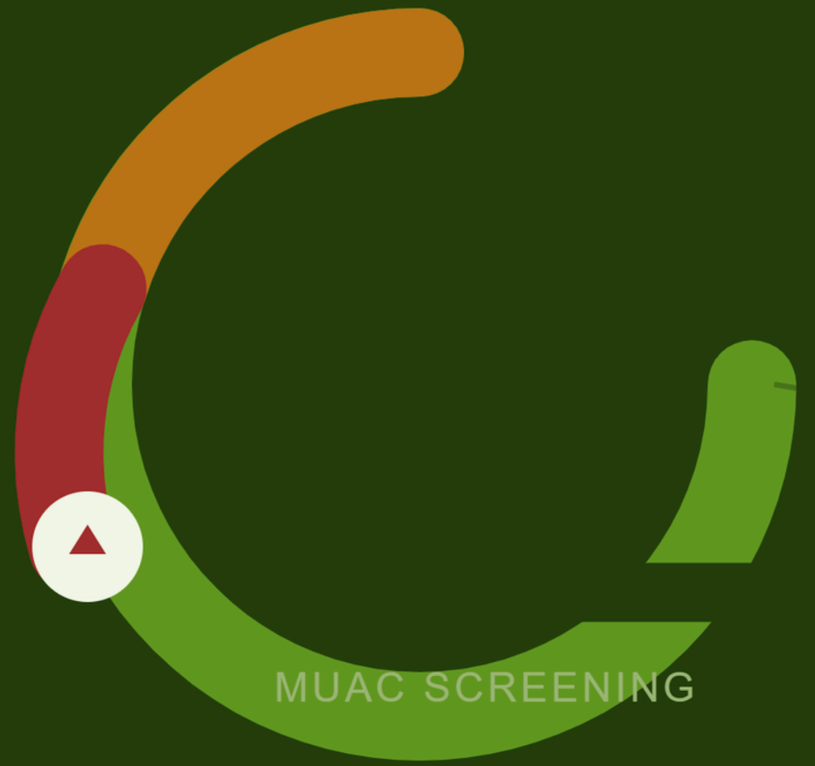
https://www.ox.ac.uk/news/2023-06-15-ai-could-help-detect-unregulated-sources-air-pollution-south-asia-new-project-shows
https://neurips.cc/virtual/2024/100569: Mapping Air Pollution Sources with Sequential Transformer Chaining: A Case Study in South Asia

CLIMATE-SENSITIVE DISEASE SERIES

CASE STUDY 03

Child wasting

Drought and crop failure drive malnutrition



45M

children under 5 affected by wasting

Source: Our World in Data (UNICEF/WHO/WB)

MALARIA · ARI · CHILD WASTING

Live poll 6 of 8

After a severe climate shock, how quickly can acute child malnutrition begin to rise?

A Within days

B Within 6 to 8 weeks

C After 1 to 2 years

D After a decade or more

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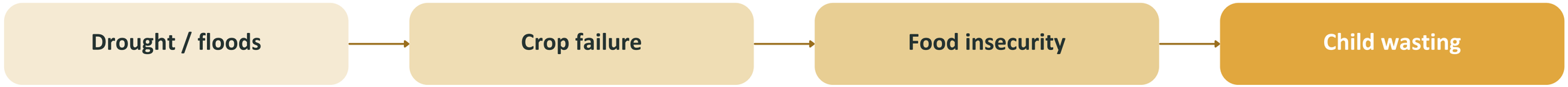
Scan or type to vote

From Drought to Wasting in Weeks

42.8M
children wasted, 2024 (6.6%)

12.2M
severely wasted (1.9%)

~1M
associated child deaths per year



Global acute malnutrition rises within 6–8 weeks of drought onset in pastoralist communities (12–17 weeks in settled communities).

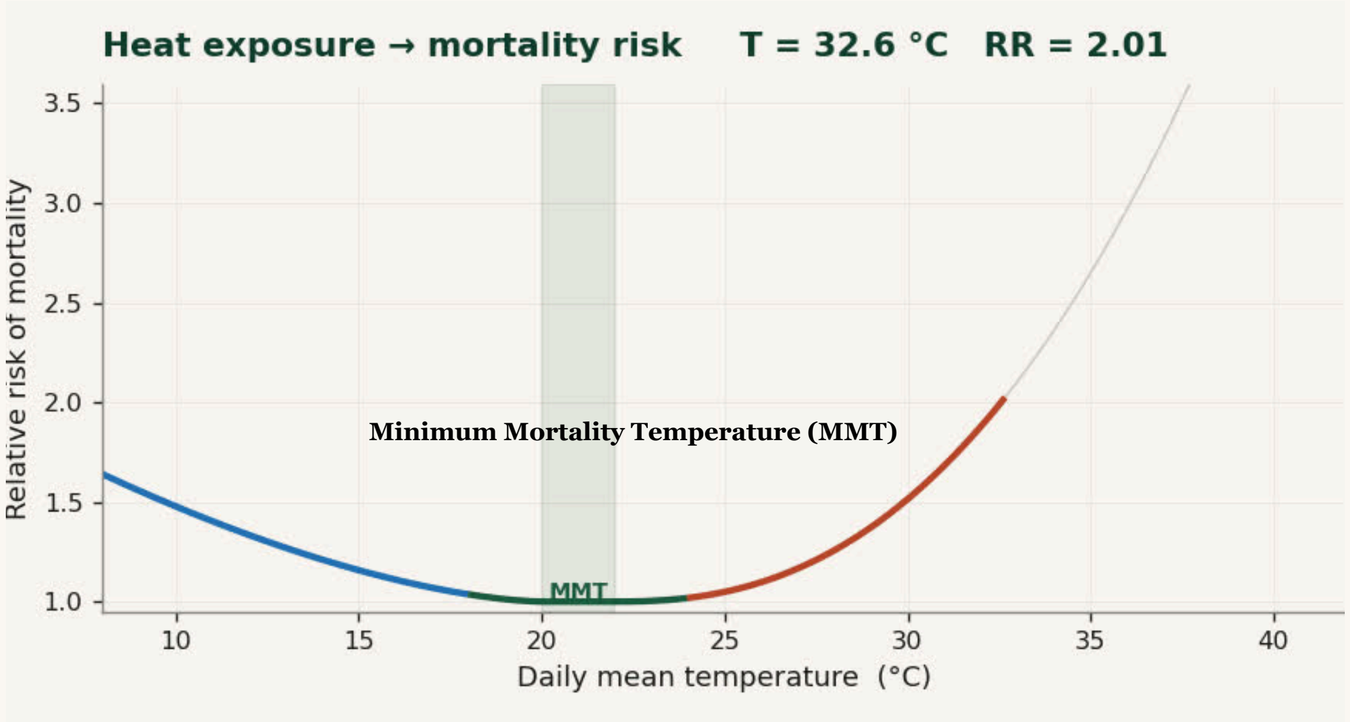
- **Drought indices (SPEI)** link rainfall-evapotranspiration deficits to global and severe acute malnutrition (GAM/SAM).
- **WASH pathway:** floods and drought contaminate water → diarrhoeal disease → nutrient loss → wasting.
- Ethiopia 2025: **~900,000 children at risk of severe wasting** amid drought and displacement (UNICEF).
- **The pathway is socially mediated** — household income, caregiver education and water access determine whether a climate shock becomes a nutrition crisis.

Sources: *UNICEF/WHO/World Bank JME (2025 edition) · Klapka et al. (2026) J Human Nutrition & Dietetics · UNICEF USA (2025).*

STUDY 3

Heat Exposure vs Child Wasting/WHZ

Heat stress → maternal nutrition, gestation, food security → wasting/WHZ



Heat exposure → mortality risk follows a J/U-shaped curve. Stunting shows analogous dose-response in cohort studies.

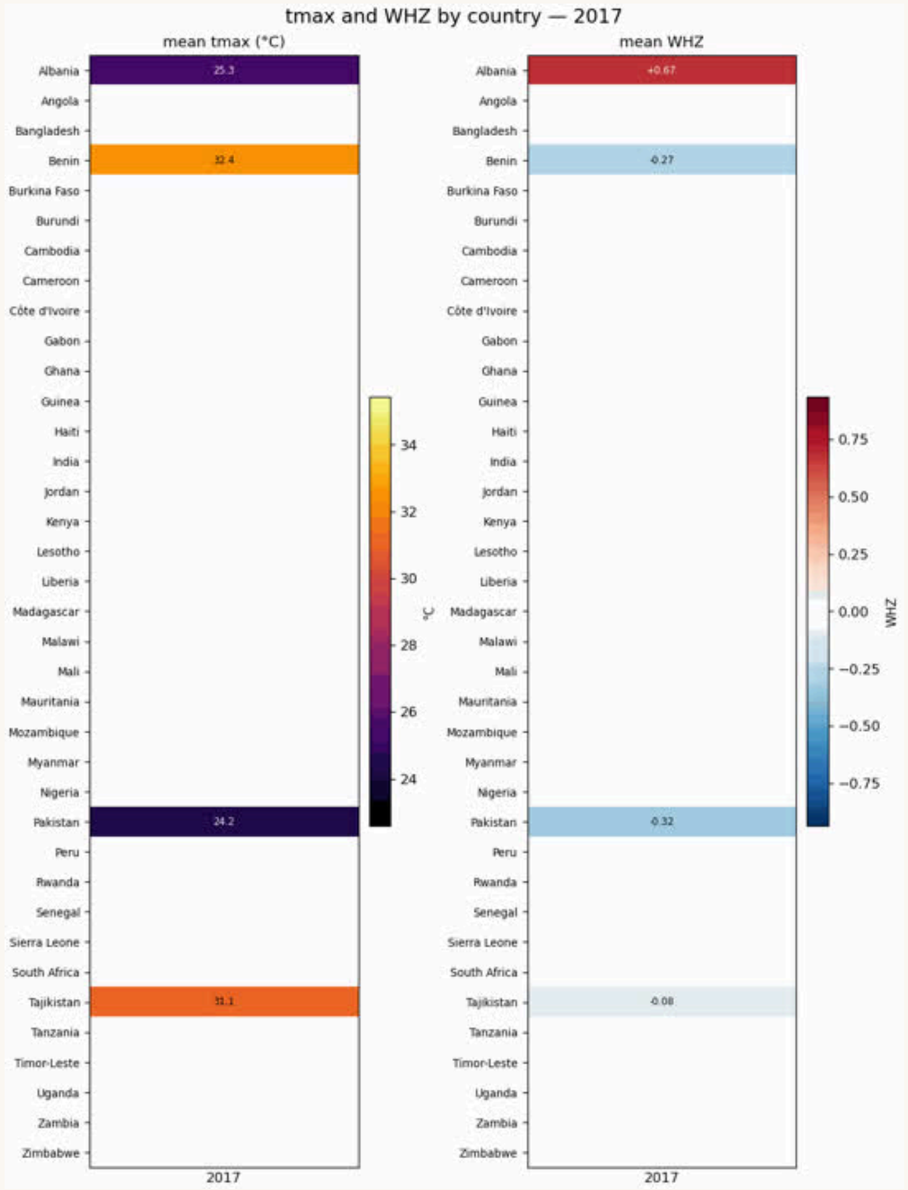
WHZ outcome: It tells us how a child's weight compares with a healthy reference population for their height and age.

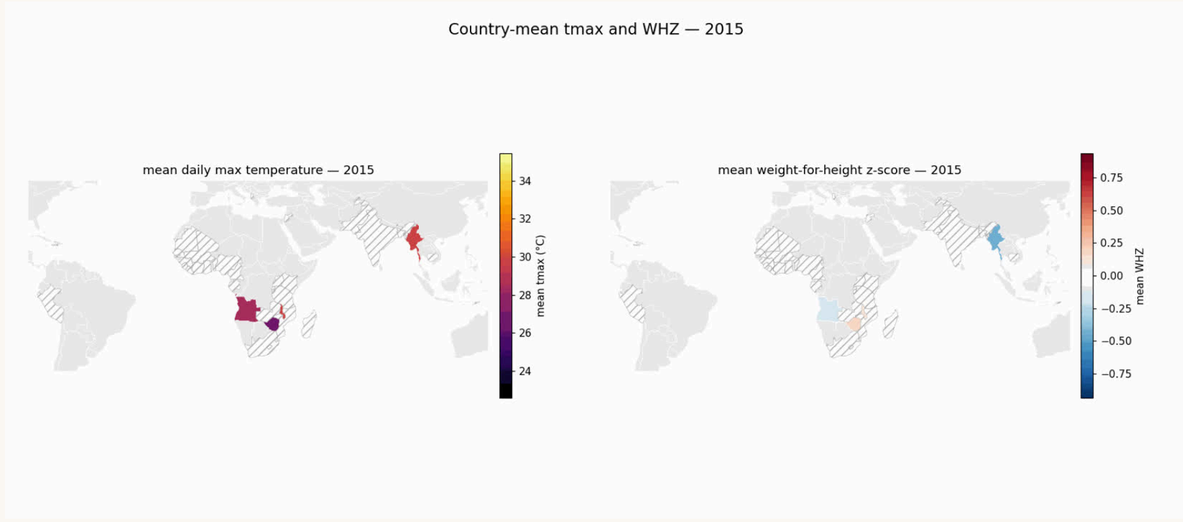
- WHZ = Weight-for-Height Z-score — how far a child's weight deviates from the WHO median weight for a healthy child of the same height and gender, measured in standard deviations
- DHS / MICS clusters, geo-tagged
- Heat-day count in 1000-day window
- Maternal heat exposure in pregnancy
- Adjust: wealth, breastfeeding, diet

https://doi.org/10.1016/j.envint.2024.108691.
(https:/www.sciencedirect.com/science/article/pii/S0160412024002770)

STUDY 3

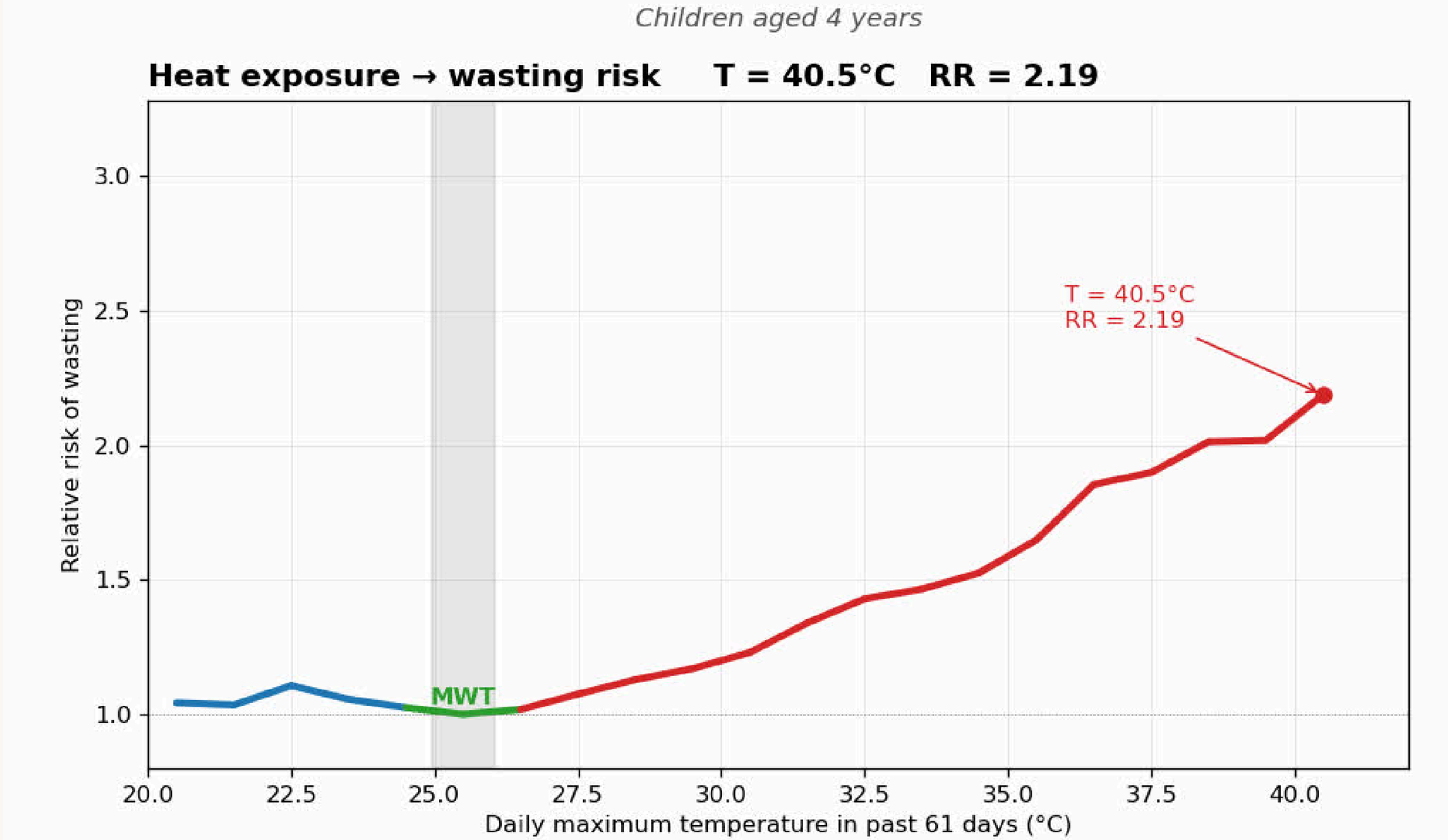
Heat → WHZ — Results





- **WHZ = 0** → exactly at the WHO healthy median.
- **Negative WHZ** → child is lighter than the median for their height (thin for their stature). This is the definition of wasting, which reflects acute undernutrition (recent food shortage, illness, or both — distinct from stunting, which is chronic).
- **WHZ < −2** → moderate wasting
- **WHZ < −3** → severe acute malnutrition (SAM) — high mortality risk, the clinical emergency threshold.
- **Positive WHZ** → heavier than median for height (can shade into overweight at very high values, but small positives just mean well-nourished).

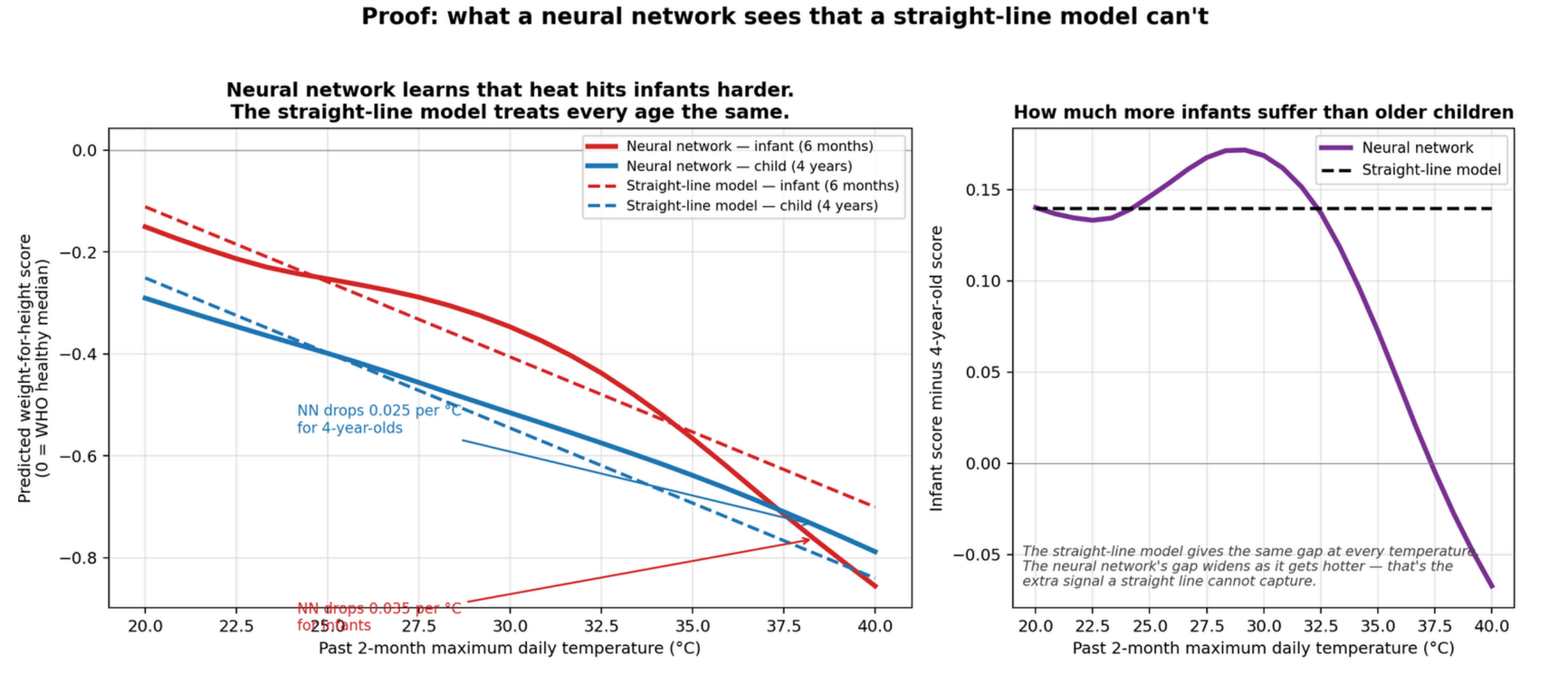
Improving Data Interpretation Through Visualization

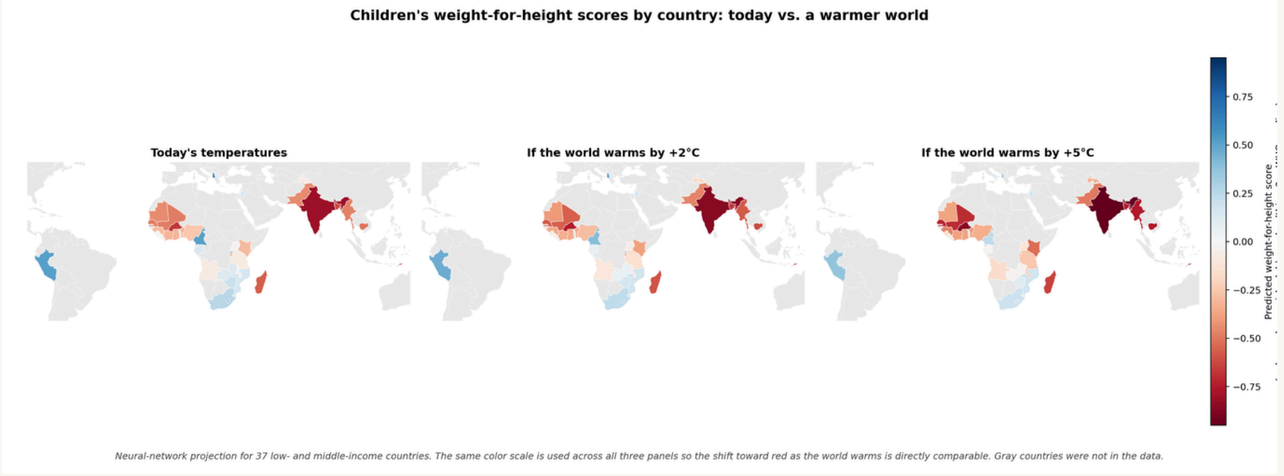


Heat exposure → wasting risk follows a J-shaped curve. MWT = temperature with the lowest wasting risk; bins need ≥30 children.

Improving Data Interpretation Through Visualization

A two-layer feed-forward neural network (64 → 32 ReLU units) trained on 64,000 children and tested on 16,000, predicting weight-for-height from temperature, age, household and sanitation conditions, and country. Unlike the linear model it learns that heat hurts infants more than older children.





SECTION 04

Heat-Related Illness in the General Population

A retrospective cohort study, 2017–2022 · PharMetrics® Plus, mapped to OMOP

141,672
PEOPLE AFFECTED

285,555
HRI EVENTS

67.4 yrs
MEAN AGE

Live poll 7 of 8

By roughly how much does heat-related illness in adults 65+ exceed that in adults 18–64?

A About twice as high

B Three to five times higher

C About ten times higher

D It is actually lower

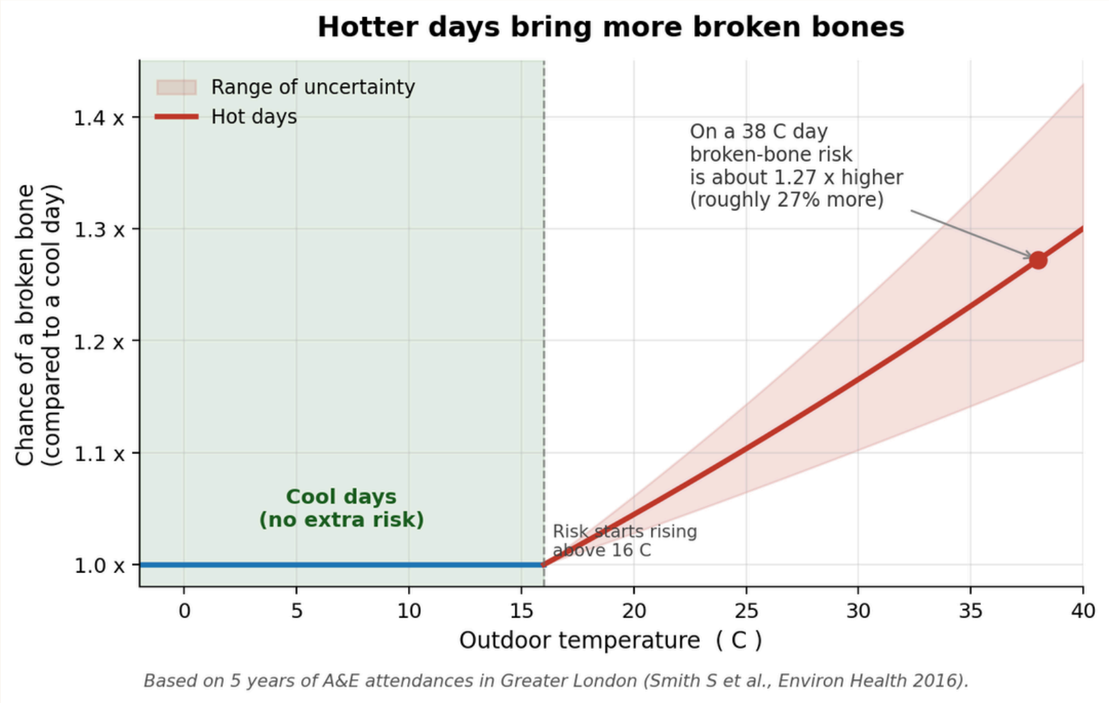
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Scan or type to vote

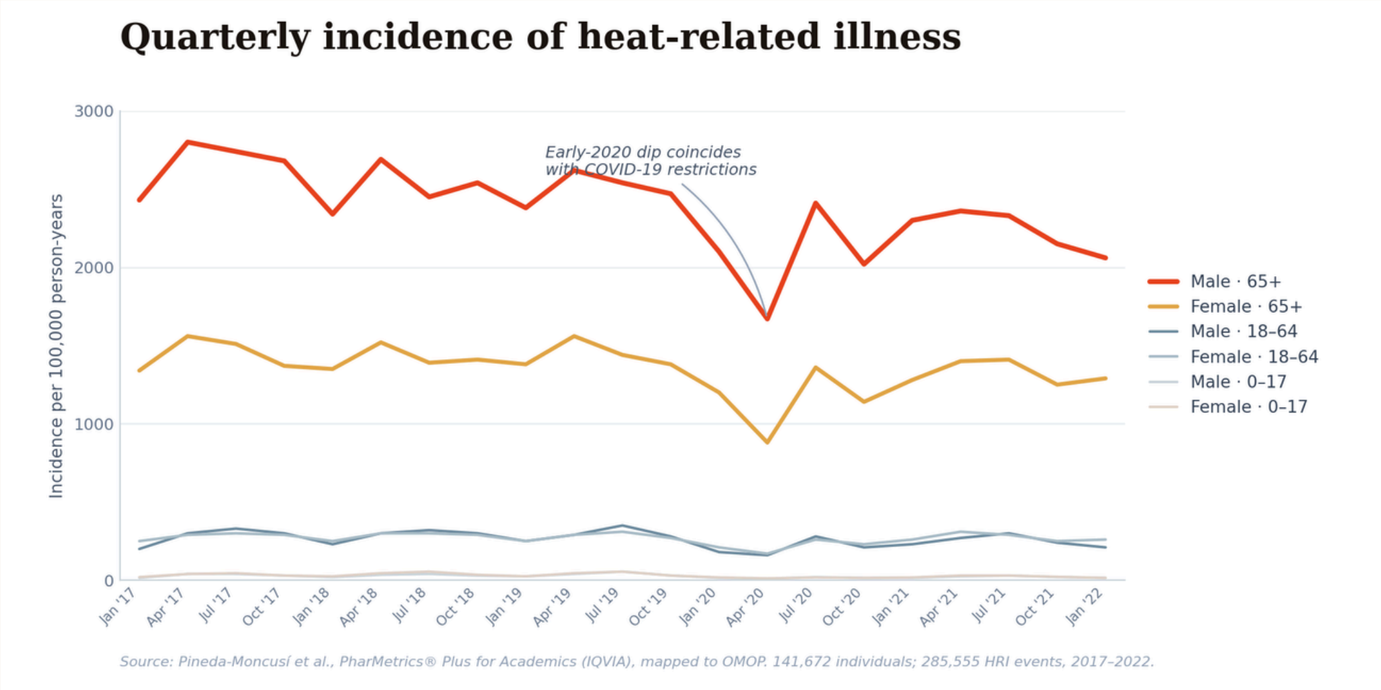
STUDY 4

Heat-related illness in OMOP network studies

relevance to musculoskeletal research



Outdoor temperature increases, fracture risk also increases.



Older adults have much higher recorded incidence of heat-related illness, particularly men aged 65+

Khalid S, et al. Incidence of Heat-Related Illness in the United States, 2017–2022. University of Oxford.

Live poll 8 of 8

What is the biggest limitation of using historical climate-health data to answer adaptation questions?

A Historical data are not useful

B Future climate may not resemble the past

C Health data cannot be modelled with AI

D ML cannot capture nonlinearity

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Scan or type to vote

FUTURE DIRECTIONS

Open Problems for the CCAI Community

Methodological frontiers

- **Integrate CMIP6 / SSP climate projections** into forecasting — not just historical weather.
- Causal & transferable ML; domain adaptation across regions.
- Foundation models & LLMs: news-NLP food-crisis forecasting already shows a 46% accuracy gain.
- Uncertainty quantification → probabilistic, decision-ready alerts.

Practice & equity

- **Equity-centred co-design** with LMIC health systems; open data & reproducibility.
- Underexplored: climate–ARI fusion; concurrent wasting + stunting; compound climate shocks.
- Sustain deployments beyond pilot funding — the EPIDEMIA lesson.

Several important directions:

- **Bring future climate projections into health models.**
- **Models that can transfer across regions.**
- **Stronger causal reasoning.**
- **Uncertainty quantification.**
- **Design these systems with health systems and affected communities.**

The biggest gap: most models learn from past weather — so they cannot answer the adaptation questions policymakers actually ask.

Sources: *Colón-González et al. (2021) · Balashankar et al. (2022) Science Advances 8:eabm3449 · scoping reviews (2024–26).*

Thank You

Bluesky: @phi-lab.bsky.social

Human health and the health of the planet are one system — and the data is finally good enough to act on it.
www.terrahealth.net

Questions & Discussion

usman.nazir@ndorms.ox.ac.uk

Extras