



# Artificial Intelligence for Planetary Health

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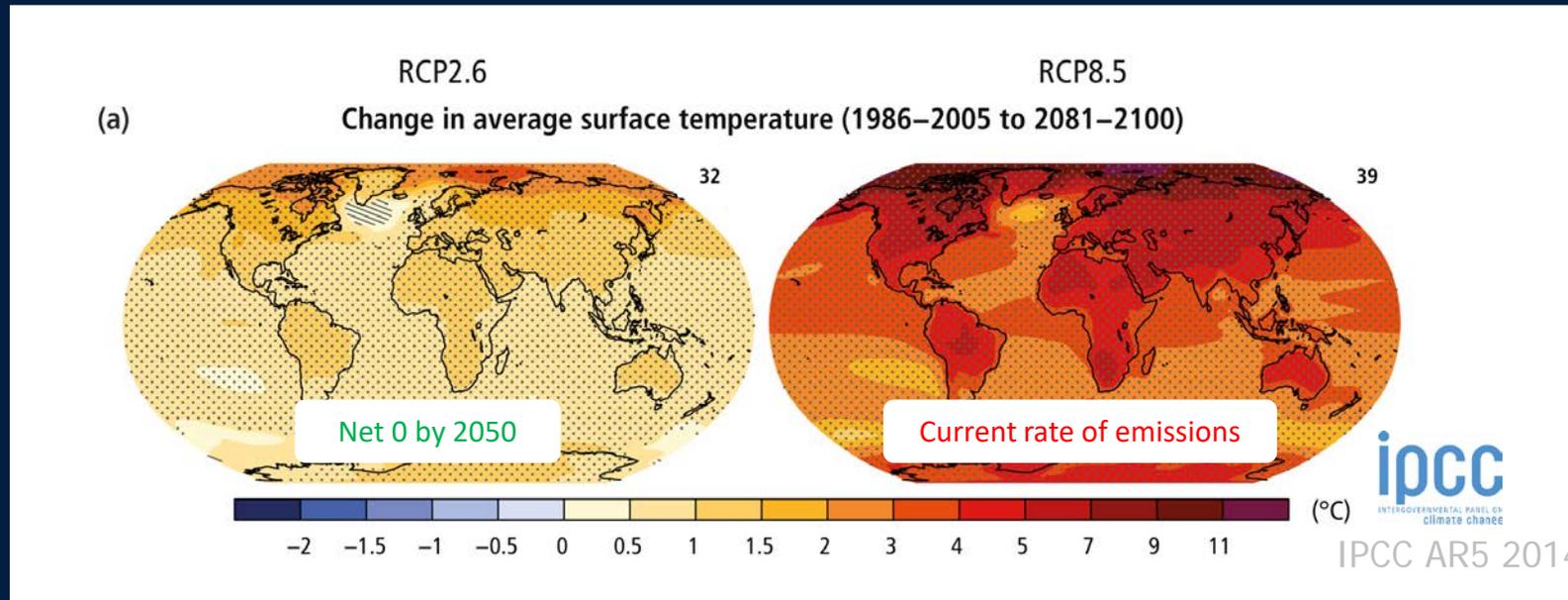
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[www.ndorms.ox.ac.uk/planetary-health-informatics](http://www.ndorms.ox.ac.uk/planetary-health-informatics)



Planetary  
Health  
Informatics

# A Rapidly Warming World



“Climate change is the biggest global health threat of the 21<sup>st</sup> century”  
Lancet Commission 2020

# Climate-Health Impacts

- Direct
- Indirect
- Long-term

Increasing Levels of Carbon Dioxide and Short-Lived Climate Pollutants



Rising Temperature



Rising Sea Levels



Increasing Extreme Weather Events



**Demographic, Socioeconomic, Environmental, and Other Factors That Influence the Magnitude and Pattern of Risks**

Geography  
Ecosystem change  
Baseline air and water quality  
Agricultural and livestock practices and policies

Warning systems  
Socioeconomic status  
Health and nutritional status  
Access to effective health care

## EXPOSURE PATHWAYS

Extreme Weather Events

Heat Stress

Air Quality

Water Quality and Quantity

Food Supply and Safety

Vector Distribution and Ecology

Social Factors

## EXAMPLES OF HEALTH OUTCOMES



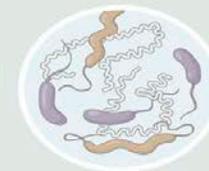
- Injuries
- Fatalities
- Mental health effects



Heat-related illness and death



- Exacerbations of asthma and other respiratory diseases
- Respiratory allergies
- Cardiovascular disease



- Campylobacter infection
- Cholera
- Cryptosporidiosis
- Harmful algal blooms
- Leptospirosis



- Undernutrition
- Salmonella food poisoning and other foodborne diseases
- Mycotoxin effects

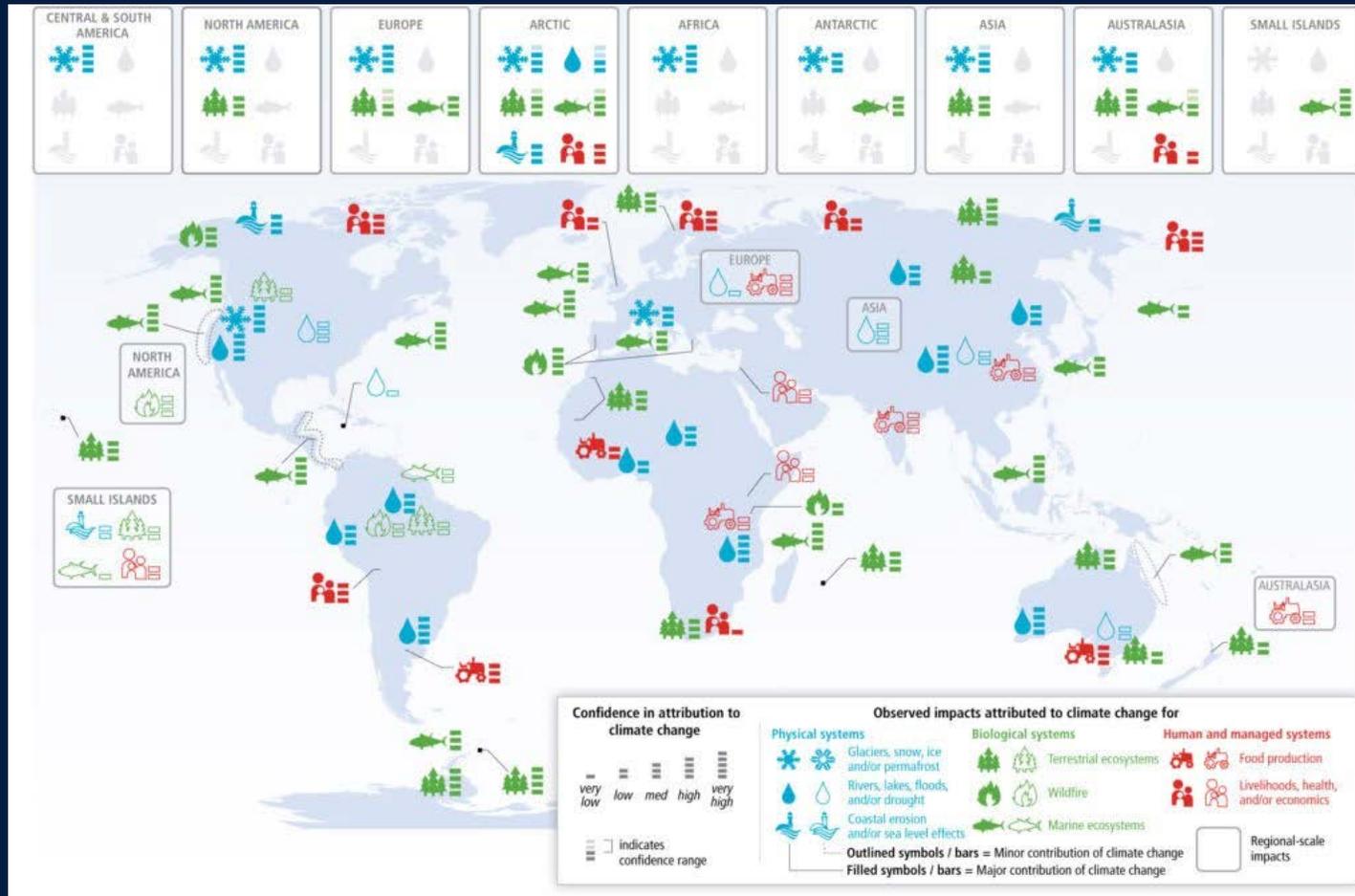


- Chikungunya
- Dengue
- Encephalitis (various forms)
- Hantavirus infection
- Lyme disease
- Malaria
- Rift Valley fever
- West Nile virus infection
- Zika virus infection



Physical and mental health effects of violent conflict and forced migration (complex and context-specific risks)

# Planetary Health



“This is the first time a global generation of children will grow up in a world made far more dangerous and uncertain as a result of a changing climate and degraded environment.”  
UNICEF

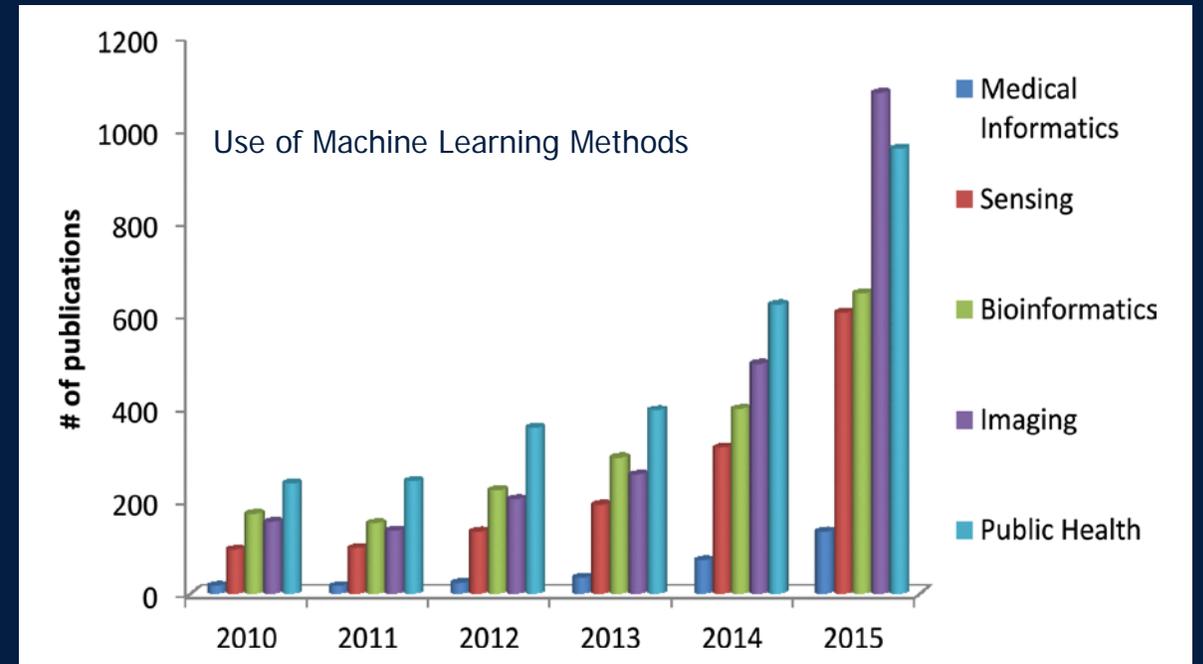
Cramer et al. Detection and attribution of observed impacts. Climate Change 2014, IPCC 5<sup>th</sup> AR



# The Role of Analytics

Providing Real time, real-world data

Improving knowledge on climate and health



Ravi et al. IEEE Biomed & Health Informatics 2017

# The Role of Analytics

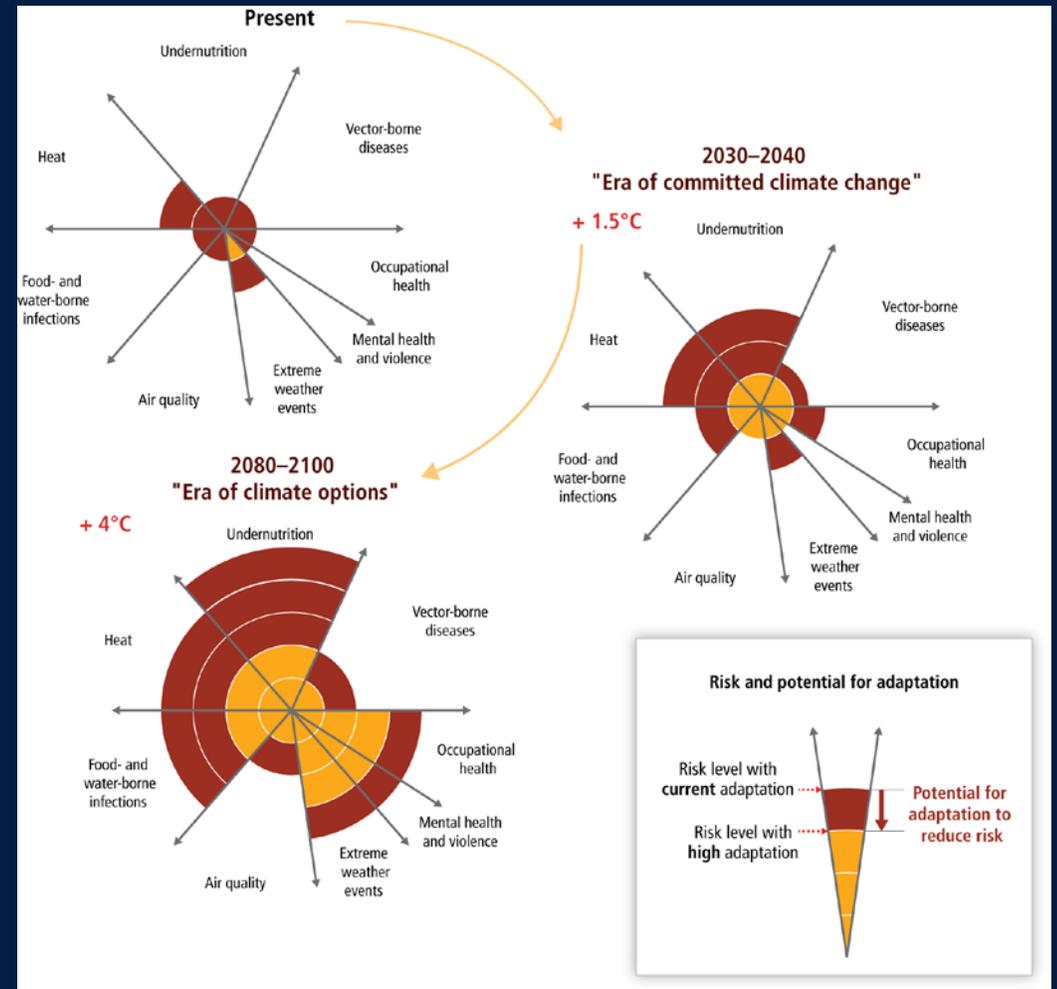
Providing real-world data

Improving knowledge on climate and health

Adaptation of health systems

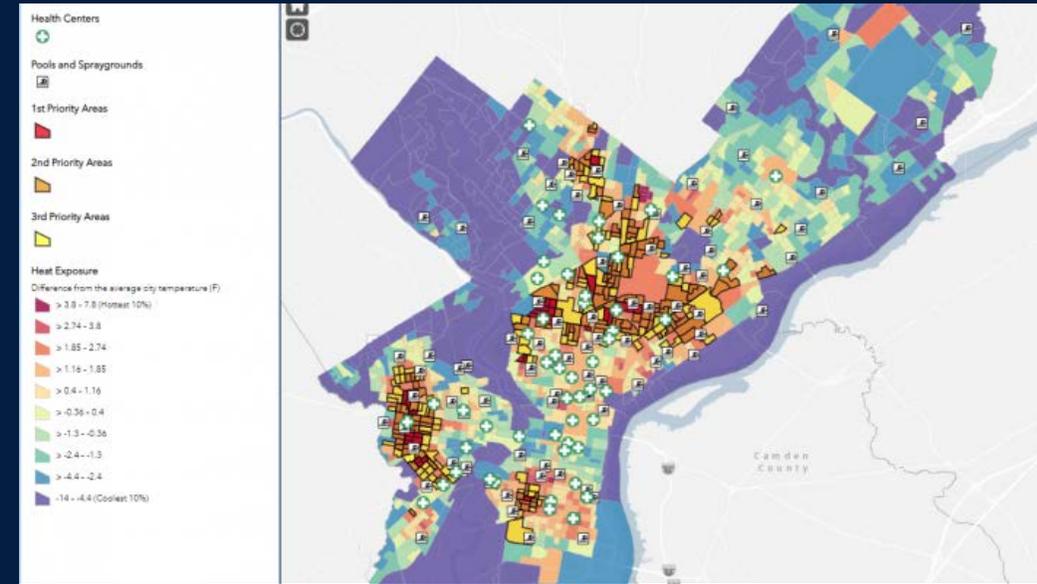
Climate impact on 8 health sectors and potential for mitigation through adaptation.

Smith et al. Human health: impacts, adaptation, and co-benefits.  
*Climate Change IPCC 5<sup>th</sup> AR 2014*



# Early Warning Systems

- Traditionally based on local knowledge
- Intelligent EWS based on
  - Expert Knowledge
  - Real-time big data
  - Advanced analytics



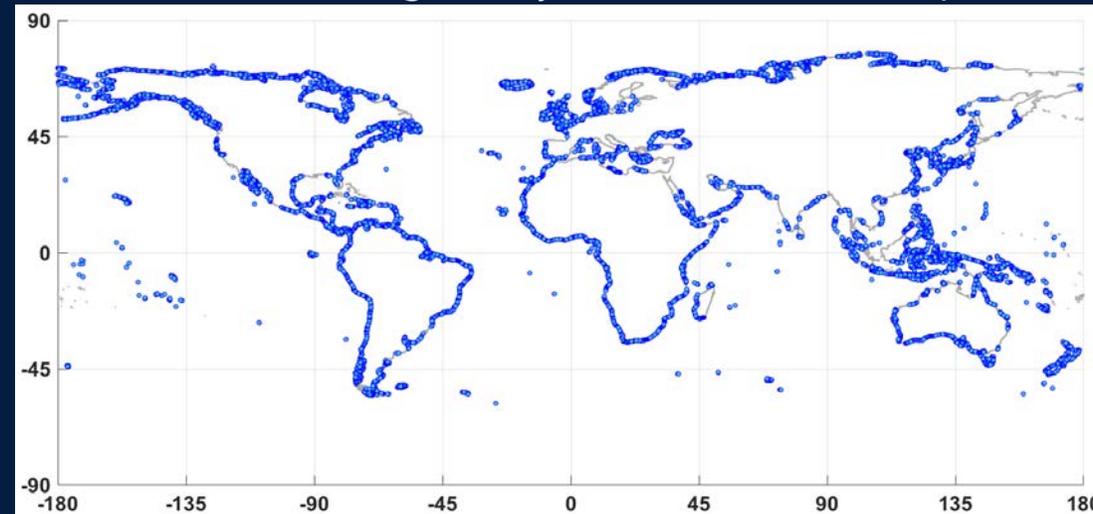
Heat risk index Philadelphia, USA.



Personalised early warning system for those most vulnerable to high levels of pollution

Credit: londonair.org.uk

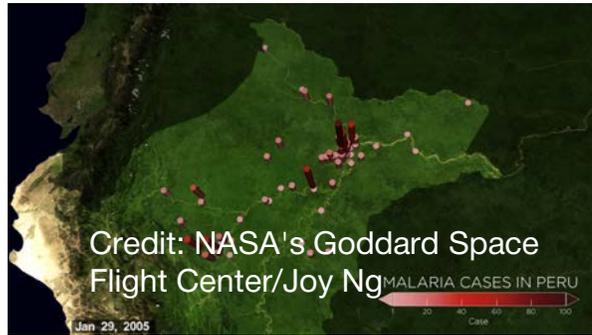
Adversarial network image analysis models for flood prediction



# Predicting Disease Outbreaks



Satellite data from Landsat series combined with ground data on precipitation, temperature, soil moisture, vegetation



Credit: NASA's Goddard Space Flight Center/Joy Ng

Computational models tracking human and environmental events

Predicting malaria outbreaks in Peru at household level

Schmidt et al. ICLR 2019. arXiv:190

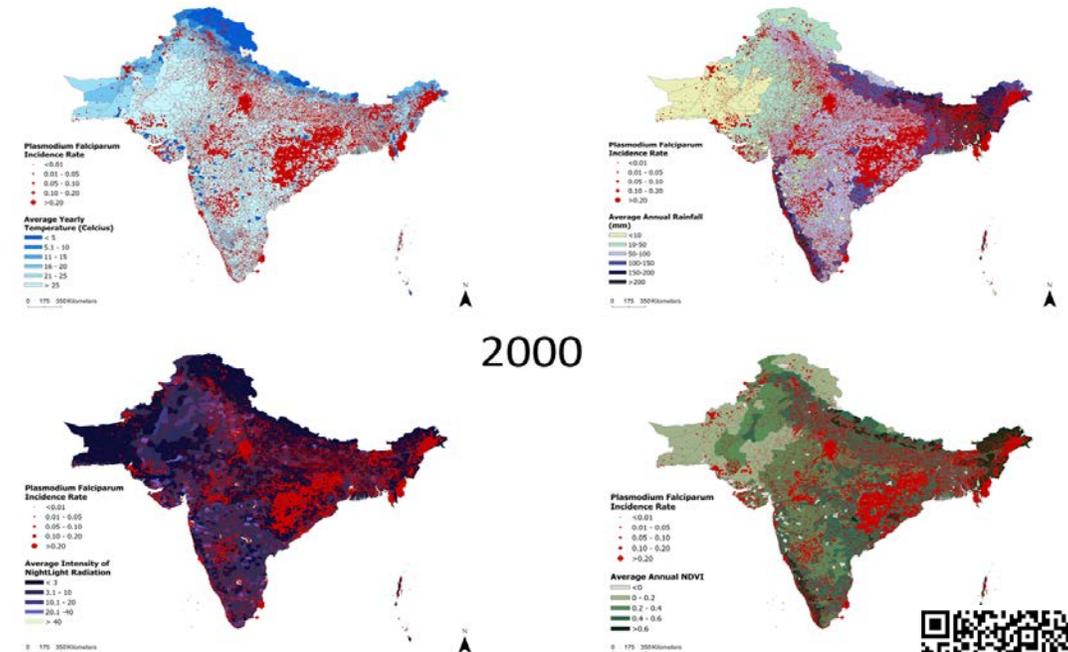


## PREDICTING MALARIA OUTBREAKS USING EARTH OBSERVATION MEASUREMENTS AND SPATIO-TEMPORAL DEEP LEARNING MODELLING: A SOUTH ASIA CASE STUDY FROM 2000 TO 2017

Usman Nazir<sup>1</sup>, Muhammad Talha Quddoos<sup>1</sup>, Momin Uppal<sup>1</sup>, Sara Khalid<sup>2</sup>

<sup>1</sup>Lahore University of Management Sciences, <sup>2</sup>Centre for Statistics in Medicine, University of Oxford

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Khalid et al. *NeurIPS* 2023



# AI and Biodiversity

IMAGE

BROWSE... No file selected

Detection threshold:

0 0.68 1

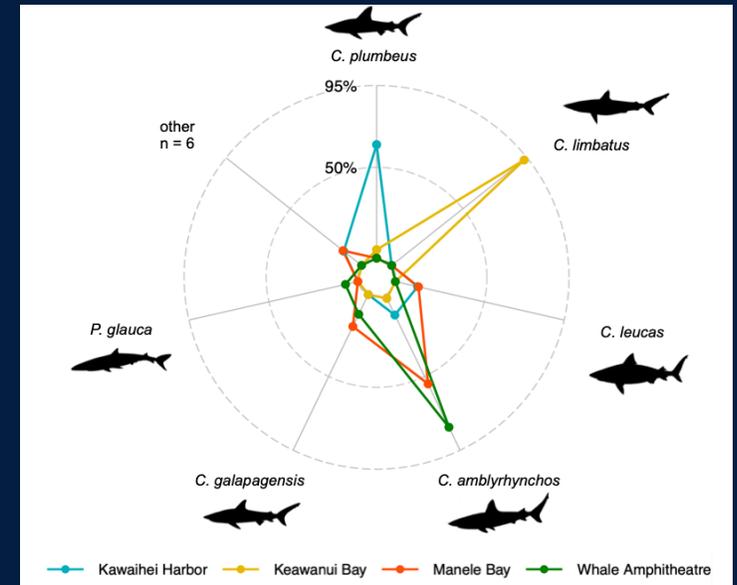
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PROCESS DETECT VIDEO PLAY VIDEO

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Shark	Prediction
Carcharhinus limbatus	94.15 %
Carcharhinus plumbeus	4.13 %
Carcharhinus amblyrhynchos	0.47 %
Galeocerdo cuvier	0.44 %
Carcharodon carcharias	0.39 %



- Remote monitoring of endangered species using underwater cameras, e-DNA, and AI

# AI and Advanced Analytics

## -Future cities

- Urban thermal comfort
- Land use optimisation
- Increased vegetation cover

## - Transport modelling

- Reduced carbon footprint
- Physical activity optimization



*“Climate Change and AI Recommendations for Government Action”*

# AI and Advanced Analytics

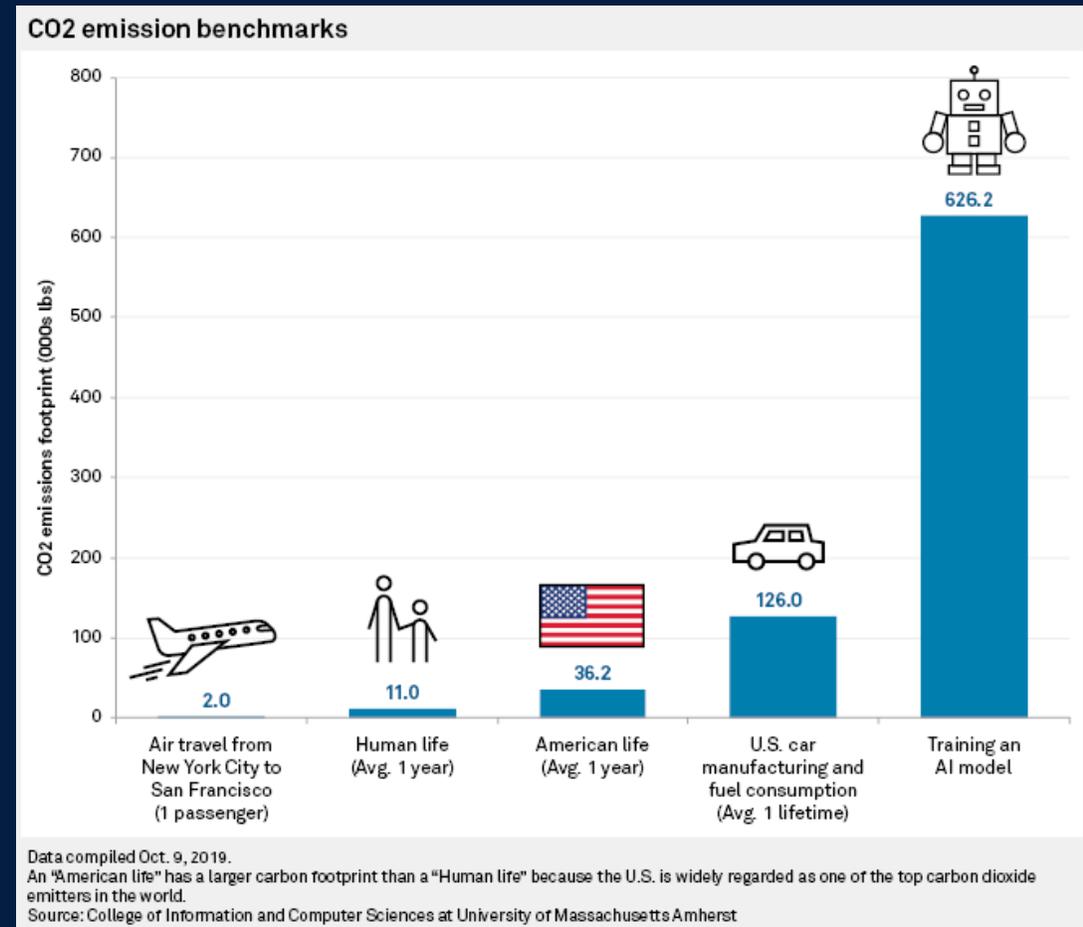
## -Future cities

- Urban thermal comfort
- Land use optimisation
- Increased vegetation cover

## - Transport modelling

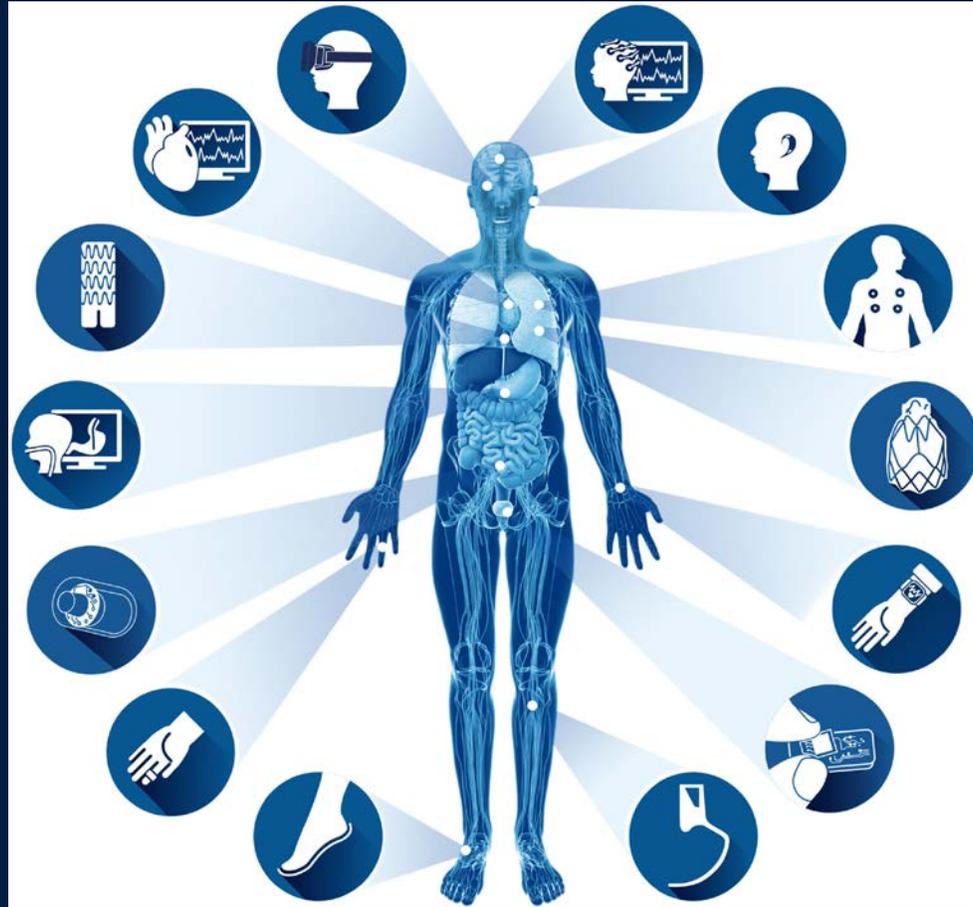
- Reduced carbon footprint
- Physical activity optimization

## -Carbon footprint of AI



# Real-world Data in Healthcare

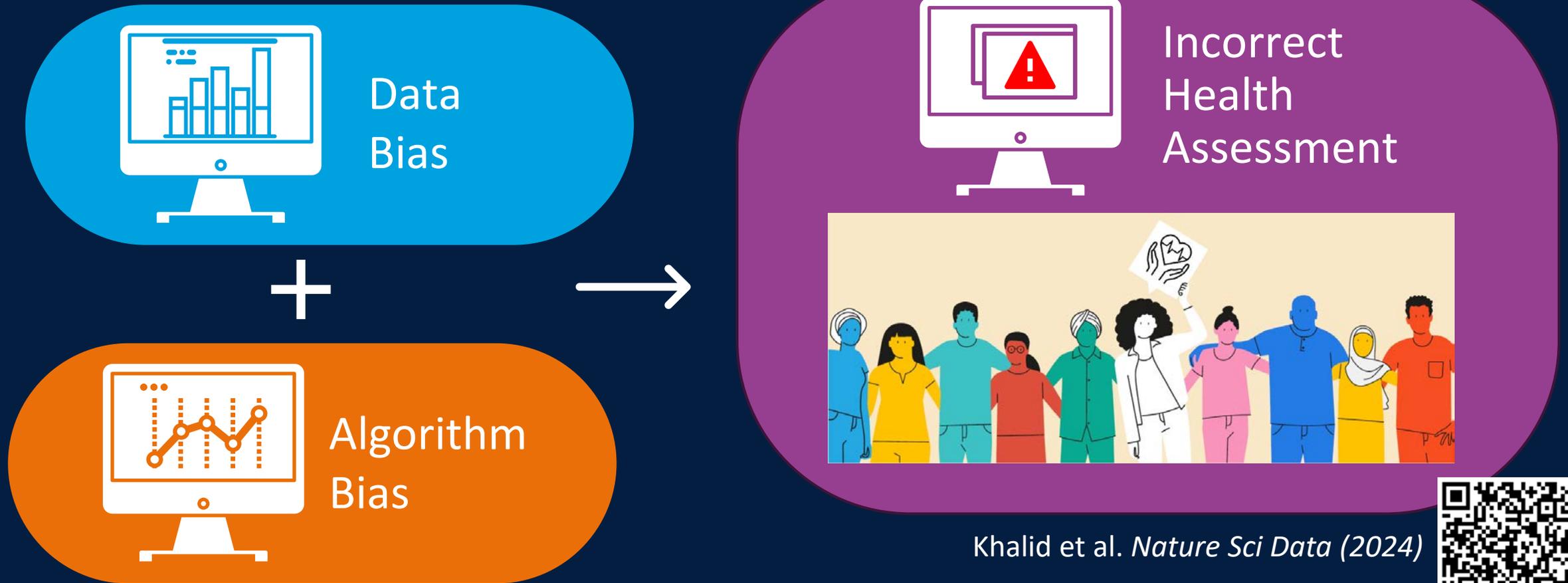
- Fair, safe, and ethical use
- Good governance and ownership
- Multi-modality linkages
- Harmonisation
- Privacy preservation



Ravi et al. IEEE Biomed & Health Informatics (2017)

- **Reliable and representative?**

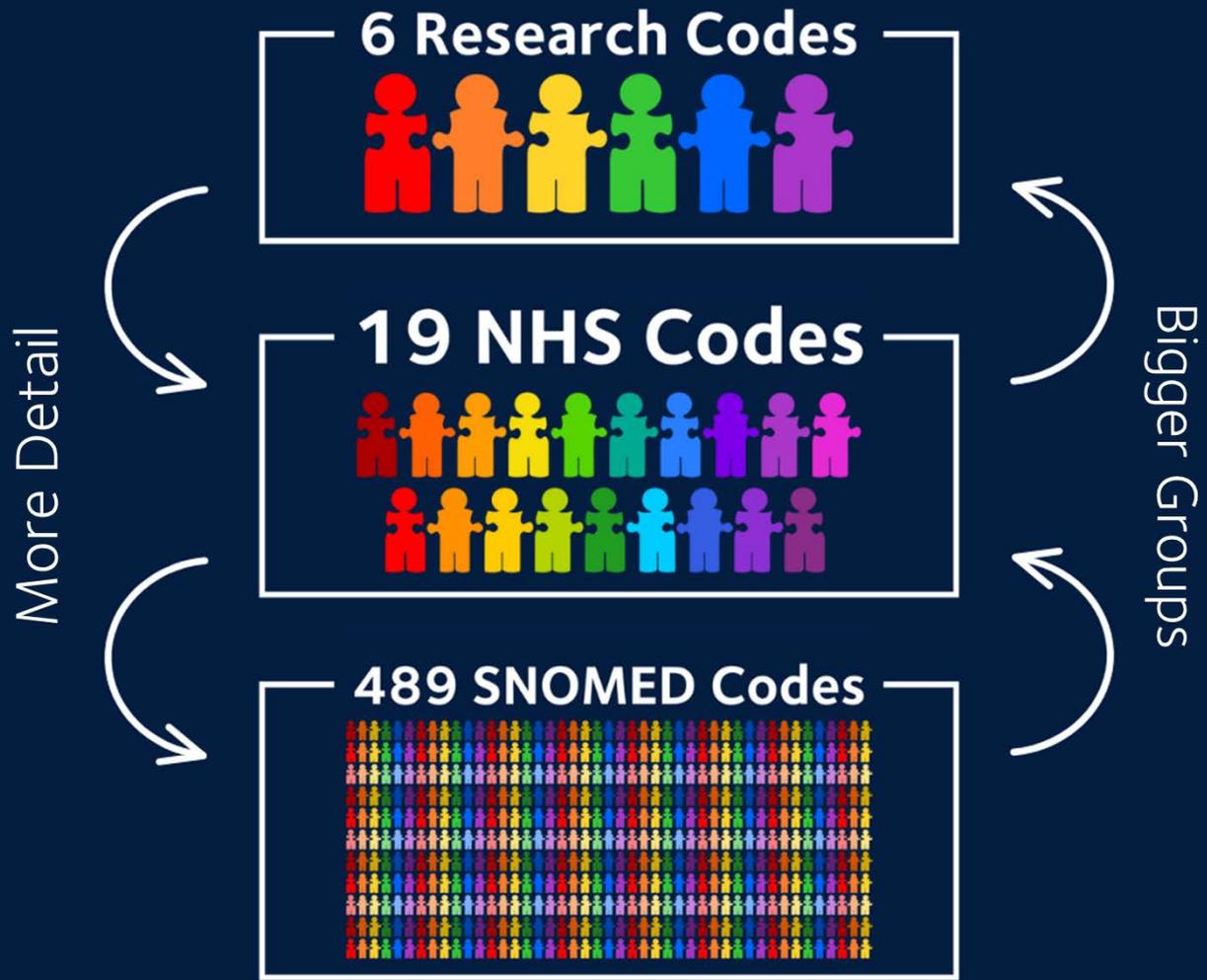
# Real-world Data, AI & Health Equity



# Real-World Data, AI & Health Equity

**60 Million**  
de-identified patient records

Do diverse ethnic groups have access to healthcare?



# Federated Distributed Networks and Common Data Models

- Patient-level data **not shared**
- Aggregated results **shared**
- Multi-site network studies
- **Data harmonisation is key**

## OMOP Common Data Model (CDM)

Imagine Health Databases as different types of sockets

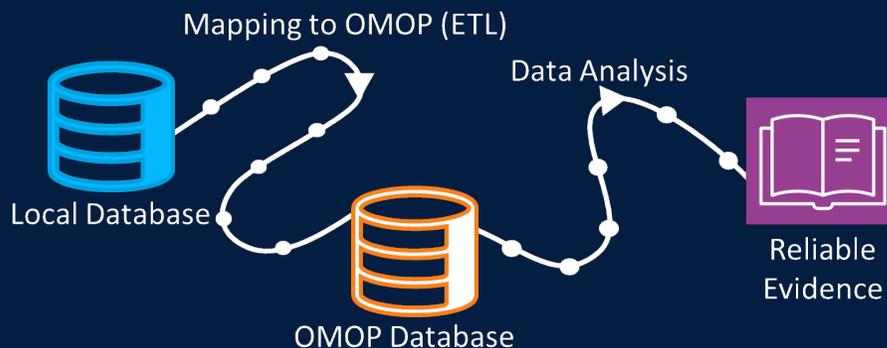


We want to use one tool (for us, that's code for analysis)

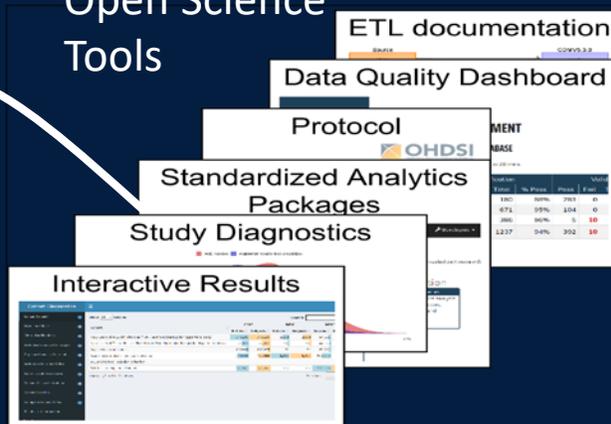


We need an adaptor – That's the OMOP CDM

## Health Data and Methods Standardization

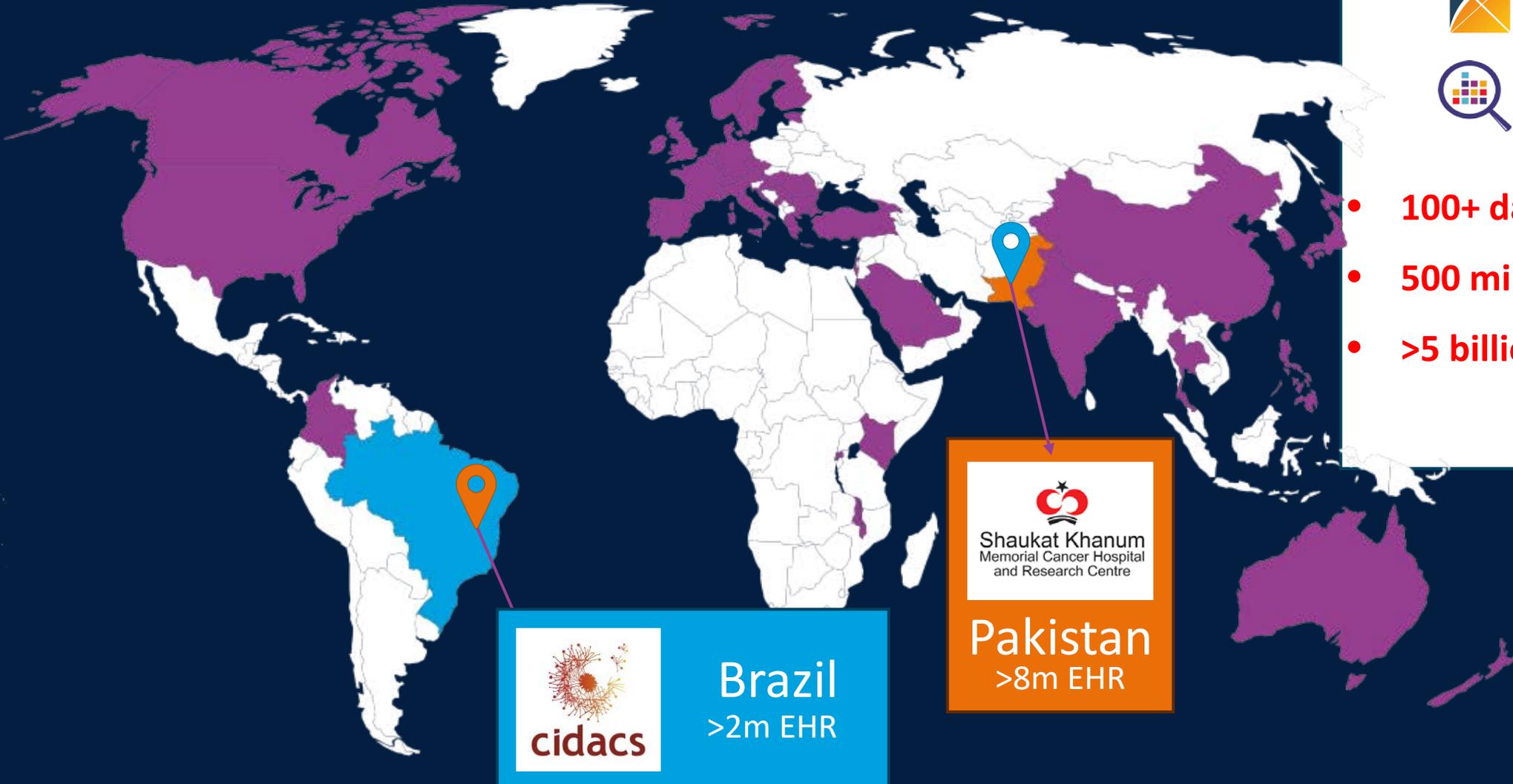


## Open Science Tools



Source: ohdsi.org

# OMOP International Data Network



- 100+ data sources
- 500 million patients
- >5 billion records (OMOP)

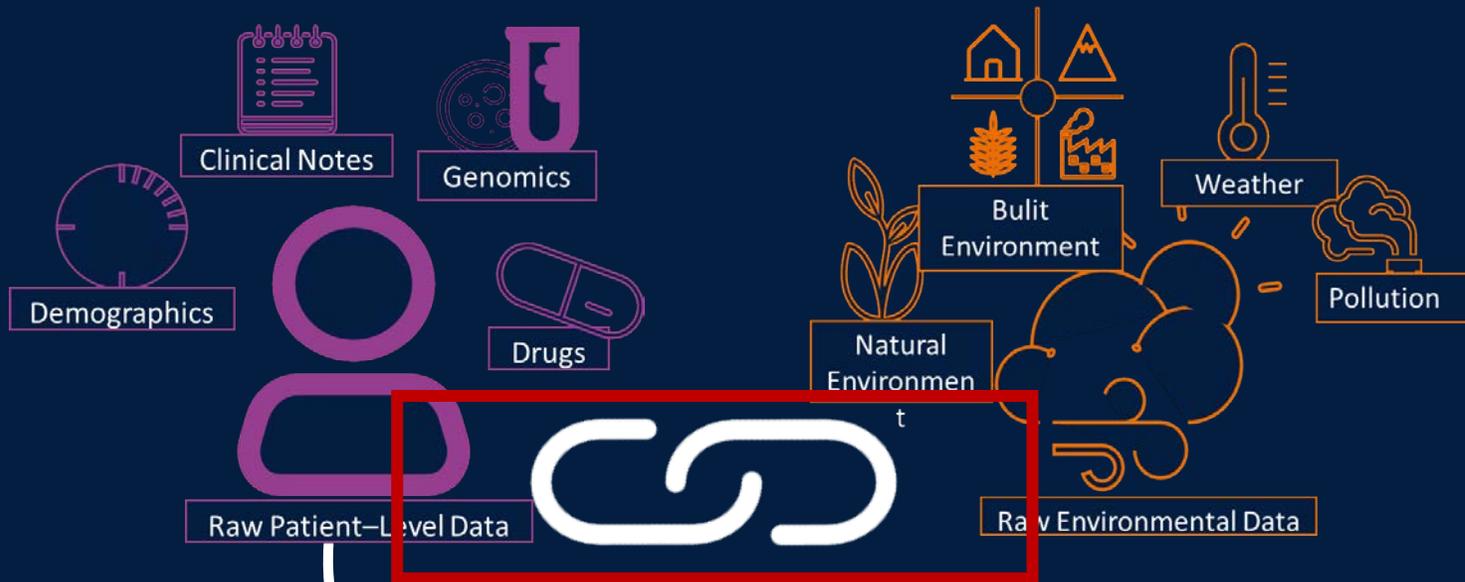
  
Shaukat Khanum  
Memorial Cancer Hospital  
and Research Centre

**Pakistan**  
>8m EHR

  
cidacs

**Brazil**  
>2m EHR

# Intersectional Determinants of Health and Complex Exposome Linkages



⊗	█	█	█	█	█	█	█	█
⊗	█	█	█	█	█	█	█	█
⊗	█	█	█	█	█	█	█	█
⊗	█	█	█	█	█	█	█	█

Geospatially linked patient level data



Health Outcomes



Resource Distribution

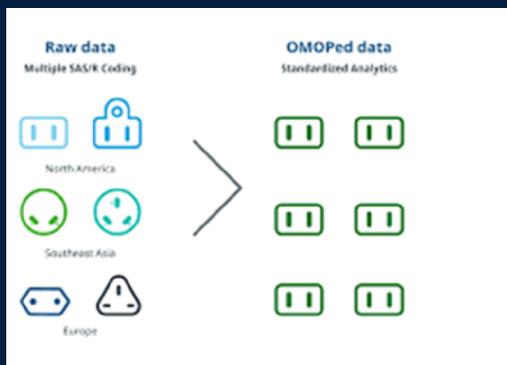
Environmental Pollution  
Volume 334, 1 October 2023, 122217

Changes in air pollution exposure after residential relocation and body mass index in children and adolescents: A natural experiment study ☆

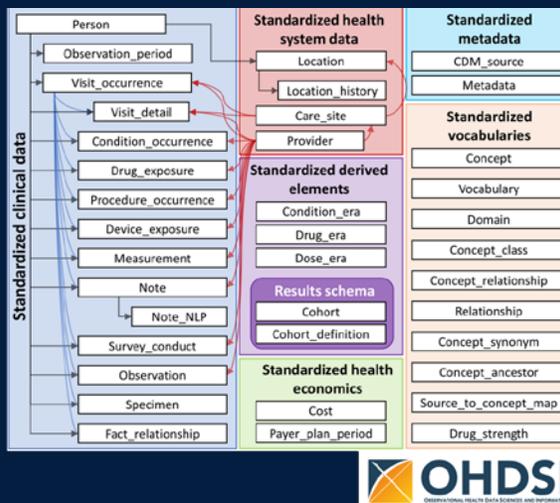
Sarah Warkentin<sup>a</sup>, Jeroen de Bont<sup>b</sup>, Alicia Abellan<sup>c</sup>, Andrea Pistillo<sup>c,d</sup>, Apolline Saucy<sup>e</sup>, Marta Cirach<sup>a,d,e</sup>, Mark Nieuwenhuijsen<sup>a,d,e</sup>, Sara Khalid<sup>f,g</sup>, Xavier Basagaña<sup>a,d,e</sup>, Talita Duarte-Salles<sup>c,h,i</sup>, Martine Vrijheid<sup>a,d,e,1</sup>



# Infrastructure for Large-scale Planetary Health Analytics



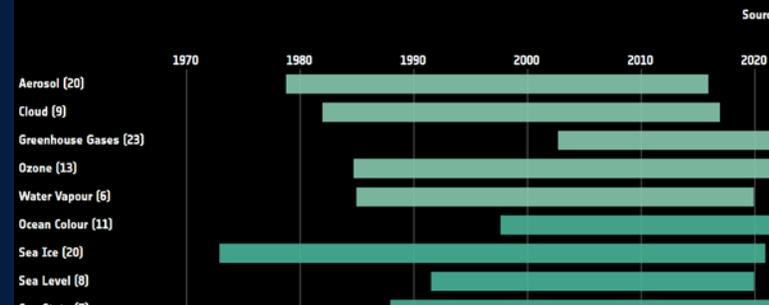
Common data models and standardised analytics



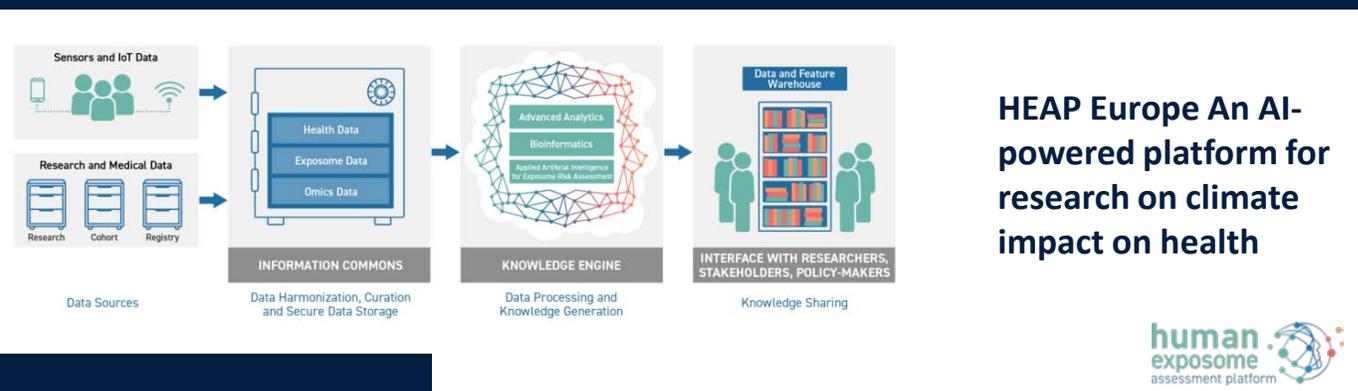
## The climate record



Get free and open access to all Essential Climate Variable data products developed by the ESA Climate Change Initiative.



ESA CCI ECV Datasets



HEAP Europe An AI-powered platform for research on climate impact on health



A project receiving funding from the European Union's Horizon 2020 Research and Innovation programme under Grant Agreement N. 101009185

DeepCube  
Explainable AI pipelines for big Copernicus data



Deep Cube Using AI to analyse Copernicus satellite data and predict climate impacts

# Handle with Care

## Top scientists call for caution over artificial intelligence

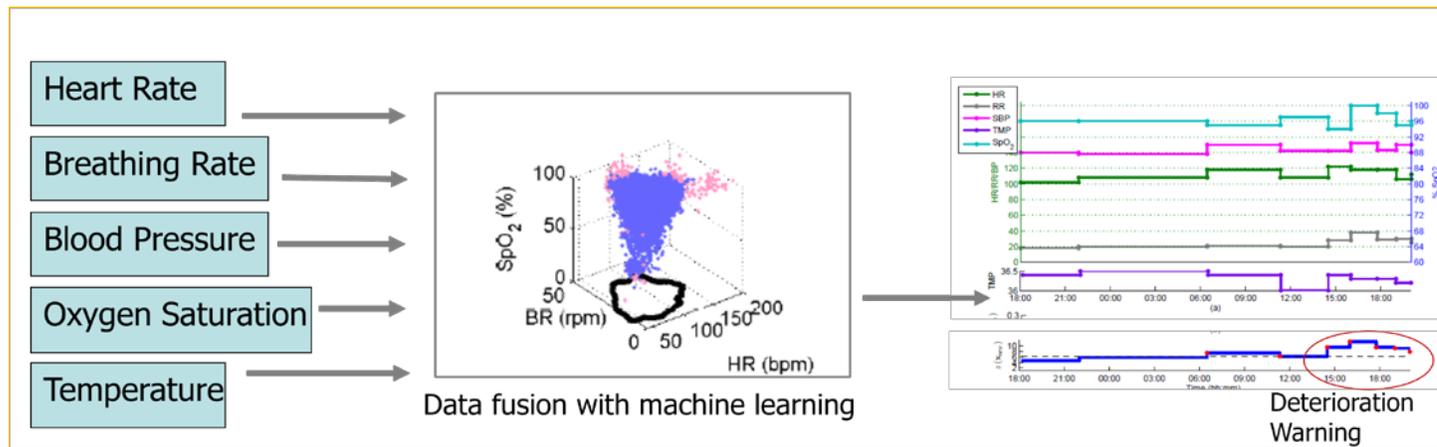
Artificial intelligence has the potential to eradicate disease and poverty, say world's top scientists, but researchers must not create something which cannot be controlled

Artificial intelligence must be carefully considered, say scientists Photo: REX





# Remote Patient Monitoring, Disaster/Conflict/Future Shocks Monitoring



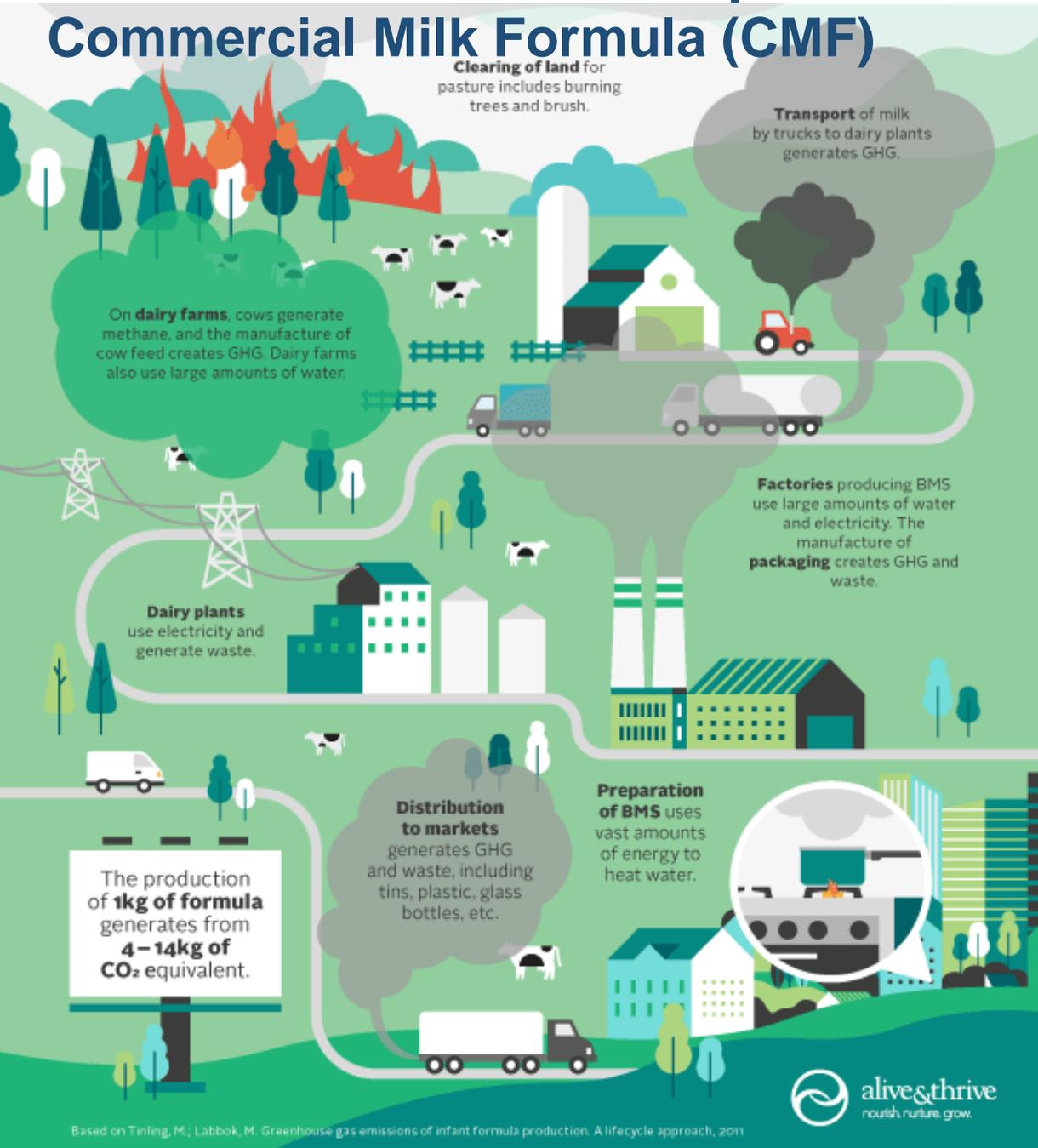
Home monitoring kit for remote management of Covid-19 infection



Khalid et al. IEEE Trans Biomed Eng 2012  
DOI: 10.1109/TITB.2012.2212202

Santos et al. Front. Digit. Health  
<https://doi.org/10.3389/fdgth.2021.630273>

# Massive Environmental Impact of Commercial Milk Formula (CMF)



## The Green Feeding Tool shows that

In LMICs alone, the use of CMF for infants aged < 6 months results in annual footprints of:

**6.0-7.5 billion kg CO<sub>2</sub> eq.,** which equates to:

- 2 million cars on roads per year, requiring
- 318 million trees to absorb CO<sub>2</sub>

**2.6 trillion liters of water,** which equates to:

- 1 million Olympic swimming pools
- 10% of the volume of Poyang Lake, China
- 1.3 times Sirindhorn Dam reservoir, Thailand
- 2 years of water use in New York, USA
- 13 years of water use in Paris, France



# Mosquito borne disease prediction

Noboru Minakawa

Institute of Tropical Medicine, Nagasaki University

# DAILY NATION

MR. YAN  
APT 207

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Kisumu: 41882/43278  
COURTESY



No. 11570, Nairobi, Thursday, February 12, 1998

Price KSh25/00

(TSh400/00)

# Panic as 1,500 die of malaria

## Epidemic killing 45 a day in Wajir

By MOHAMMED ADOW and HENRY NYARORA  
The malaria outbreak in parts of Kenya has taken a heavy toll in Wajir District, where health officials report it has claimed more than 1,500



**INSIDE**

Issues behind the violence in Rift Valley  
PAGE 18

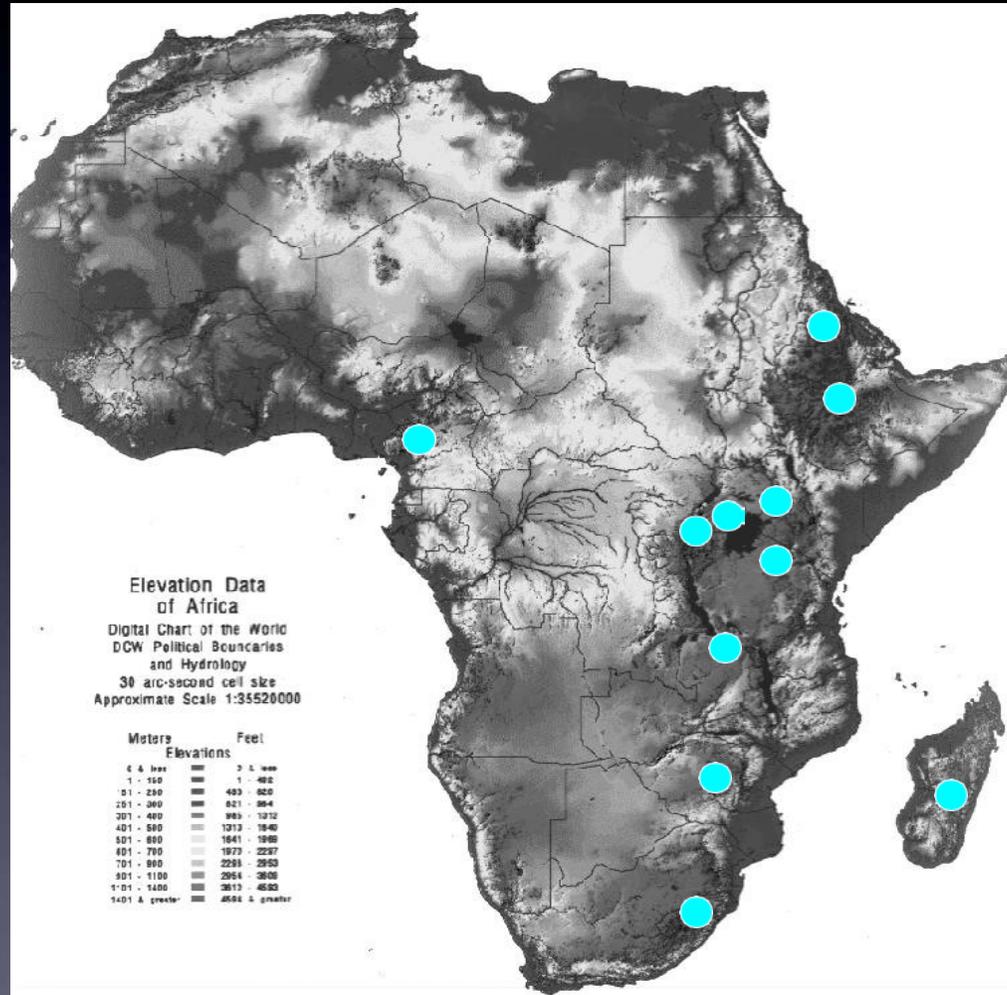
Kenya for diplomacy in Iraq issue  
BACK PAGE

Kabila snubs Jesse Jackson  
PAGE 8

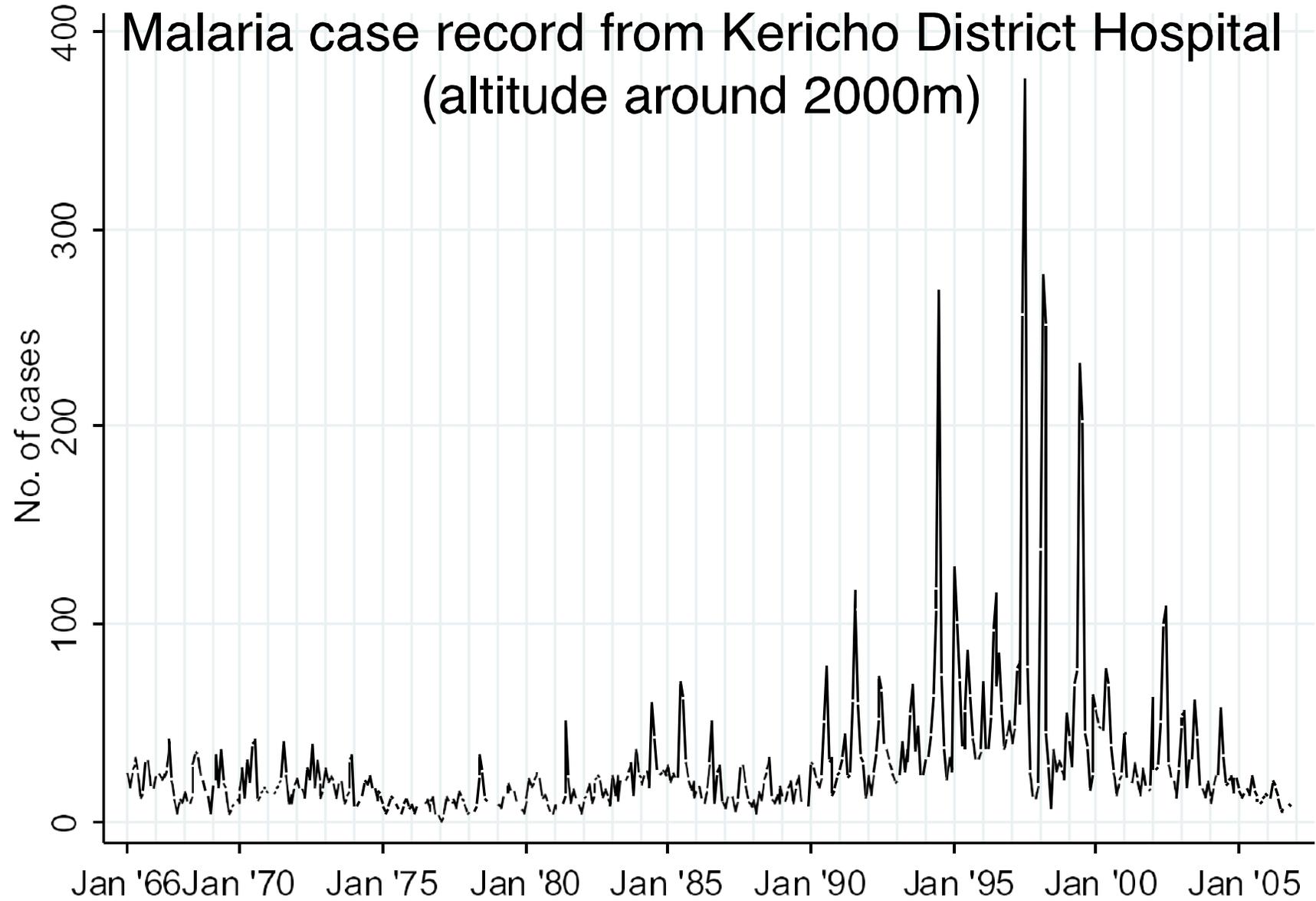
Latest results

# Highland malaria

Malaria epidemics occurred  
in the highland areas above 1500m in 90's



Eritrea  
Ethiopia  
Cameroon  
Kenya  
Uganda  
Rwanda  
Burundi  
Tanzania  
Zambia  
Zimbabwe  
South Africa  
Madagascar

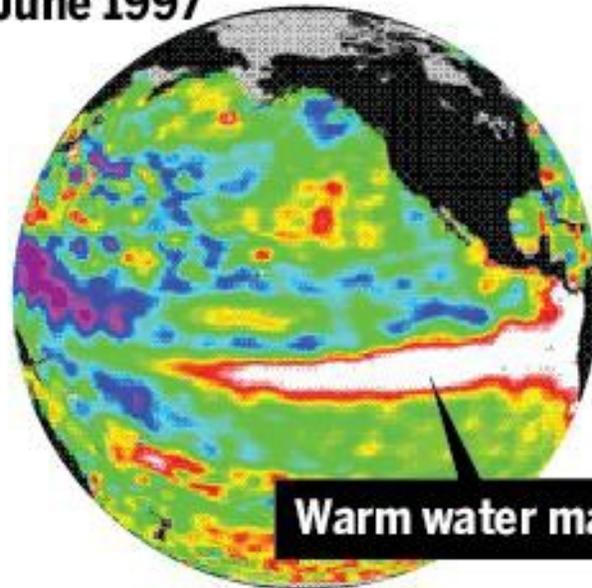


# Climate change or climate variability?

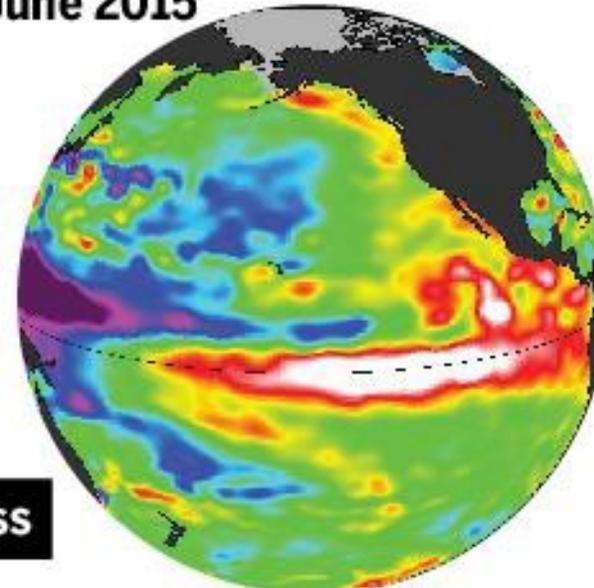
## El Niño growing

Although the trend could change in coming months, warming waters in the Pacific Ocean could bring soaking winter storms – as they did in the 1997-98 rainy season.

June 1997

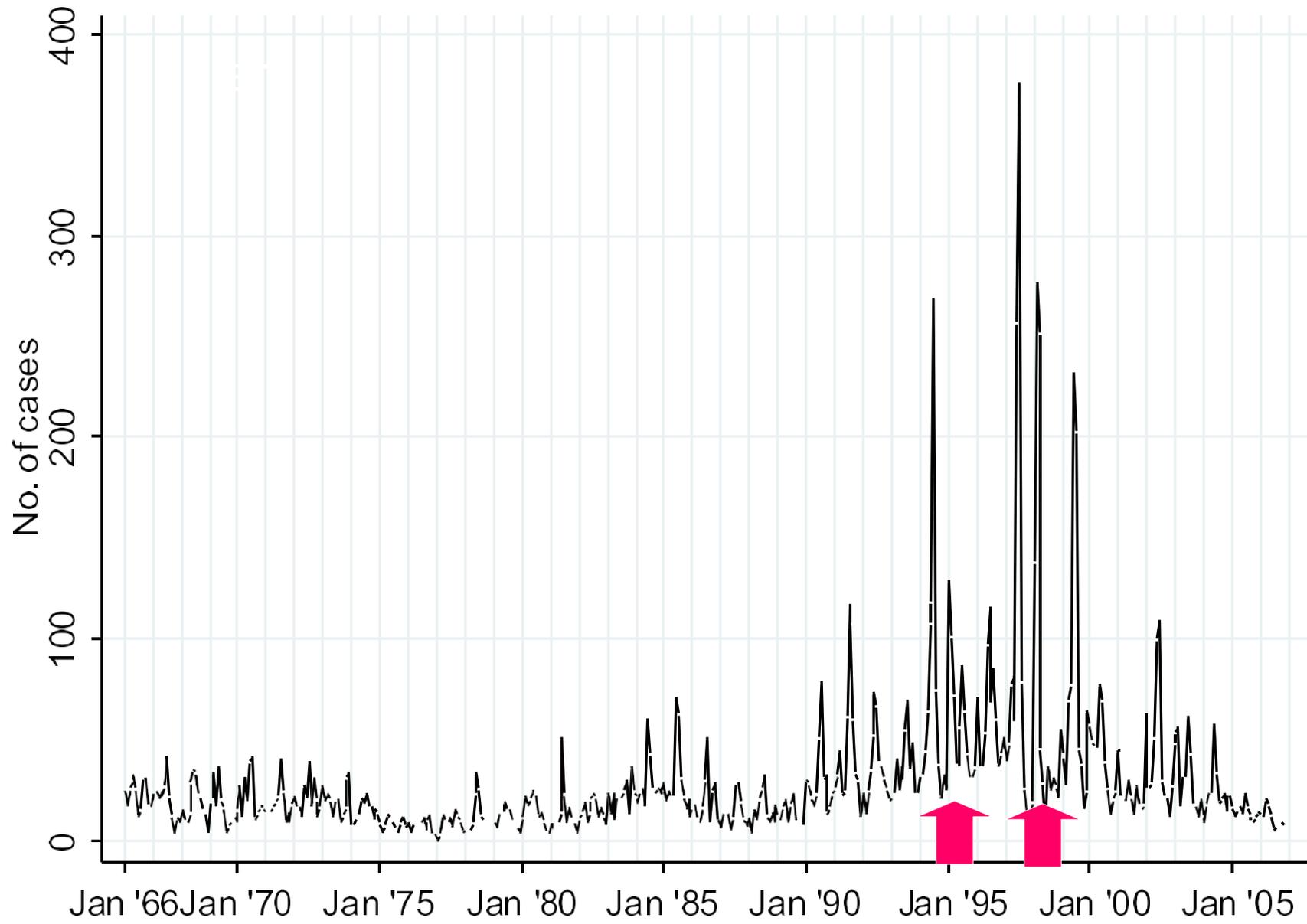


June 2015



Source: NASA; Jet Propulsion Laboratory

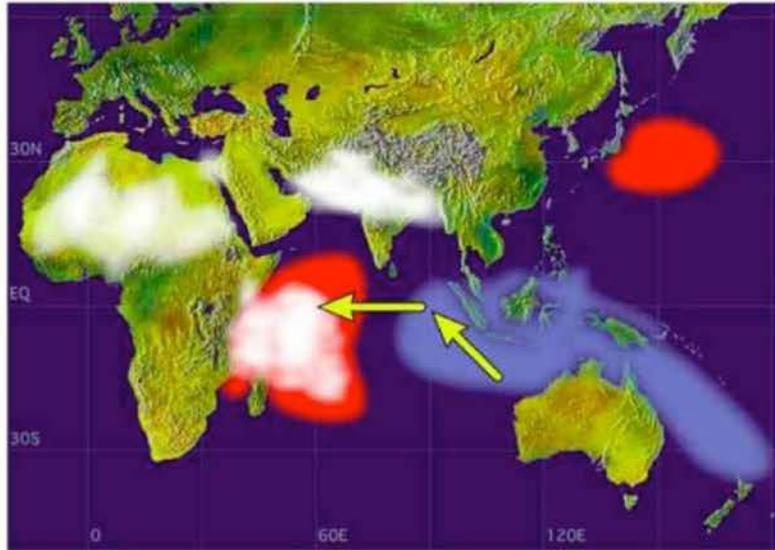
BAY AREA NEWS GROUP



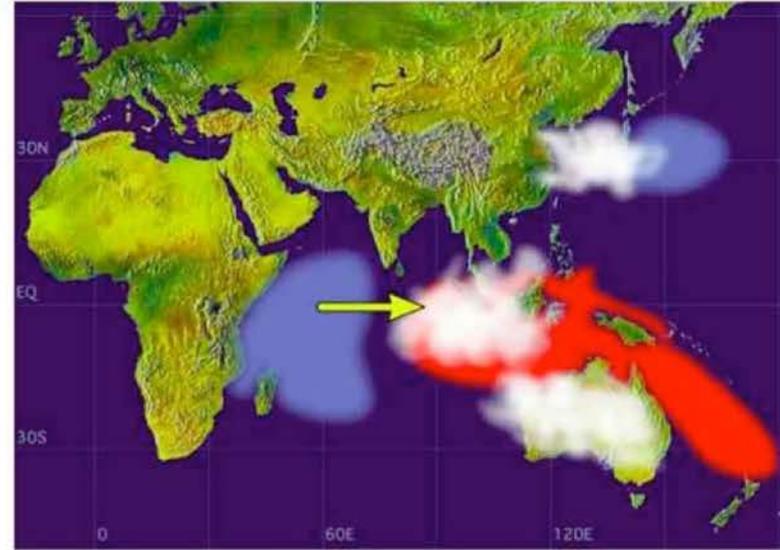
Hashizume, Minakawa et al. PNAS (2009) 1857-1862

# Indian Ocean Dipole Mode

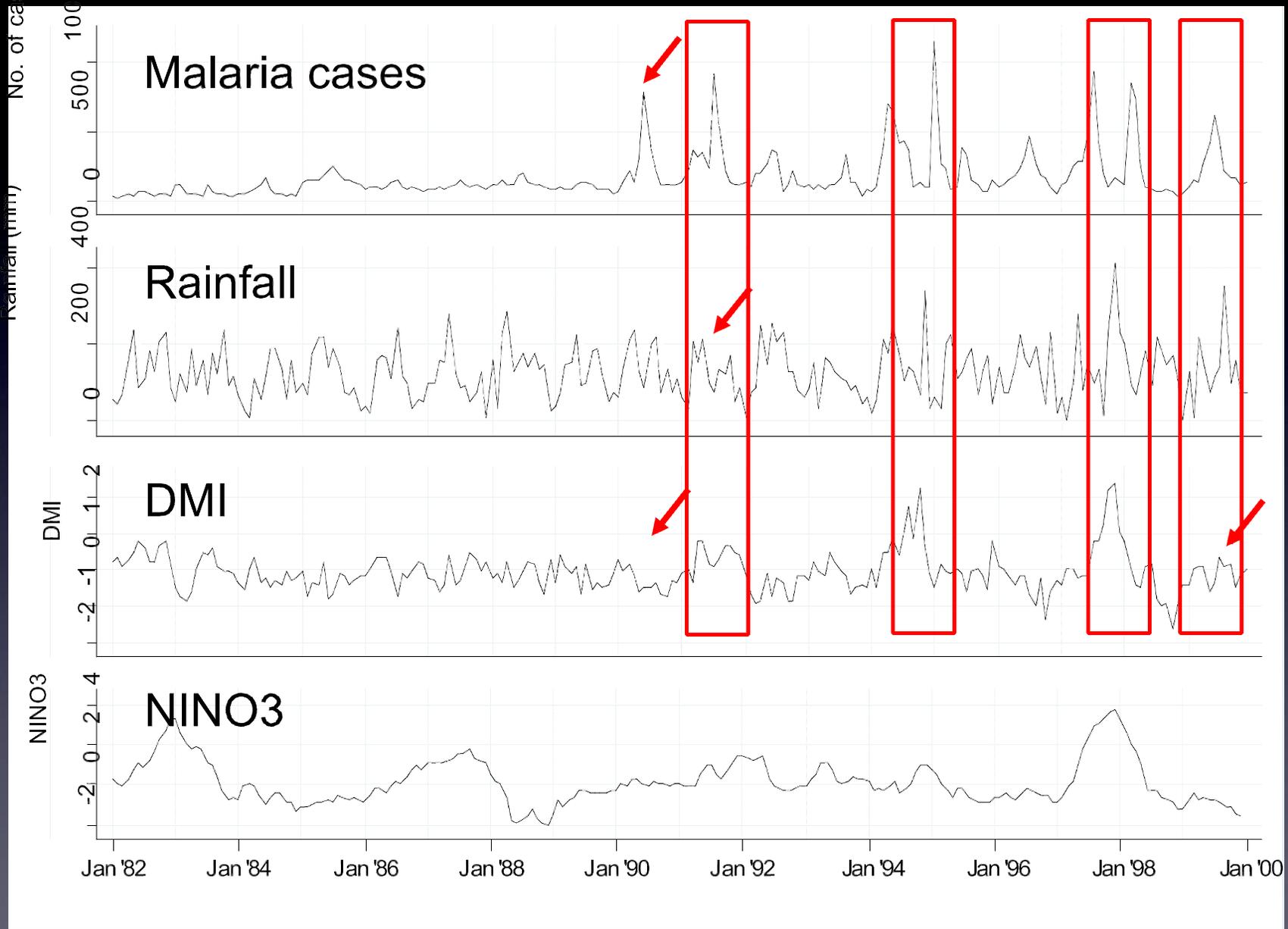
Positive Dipole Mode



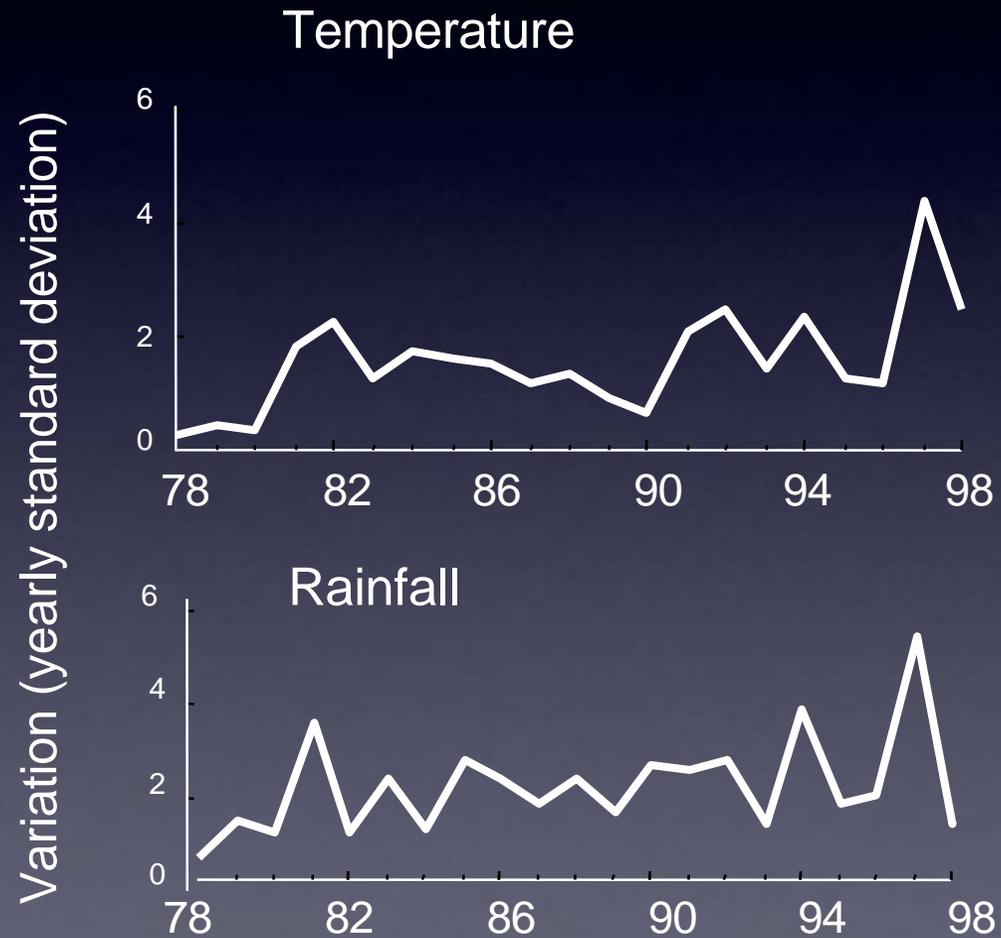
Negative Dipole Mode



# Nandi



# Climate variation (Nandi, Kenya)



# Outbreaks of Rift Valley Fever and cholera also occurred during the period

## An outbreak of Rift Valley fever in Northeastern Kenya, 1997-98.

Woods CW, Karpati AM, Grein T, McCarthy N, Gaturuku P, Muchiri E, Dunster L, Henderson A, Khan AS, Swanepoel R, Bonmarin I, Martin L, Mann P, Smoak BL, Ryan M, Ksiazek TG, Arthur RR, Ndikuyeze A, Agata NN, Peters CJ; World Health Organization Hemorrhagic Fever Task Force. *Emerg Infect Dis.* 2002 Feb;8



Flood during the period

## Cholera in 1997.

*Wkly Epidemiol Rec.* 1998 Jul 3;73(27):201-8.

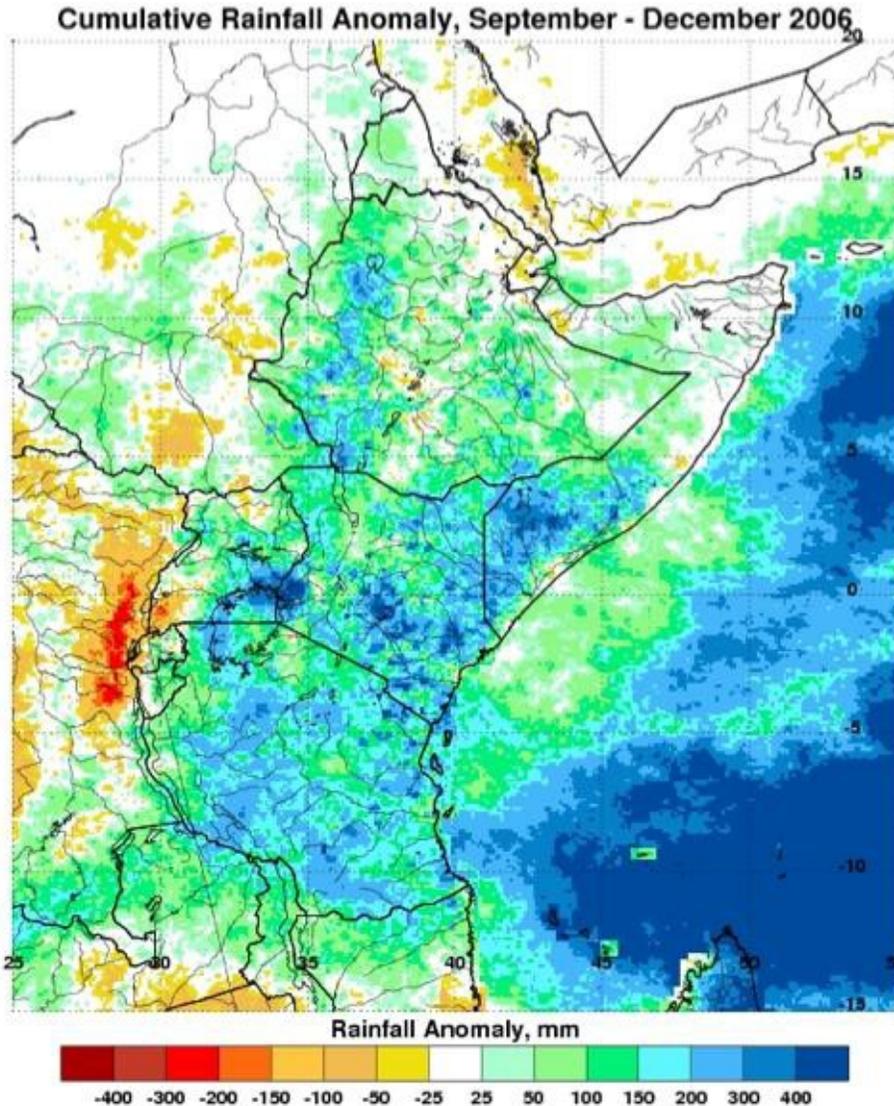
## Effect of 1997-98 El Niño on highland malaria in Tanzania.

Lindsay SW, Bødker R, Malima R, Msangeni HA, Kisinza W. *Lancet.* 2000 Mar 18;355(9208):989-90.



We found several sick children

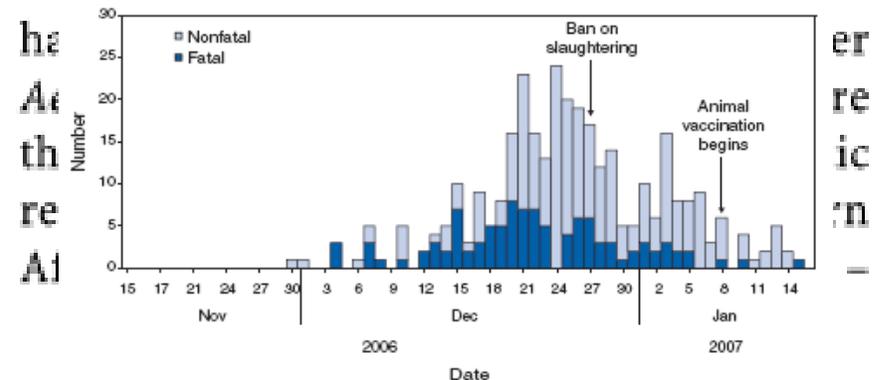
2006年に東アフリカで発生した、乾燥地域における季節外れの多雨は、洪水を引き起こし、感染症（リフトバレー熱）の流行につながった。



## Outbreaks of Rift Valley fever in Kenya, Somalia and United Republic of Tanzania, December 2006–April 2007

Unusually heavy rainfall was recorded in eastern Africa between October and December 2006, leading to flooding in several regions of Ethiopia, Kenya, Somalia

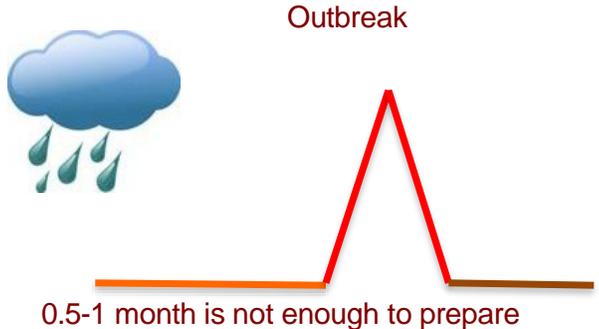
FIGURE 3. Number of reported Rift Valley fever cases (n = 330), by date of illness onset — Kenya November 2006–January 2007\*



\* As of January 25, 2007, for cases with known date of onset.

# Prediction provides enough time to prepare for disasters

(1) We can predict a malaria outbreak after heavy rain. But **not enough time** to prepare for it.

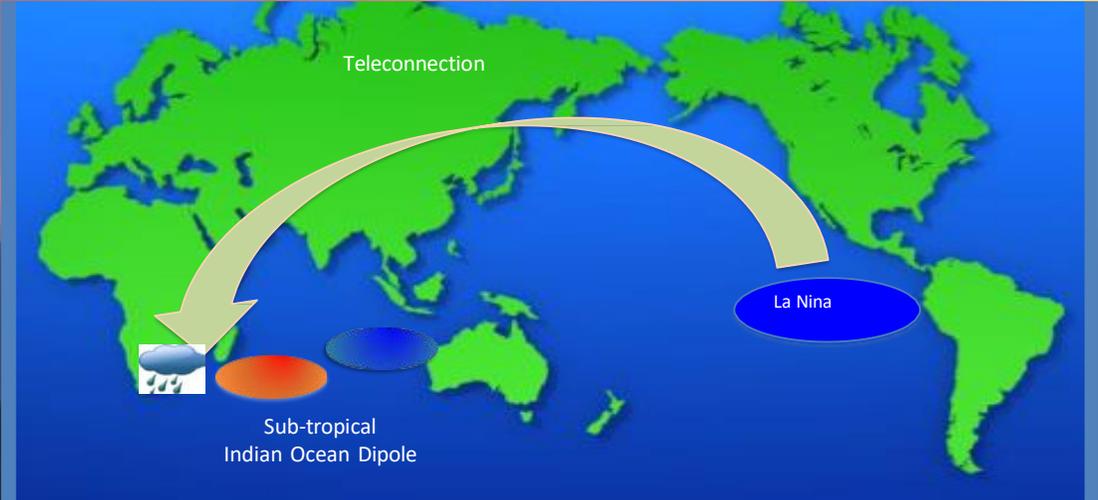
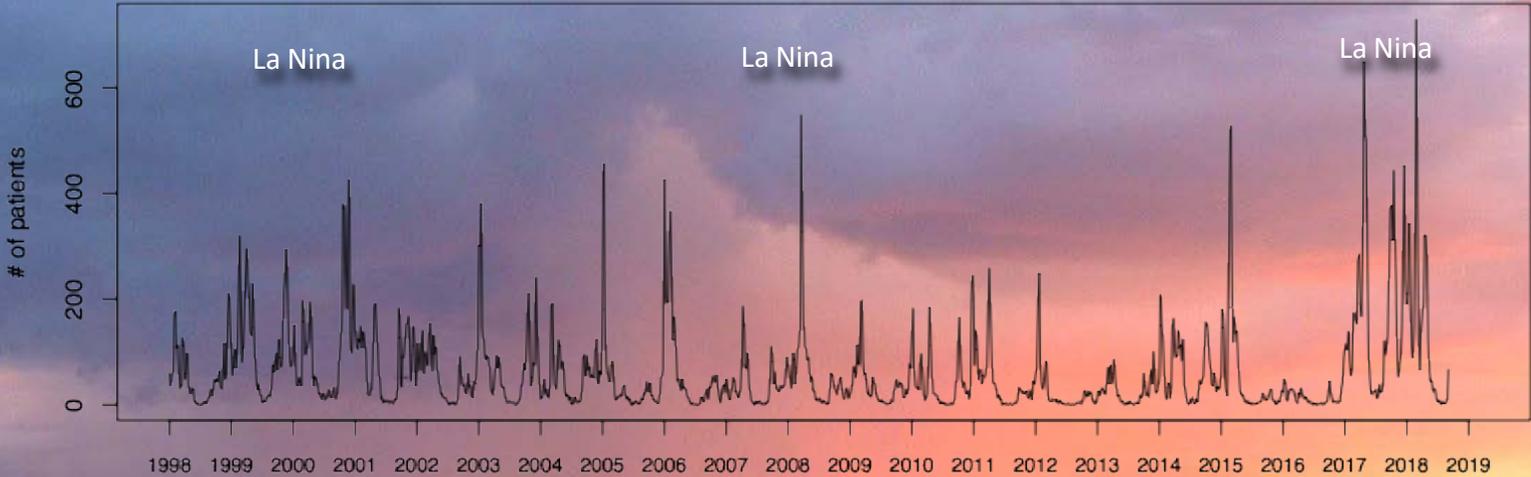


(2) If we can predict heavy rain in a few months before, we will have **enough time** to prepare for it

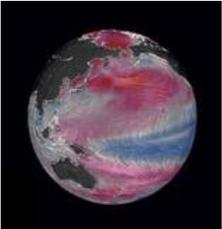
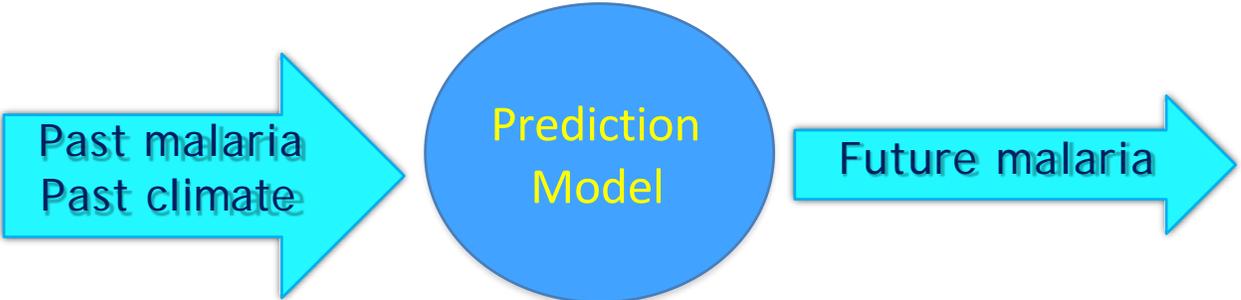
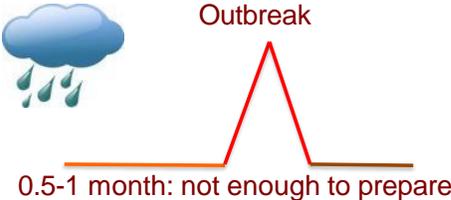




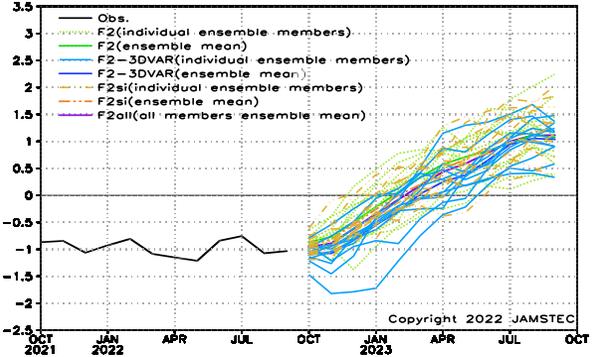
# Malaria cases in South Africa



# Importance of prediction



Earth Simulator (Super computer)



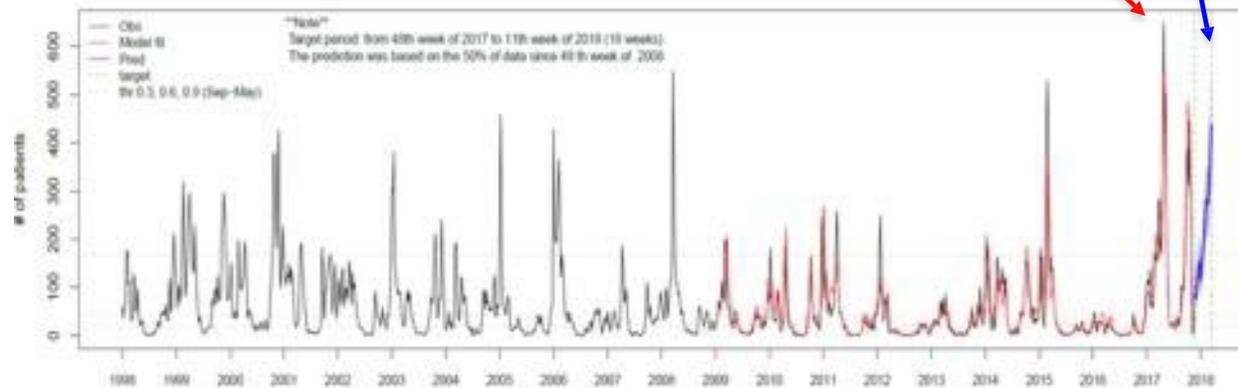
# Climate-based modes (statistical and ML)

Successfully predicted the 2017~18 season outbreak in the dry season



Using machine learning and statistical models.

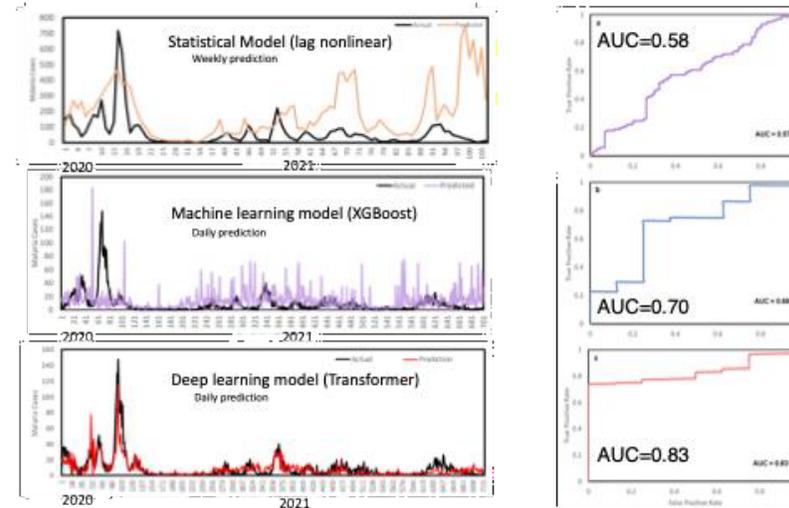
Prediction



Malaria cases in Limpopo (South Africa) since 1998

# Comparison of 3 models: statistical, ML and DL

- **Statistical model:** Good enough for a few month prediction
- **Machine learning model:** Better than the statistical model for one year prediction.
- **Deep learning model:** Best! Performs better than the others throughout a year.



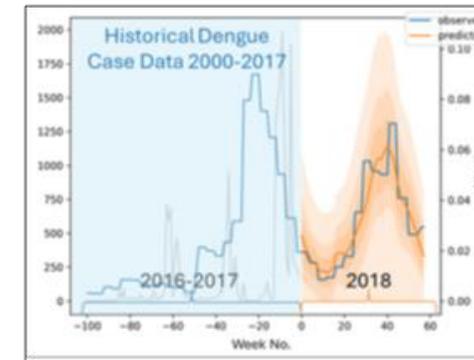
## Developing a generalized model

### Applied

- Nation wide **dengue hospital case** data from 2001 to 2017.
- Predicted the 2018 cases.

### Results

- **High correlation** ( $R^2 = 0.92$ ) between actual cases and predicted cases
- Model used 17 climate variables, and **daily max temp** and **rainfall** were important.



Utilizing a novel high-resolution malaria dataset for climate-informed predictions with a deep learning transformer model.  
Pillay MT, Minakawa N, Kim Y, Kgalane N, Ratnam JV, Behera SK, Hashizume M, Swejld N.  
Sci Rep. 2023 Dec 28;13(1):23091. doi: 10.1038/s41598-023-50176-3.

# Scenario: Climate-Driven Disease Outbreak in Urban Slums

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- A densely populated coastal city has been experiencing record-breaking rainfall and rising sea levels due to climate change.
  - Widespread flooding in urban slums, causing stagnant water to collect in poorly drained areas.
  - Cases of cholera, dengue fever, and leptospirosis have surged - overwhelming the local healthcare system.
  - Compounding the problem, power outages have disrupted communication networks - difficult to coordinate relief efforts.
1. What AI-driven health technologies can enable early disease detection, remote diagnosis, and treatment in flood-affected, inaccessible areas?
  2. How can AI-powered surveillance systems track and predict disease outbreaks in real time?
  3. How do we ensure that AI-driven health interventions reach marginalized and high-risk communities, especially in low-connectivity and resource-poor settings?
  4. How can governments integrate AI into climate adaptation and health resilience strategies to proactively manage climate-driven disease risks?
  5. With power outages and damaged infrastructure, how can AI and digital health tools function effectively?
  6. What alternative energy solutions and climate-resilient digital health infrastructures should be prioritized?