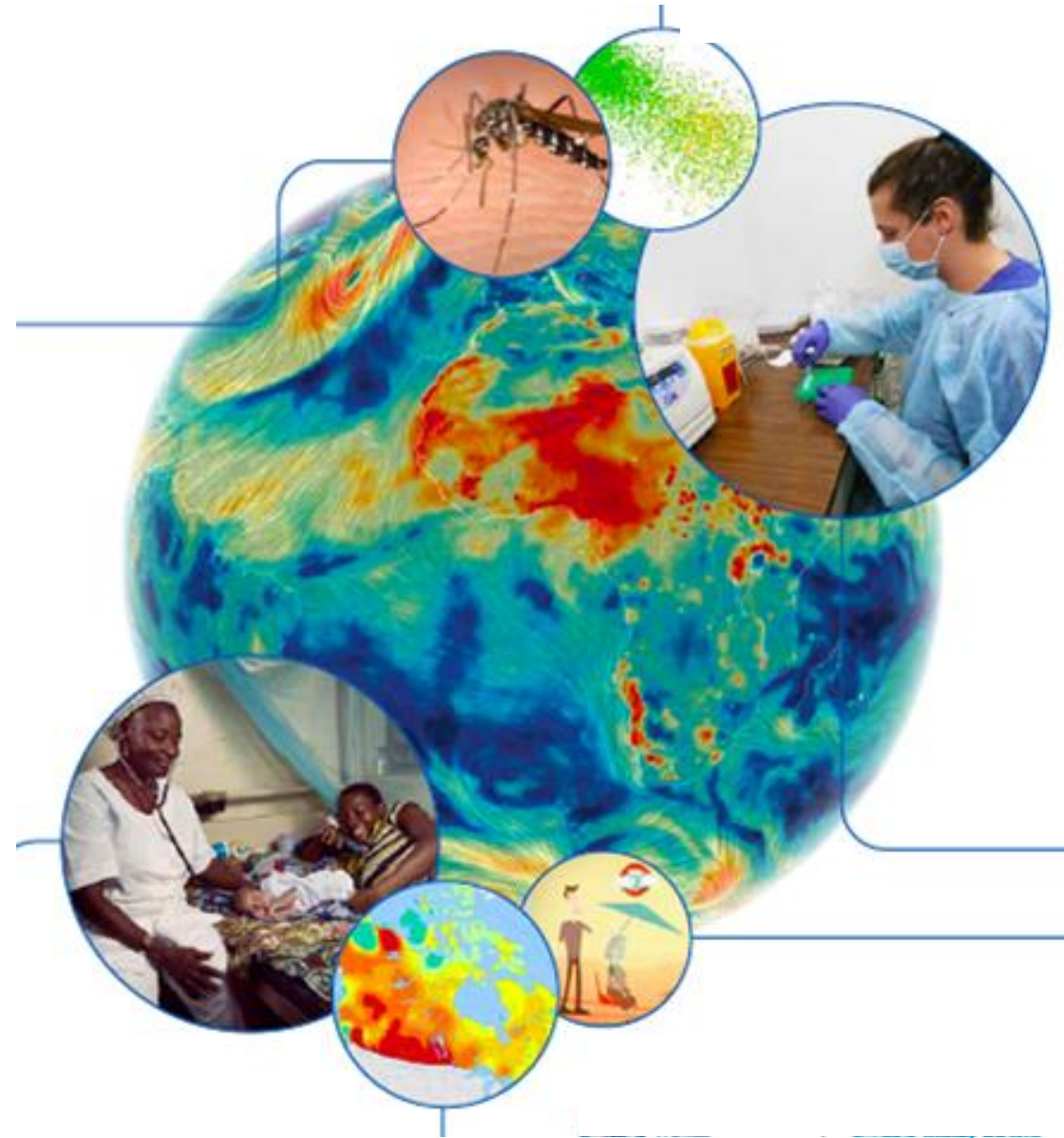


Part 4

# CLIMATE-HEALTH APPLICATIONS

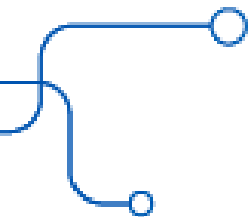
Improving public health decision-making  
in a new climate



## Part 4 – CLIMATE-HEALTH APPLICATIONS

### Sections

- 4.1 Introduction to climate-informed health Early Warning Systems (EWS)
- 4.2 Using climate/weather-health associations - Forecasting models: climate-driven dengue early warning systems
- 4.3 Using climate/weather-health associations - Projection of future health outcomes



## Section 4.1: Introduction to climate-informed health Early Warning Systems (EWS)

### Learning objective:

- Understand what climate-informed health Early Warning Systems (EWS) are and their usefulness
- Outline the core components of climate-informed health EWS
- Describe fundamental concepts and requirements for implementing climate-informed health EWS

### Resources:

- [CDC Building Resilience Against Climate Effects \(BRACE\) Framework](#)
- [Assessing Health Vulnerability to Climate Change: A Guide for Health Departments](#)
- [WHO-WMO \(2015\) Heatwaves & Health: Guidance on Warning-System Development](#)
- [WHO \(2021\) Climate change and health: Vulnerability and adaptation assessment](#)

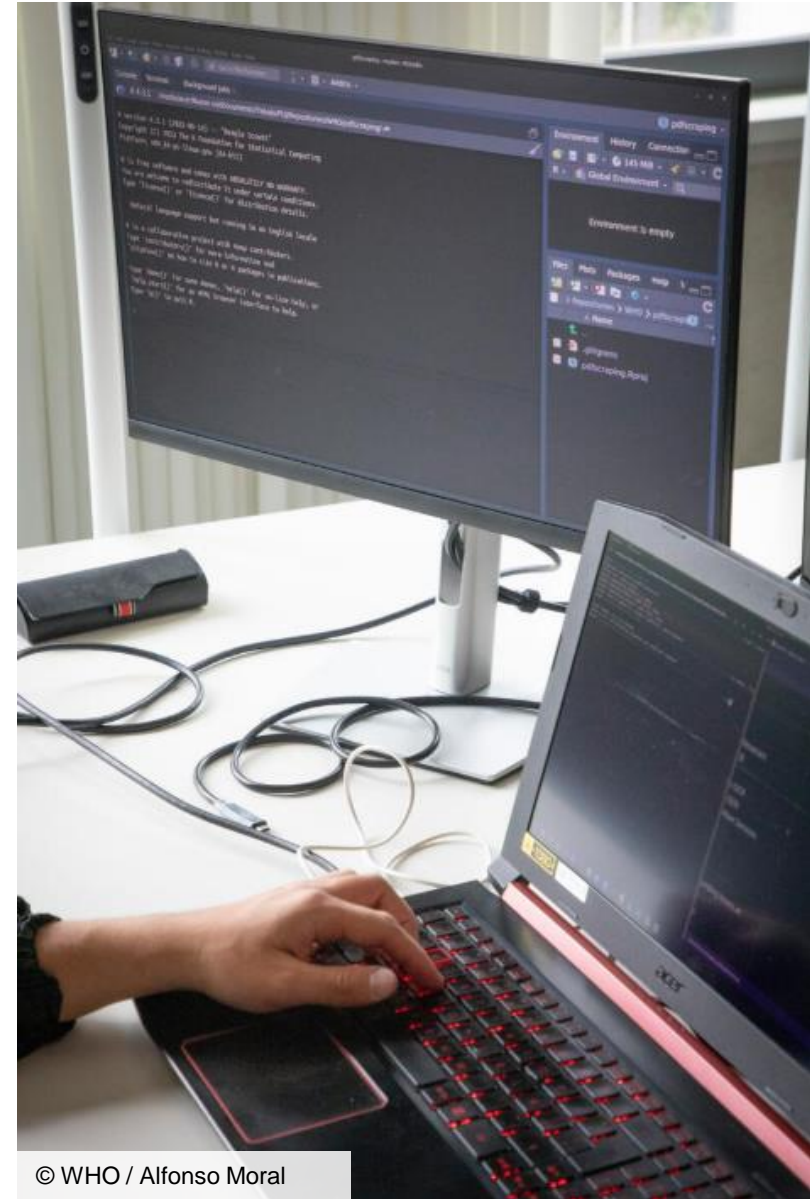
### Further learning opportunities:

- [Climate Services for Health Fundamentals and Case Studies for improving public health decision-making in a new climate](#)



# Learning objectives

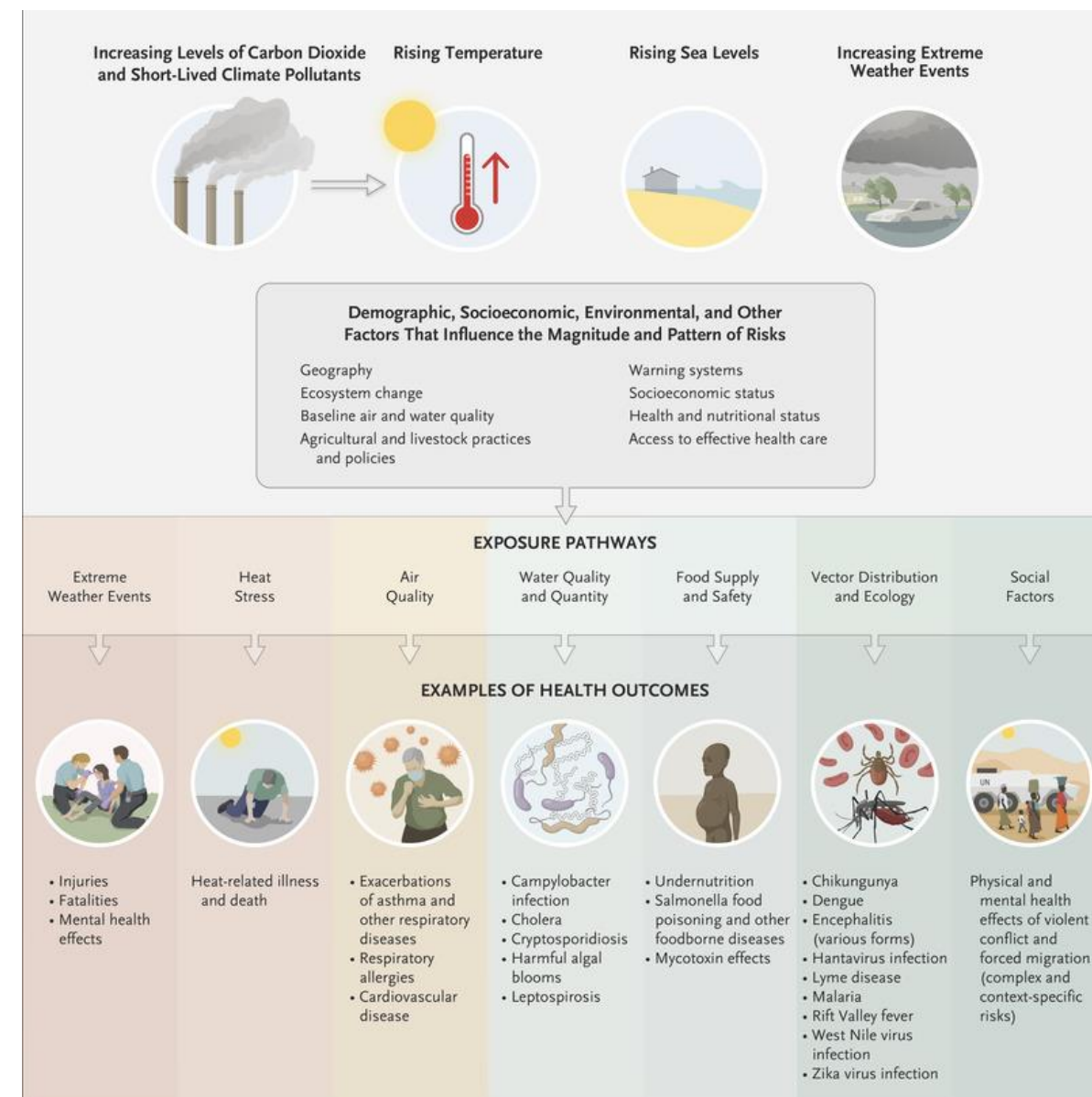
- Understand what climate-informed health Early Warning Systems (EWS) are and their usefulness
- Outline the core components of climate-informed health EWS
- Describe fundamental concepts and requirements for implementing climate-informed health EWS



© WHO / Alfonso Moral

# Why climate-informed health EWS are increasingly important for health systems

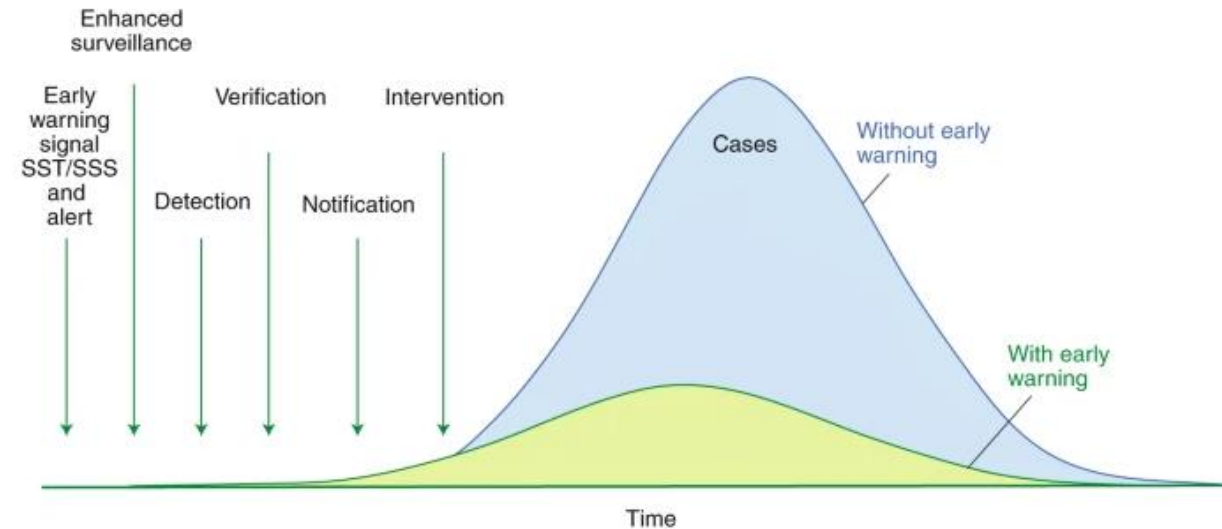
- Climate-related health risks are increasing
- Climate-informed health EWS allow for earlier action and more targeted resource allocation
- Climate-informed health EWS are key to strengthening health systems' resilience to climate change



Haines et al, N Engl J Med 2019; 380:263-273

# Definition and aim of climate-informed health EWS

- “**Integrated systems** that timely monitor climate and climate-related health determinants to dynamically evaluate and communicate future health risks to **trigger prompt public health action**”
- EWS aim to produce health risk forecasts and issue **risk alerts**
- The alerts can provide **additional lead time** to deploy appropriate measures and thus contribute to the prevention of avoidable diseases, illnesses, injuries, and deaths



Conceptual model of early warning system for *Vibrio* bacteria in coastal waters: environmental monitoring of sea surface temperature (SST) and salinity (SSS).

Semenza JC, Nature Immunology 2020, 21: 484-7.

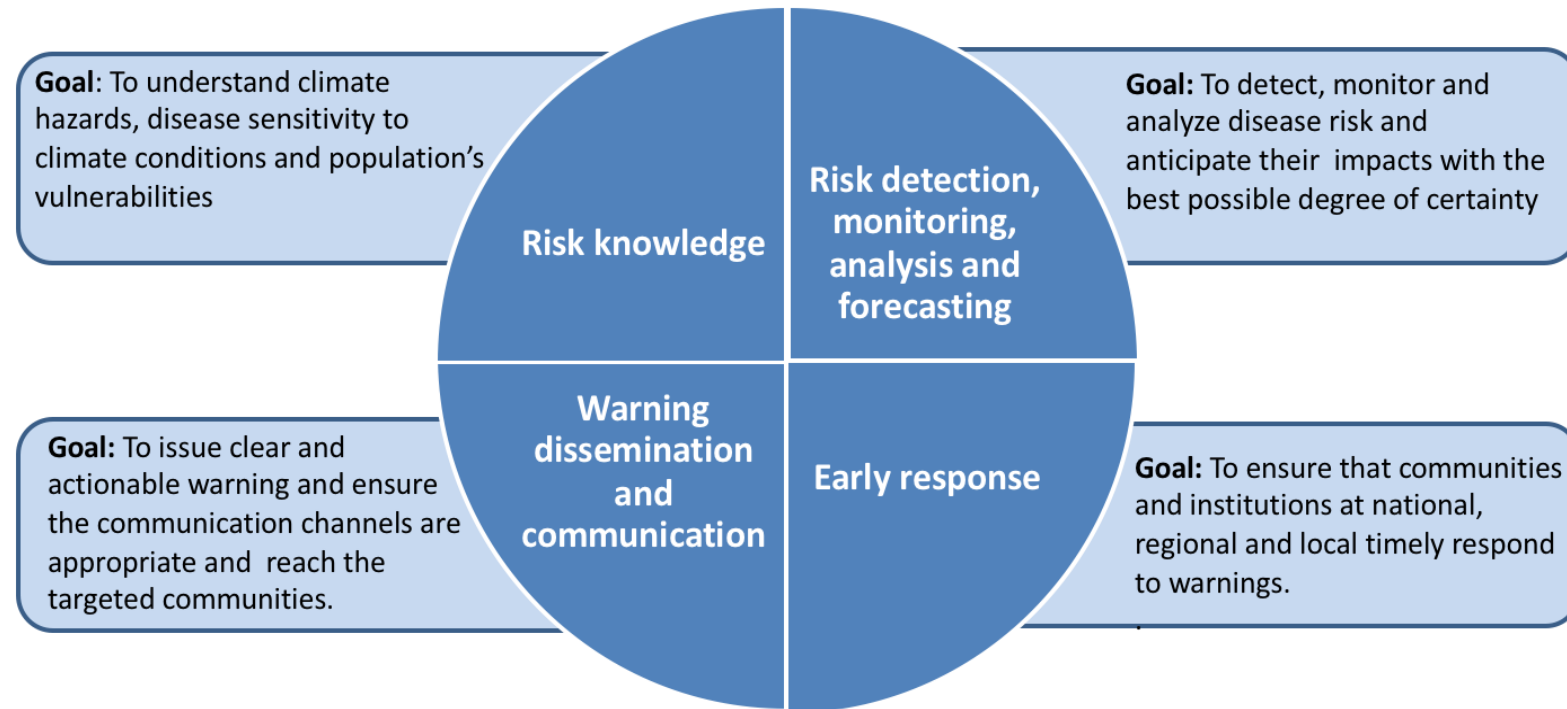


# Core elements of climate-informed health EWS

Climate-informed health EWS are composed of **four core elements**:

- 1) knowledge of the disease risks,
- 2) risk detection, monitoring, analysis, and forecasting,
- 3) warning dissemination and communication
- 4) early response

## ELEMENTS OF A CLIMATE-INFORMED DISEASE EARLY WARNING SYSTEMS



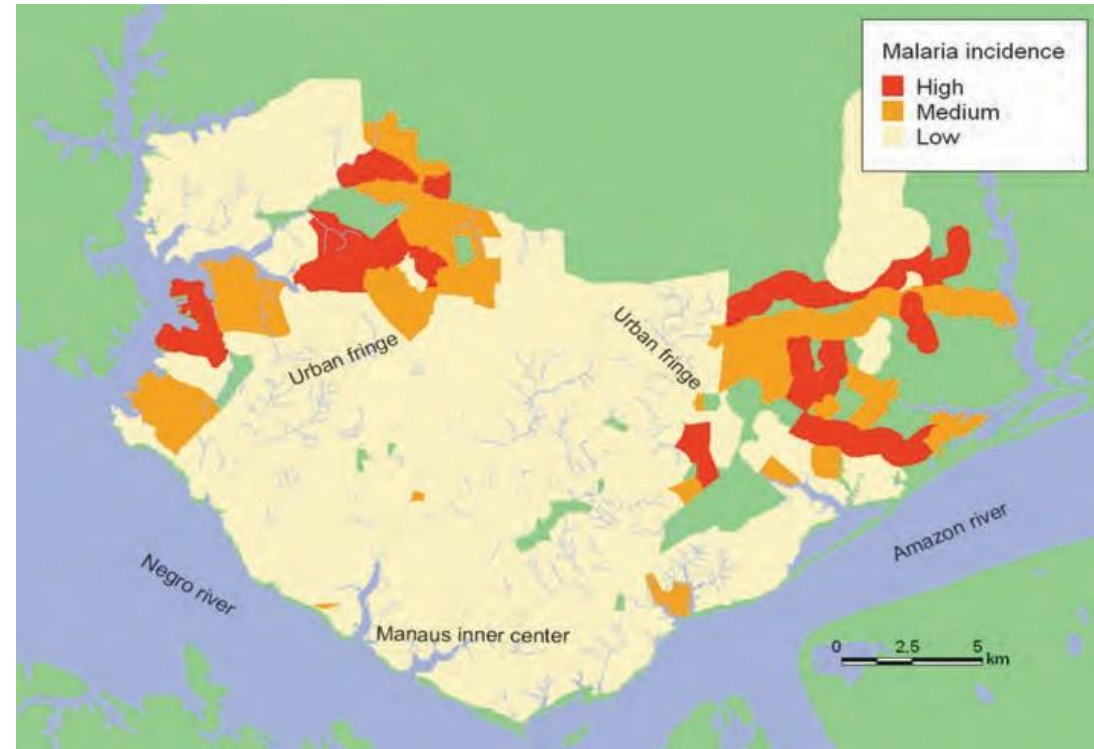
# Core elements of climate-informed health EWS:

## Risk Knowledge

*To understand climate hazards, sensitivity to climate conditions, and population vulnerabilities*

### What to do:

- Define pathways of climate impacts on health.
- Correlate historical health and climate data spatially and temporally to understand linkages between climate and health conditions.
- Evaluate population vulnerabilities to different hazards.
- Establish risk thresholds and determine indicators based on the known climate-health associations and population vulnerabilities.



Classification of districts of Manaus, Brazil, by malaria incidence. ([Protecting health from climate change: vulnerability and adaptation assessment. WHO 2013](#))



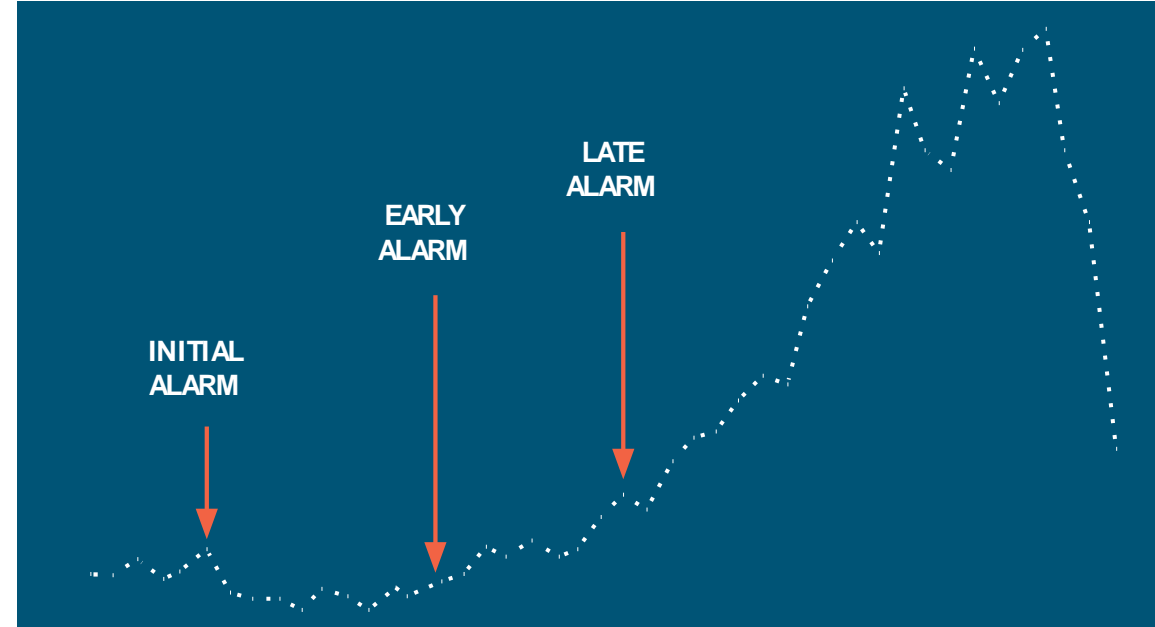
# Core elements of climate-informed health EWS:

## Risk detection, monitoring, analysis, and forecasting

*To detect, monitor, and analyse health risks and anticipate their impacts to the best possible degree of certainty*

### What to do:

- Evaluate the volume of **routine data** available
- Sign **data sharing agreements** with key stakeholders
- Build **integrated surveillance systems** by integrating data from various sources
- Produce and validate **predictive models**
- Set **risk thresholds**
- Regularly **calibrate the forecasting algorithm** to ensure they capture changes in disease transmission dynamics



# Core elements of climate-informed health EWS:

## Warning dissemination and communication

*To issue clear and actionable warnings and ensure that communication channels are appropriate to reach the targeted communities*

### What to do:

- Evaluate **communication channels** to reach out to key stakeholders and communities
- Define a warning communication **protocol**
- Identify the warnings with an authoritative **emblem or logo**
- Craft **standard messages** in the local languages and appropriate to the educational level of the targeted populations

# Core elements of climate-informed health EWS:

## Early response

*To ensure that communities and institutions at the national, regional, and local levels respond in a timely manner to warnings*

### What to do:

- Evaluate response capacity and competencies at all levels
- Analyse response needs for each type of warning
- Define preparedness and response protocols
- Define the responsibilities of each type of actor to avoid duplications and ensure all necessary tasks are covered
- Establish a stakeholder coordination mechanism
- Pilot the established protocols at all levels by organising response simulations



[Early response in the aftermath of a dam collapse in Lao PDR 2018](#)

© WHO / Souvanly Thammavong



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# Fundamental knowledge needed and concepts to consider

## Six key considerations for developing climate-informed health EWS:

1. Health sensitivity to climate conditions
2. Differences between climate change, climate variability, and weather
3. Spatial and temporal scales of climate impacts
4. Non-climatic factors that affect vulnerability to climate impacts
5. Differences in health vulnerability across populations
6. Predictability and uncertainty in climate, weather forecasts, and extreme events



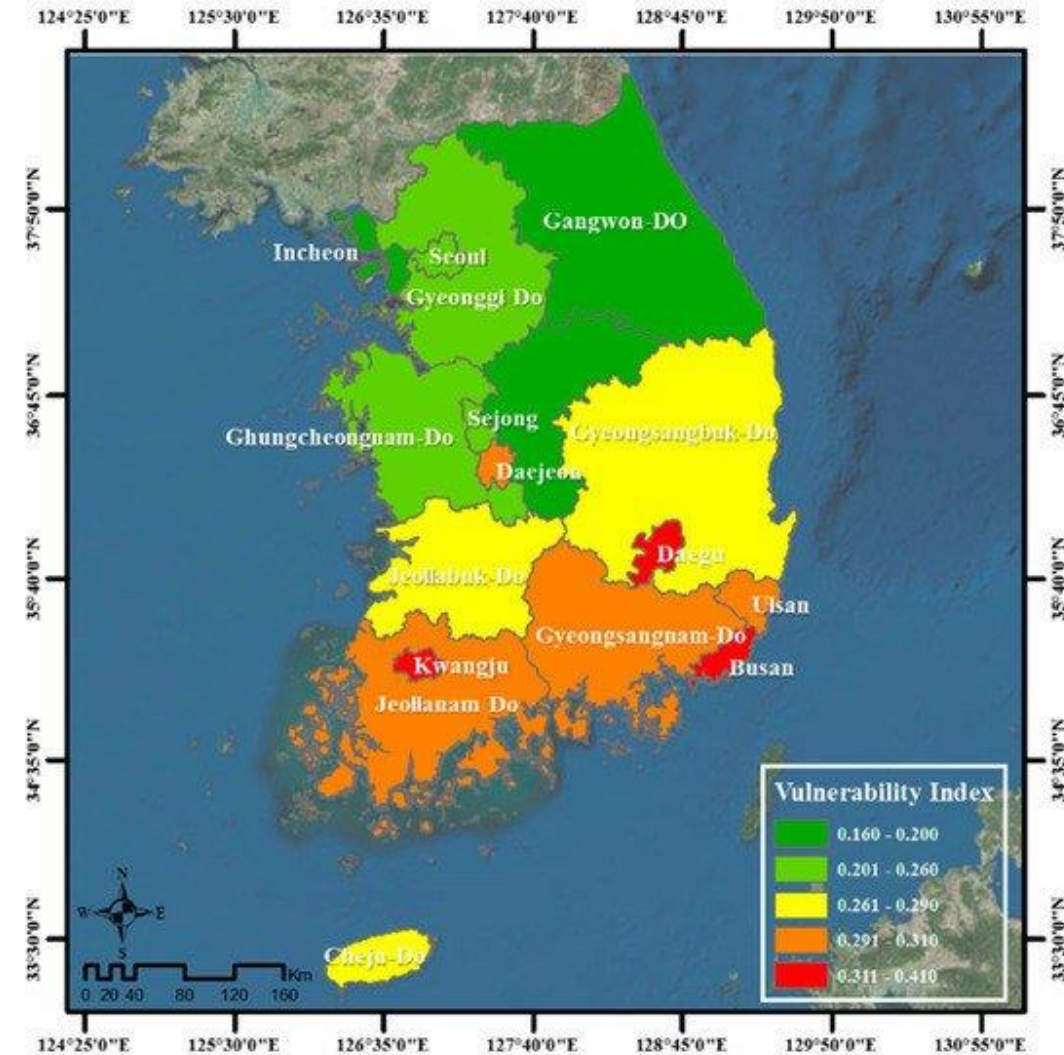
# Key considerations of climate-informed health EWS development:

## (1) Health sensitivity to climate conditions

*The extent to which the incidence of a disease and its spatial and temporal distribution are influenced by weather and climate conditions.*

### When conducting health sensitivity studies:

- Use local climate data at the appropriate spatial-temporal scale
- Use local health data collected based on standard disease case definitions
- Control for non-climate factors that may act as confounding factors
- Account for both direct and indirect effects of climate conditions on health



Health vulnerability assessment results to heat waves across South Korea in the 2040s (Oh K-Y, Lee M-J, Jeon S-W. *Development of the Korean Climate Change Vulnerability Assessment Tool (VESTAP)—Centred on Health Vulnerability to Heat Waves. Sustainability. 2017; 9(7):1103*)

# Key consideration of climate-informed health EWS development:

## (2) Time scales of climate impacts on health

*Weather, climate, climate variability, and climate change refer to changes in or states of meteorological conditions at different timescales*

### Definitions are:

- **Weather:** State of the atmosphere at a particular place and time
- **Climate:** “Averaged weather”, measurement of the mean temperature, wind, precipitation, and other variables over a period of time (**WMO uses a 30-year period to determine the average climate**)
- **Climate variability:** short-term fluctuations around the average weather
- **Climate change:** Changes in climate over a long time that show a trend over a decade or century

Timescale	Forecast & records' period and lead times	Example of health-decision applications
HISTORIC RECORD OF CLIMATE OBSERVATIONS (Observational, gridded data sets and reanalysis).	Hourly, daily, monthly or annual records of past climate conditions.	Epidemiological trend and regression analysis to understand associations of climate and health  Analysis of extreme events impacts to identify high-risk areas and populations and define priority high impact extreme events for design of response plans
WEATHER MONITORING AND NOWCASTING PRODUCTS	Current weather conditions provided in real-time or with some delay, and very short-term predictions.	Trigger emergency response plans when pre-fixed risk thresholds are exceeded.
WEATHER FORECASTS	Hourly or daily weather conditions forecasted multiple times a day from hours to around 12 days ahead.	Trigger preparedness plans when hazards are forecasted (e.g. heavy rainfall, cyclone, strong winds).  Example decisions: Identify at risk populations and disseminate public health advisories; initiate evacuations; activate emergency committees and response teams; pre-position emergency supplies; estimate needs of and strengthen emergency services; activate health impacts monitoring mechanism.
SUB SEASONAL CLIMATE FORECASTS	Average climate conditions over a week (approx.) forecasted from 2 weeks to 60 days Ahead	Trigger operational decisions months ahead of time when increase risk is forecasted. Example decisions: supplies procurement and pre-positioning; health workforce deployment; initiate communications with communities and partners to prepare response; strengthening disease surveillance and outbreak prevention and control mechanism in at risk areas
SEASONAL & INTER-ANNUAL CLIMATE FORECASTS	Seasonal climate conditions forecasted up to 6 Months / 1 year ahead.	Inform 1-5 year policy decisions for heat related health outcomes in areas with strong temperature change trends.
DECADE TO CENTURY CLIMATE INFORMATION (Climate projections)	Conditions expected at different points in time in the next 30 to 100 years and run every 5 years or upon specific needs.	Inform long-term policy decisions and Investments, for instance, heat resilient cold chains, water systems for health facilities, uninterrupted power supplies, workforce development.

Summary of weather and climate information at different time scales for health applications

For full table, see [Climate Services for Health Fundamentals and Case Studies for improving public health decision-making in a new climate](#)

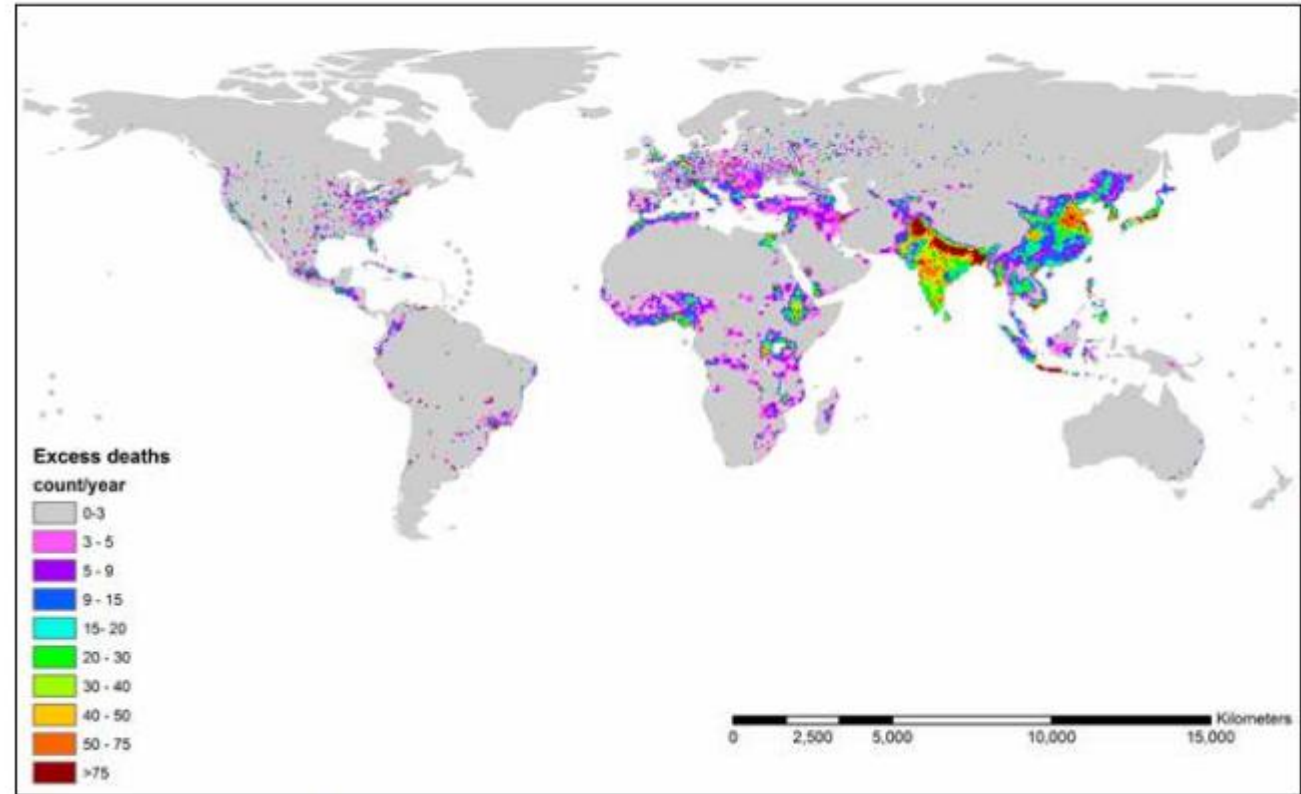
# Key consideration of climate-informed health EWS development:

## (3) Spatial scales of climate impacts on health

*Climate change affects different regions in different ways*

- **Disease patterns:** climate change affects the spatial distribution of disease by altering the distribution of environmental and social determinants of health
- **Population vulnerabilities:** vary by location and are weakened by altered disease and environment patterns from climate change

Figure 2.3 Estimated annual counts of heat-related deaths in people aged 65 years and over, by 0.5° grid cell, for BCM2 in 2050, with no adaptation assumed



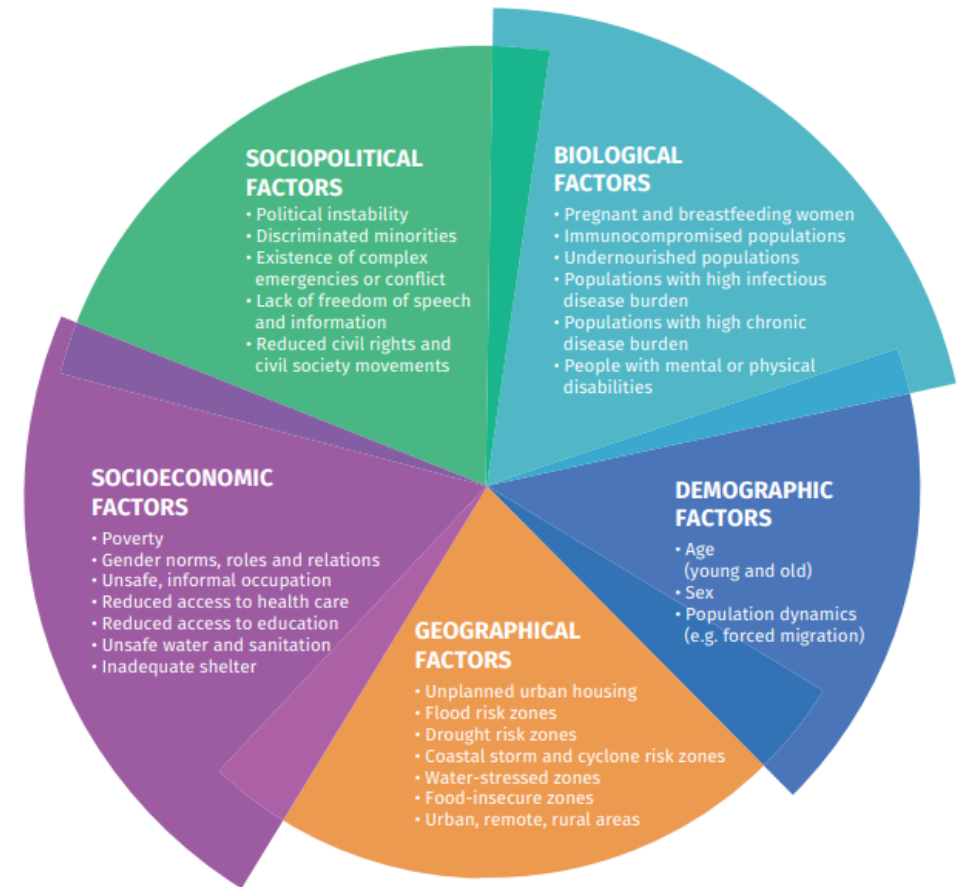
Mortality counts shown for 0.5 degree grid cells.

# Key consideration of climate-informed health EWS development:

## (4) Non-climatic factors that affect vulnerability to climate impacts

*There is a wide range of non-climatic factors that moderate the impacts of climate on health*

- **Socioeconomic factors:** education, occupation, income, or the political environment have a strong influence on risk exposure, access to health care, and adverse health conditions
- **Political factors:** political conflicts can cause massive migrations to poorly sheltered areas and disrupt community-coping mechanisms. In addition, policy decisions in other sectors can severely affect exposure to hazards (e.g., land-use policies that cause deforestation may increase exposure to flooding).



### Multiple vulnerability factors for health impacts of climate change

Source: Based on Gamble JL, Balbus J, Berger M, et al. Populations of concern. In: The impacts of climate change on human health in the United States: a scientific assessment. Washington, DC: U.S. Global Change Research Program; 2016; and Quality criteria for health national adaptation plans. Geneva: World Health Organization; 2021.



# Key consideration of climate-informed health EWS development:

## (5) Differences in health vulnerability across populations

*Subpopulations are distinct groups within a larger population that are defined by specific characteristics, such as health status, demographics, geography, ethnicity, or socioeconomic factors; certain subpopulations may be especially vulnerable to climatic hazards.*

**Demographic factors:** e.g., age, gender, migrant status

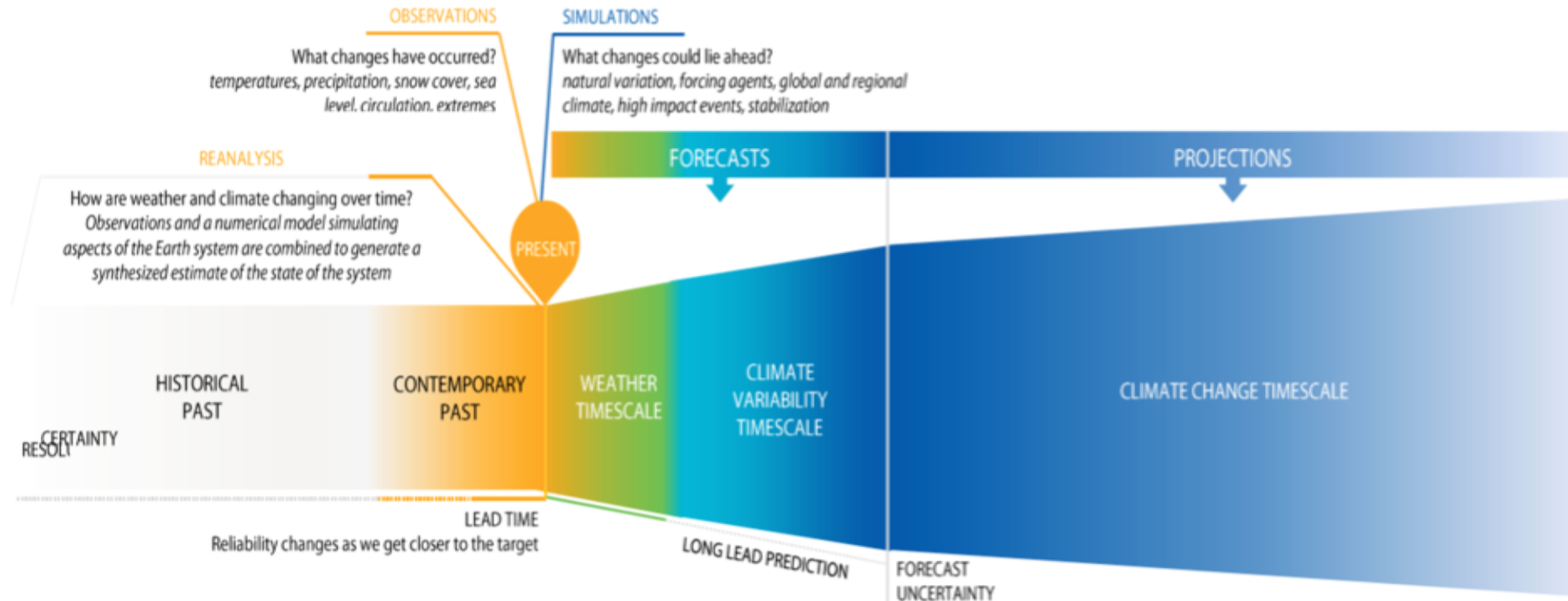
- **Baseline health status:** e.g., pre-existing health conditions, immunity
- **Cultural factors:** e.g., ethnicity, religion, hygiene habits
- **Socioeconomic factors:** e.g., nomadic character, poor working conditions, dependence on surrounding natural resources
- **Political status:** e.g., people living in conflict areas, refugees
- **Environmental & geographic factors:** e.g., flood and drought risk zones, low-lying coastal areas, cyclone-prone areas
- **Access to basic services:** e.g., education, health care, potable water, shelter

<b>Vulnerability due to demographic factors</b>	Proportion of children Proportion of women Proportion of elderly people Population density
<b>Vulnerability due to health status</b>	Populations with human immunodeficiency virus (HIV)/acquired immunodeficiency syndrome (AIDS) and immunocompromised populations Populations with tuberculosis (TB) Undernourished populations Populations with infectious disease burden Populations with chronic disease burden Mentally or physically disabled people
<b>Vulnerability due to culture or life condition</b>	Impoverished Nomadic and semi-nomadic peoples Subsistence farmers and fisherfolk Ethnic minorities Indentured labourers Displaced populations
<b>Vulnerability due to limited access to adequate resources and services</b>	Unplanned urban housing Flood risk zones Drought risk zones Coastal storm and cyclone risk zones Conflict zones Water-stressed zones Food-insecure zones Urban, remote, rural areas
<b>Vulnerability due to limited access to adequate</b>	Health care Potable water Sanitation Education Shelter Economic opportunities
<b>Vulnerability due to sociopolitical conditions</b>	Political stability Existence of complex emergencies or conflict Freedom of speech and information Types of civil rights and civil society

# Key consideration of climate-informed health EWS development:

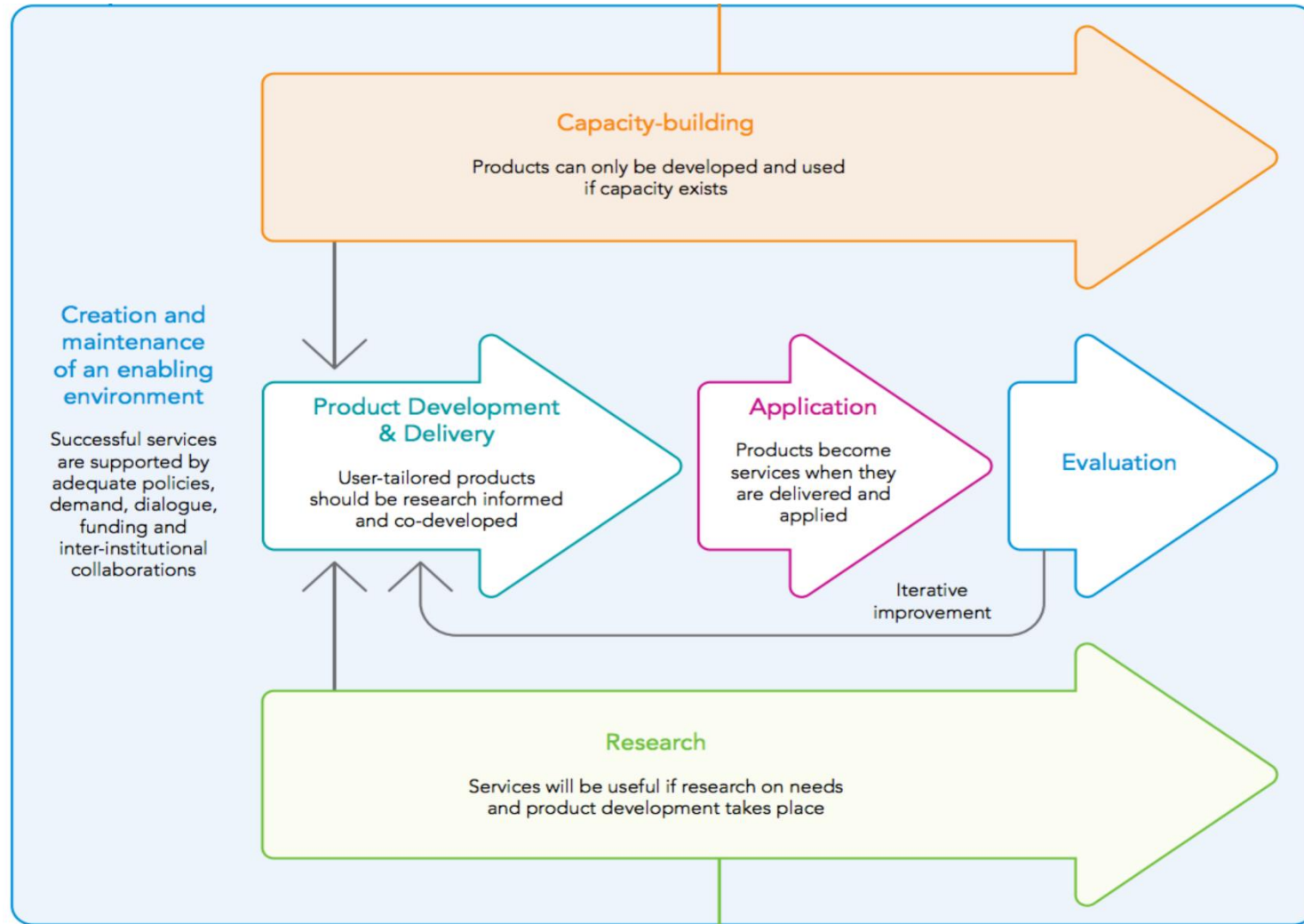
## (6) Predictability and uncertainty in climate, weather forecasts, and extreme events

Integrating weather and climate information in health prediction models can help increase the lead time for an early response. However, one should remain aware of the limitations of weather and climate forecasts.



*Certainty of weather and climate forecasts at different time scales. The width of the colored bar represents the magnitude of uncertainty*

# Requirements for climate-informed health EWS development:



## Basic requirements are:

- 1) enabling environment
- 2) adequate baseline capacities
- 3) sufficient data, information and evidence

# Requirements of climate-informed health EWS development:

## Adequate enabling environment

*The enabling environment is the structured context composed of relevant stakeholders and adequate collaboration mechanisms, including national plans, policies, mandates, and sufficient financial resources that favour the development, application, and interactive evaluation of the early warning system.*

### An enabling environment is formed by the:

- National policy and financial landscape
- Multi-sectoral partnerships and communication mechanisms
- Problem awareness and scientific and programmatic demand
- Institutional mandates, procedures, and capacities

### Promoting an enabling environment for HNAP development in Indonesia

Indonesia is among the most vulnerable countries in the world to the effects of climate change, and climate variability continues to impact public health in Indonesia. Regional climate changes show increases in air temperature of up to 1.250 °C. Climate variability and change are exacerbating health risks and outcomes, including vector-borne diseases (such as malaria and dengue) and waterborne and related diseases (such as cholera and diarrhoeal diseases). For the less direct climate-sensitive health risks (such as food and nutrition security and noncommunicable diseases), country-level monitoring and assessment to determine the projected impact of climate variability and change requires improvement. The Indonesian government has demonstrated strong political will in responding to global climate change. Since the 1990s, the country has actively contributed to global efforts to combat climate change, including the ratification of the Paris Agreement through Law No. 16/2016. At the national level, Indonesia promoted the need for adaptation efforts by developing the National Action Plan on Climate Change Adaptation in 2014. The Indonesian government, through the Ministry of Environment and Forestry (MoEF), developed the Nationally Determined Contributions (NDCs) in 2016, which are currently being updated for 2020–2030.



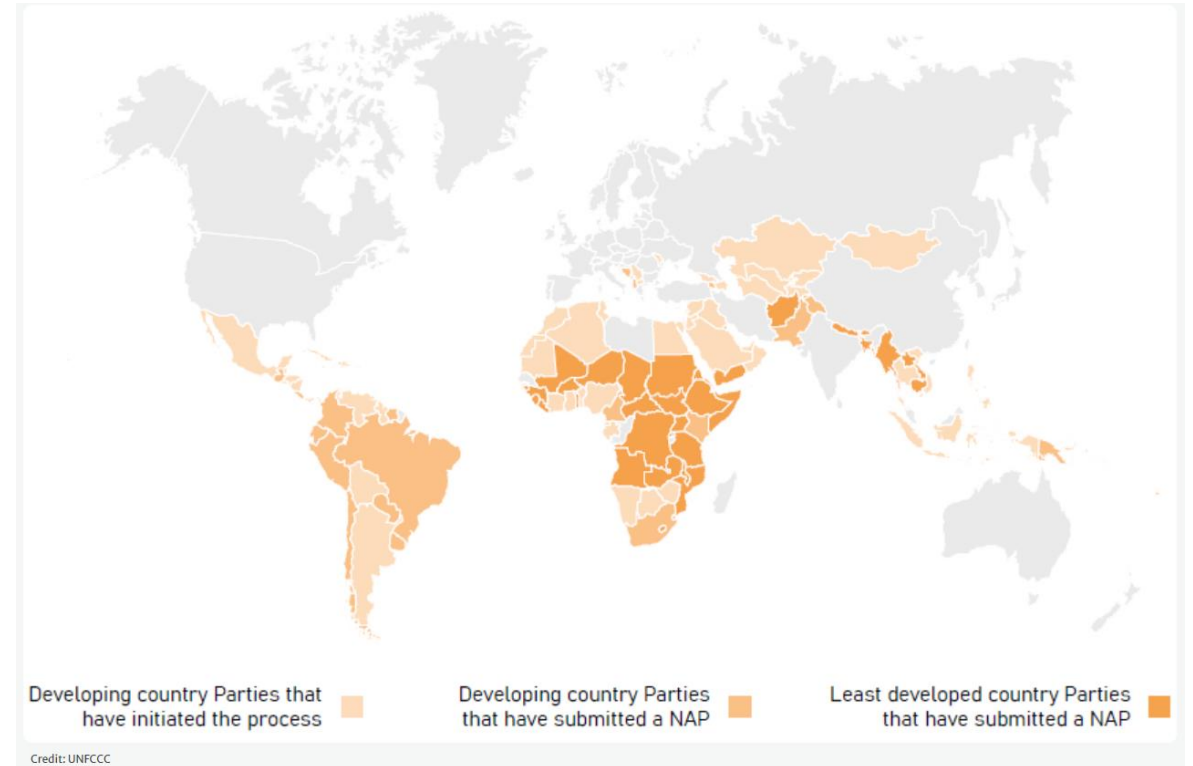
Source: WHO 2021- [Quality Criteria for Health National Adaptation Plans](#)

# Requirements of climate-informed health EWS development: National plans, policies, and mandates

*The existence and contents of relevant national plans, policies, and mandates could facilitate or hamper the development and uptake of EWS. A policy review can help identify barriers and opportunities.*

## Policy review is needed on:

- Official institutional mandates
- Preparedness and response plans and protocols
- Recognition of climate risks to health in national health plans and policies
- Prioritisation of EWS in National Climate Adaptation Plans (NAP), as well as Disaster Risk Reduction of Health Plans



Developing and Least developed countries that have submitted a NAP as of November 2023

Source: [National Adaptation Plans | UNFCCC](#)

# Requirements of climate-informed health EWS development: Multi-sectorial and multidisciplinary collaboration

*Developing EWS requires collaboration among multiple stakeholders and a diverse set of skills, which can only be achieved through multidisciplinary and multi-sectoral partnerships at both national and global levels.*

**Example of collaboration at the global level:**

**WHO-WMO Collaborative Objectives:**

- Promote the alignment of relevant policies and raise awareness of environmental and climate-related risks and solutions to protect human health
- Promote the generation and application of scientific evidence
- Develop technical mechanisms and partnerships to facilitate the development, delivery, access to and use of data and information products on weather, climate, and environmental hazards to health
- Develop and disseminate technical and normative guidance, scientific publications and tools
- Monitor progress on the access and use of reliable and relevant weather, climate, and environmental information

## Health, Environment & Climate Change Coalition

Launched by the heads of WHO, UN Environment and WMO to stimulate & strengthen collaborations across sectors and departments & with stakeholders at all levels, to promote more integrated and evidence-based policy- and decision-making to address issues at the interface of environment, climate, and health.



[The Health, Environment and Climate Change coalition \(HECCC\)](#)

## Case Study

# ECUADOR–PERU COOPERATION FOR CLIMATE-INFORMED DENGUE SURVEILLANCE: CREATING AN INTERDISCIPLINARY MULTINATIONAL TEAM

Since 2010, the Ecuador Ministry of Health has addressed health concerns linked to climate change through an integrated approach to manage the social and environmental determinants of health.

Likewise, in Peru, the Environmental Health General Directorate of the Ministry of Health implements strategies to address climate change impacts on human health as a disease-prevention approach.

The Binational Development Plan is aimed at strengthening health actions in both countries' border areas

Despite restricted funds, the binational monitoring network for dengue control using climate and health information in the border regions of Ecuador and Peru was established, along with a work plan. This promising initiative needs further support. Recommendations for next steps include seeking official recognition for the dengue surveillance network to implement its work plan as part of the Binational Development Plan and become an official part of the regional and local community development plans.



*Aedes Albopictus*. Photo credit: Centers for Disease Control and Prevention, part of the United States Department of Health and Human Services. Photo credit: James Gathany/CDC.

For the full case study, see [Climate Services for Health Fundamentals and Case Studies for improving public health decision-making in a new climate](#)



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# Requirements of climate-informed health EWS development:

## Financial resources

*Financial resources need to be available not only for the development of the EWS but also for its future continuation*

### Challenges:

- Many EWS developed so far have become unused due to a lack of sustained financial resources.

### Recommendations:

- Integrate EWS maintenance within the mandate of any of the partner institutions
- Advocate for the integration of EWS within existing core health and risk management tool kits
- Access climate change financial resources



### Guidance & Knowledge Sharing



*and many more...*

# Requirements of climate-informed health EWS development:

## Baseline capacity

*The EWS are complex systems that require high levels of human and institutional capacities to be developed and implemented. The core necessary capacities can be grouped into*

**The core necessary capacities can be grouped into:**

- **Research capacity**
  - *Identify the health sectors' and climate sectors' research partners*
  - *Evaluate national research capacities and existing collaboration mechanisms with the research community*
  - *Establish collaboration with relevant international research centres or institutions*
- **Human capacity**
  - *learn from other countries' experiences on EWS development and receive support from the experts involved in such systems*
  - *Include individuals who are participating or have participated in the development of EWS*
  - *Include members who attended specific national or international training sessions*
- **Institutional capacity**
  - *capacity to collect and provide the necessary data and information for EWS operationalisation*
  - *capacity to activate and coordinate adequate response action upon the reception of warnings*



# Requirements of climate-informed health EWS development:

## Data, information, and evidence

*Risk forecasting models aim to identify recurring patterns in climate impacts on health and use these patterns to predict risk levels at future time points based on current or projected climate conditions.*

### Data & Information

- *Generally, 30 years of data is needed to evaluate hazards that occur on a seasonal basis*
- *Shorter time series can be sufficient if the events occur on a more frequent basis (e.g., storm surges)*
- *longer time series will be needed to evaluate the impact of events that occur every couple of years (e.g., El Niño or La Niña)*

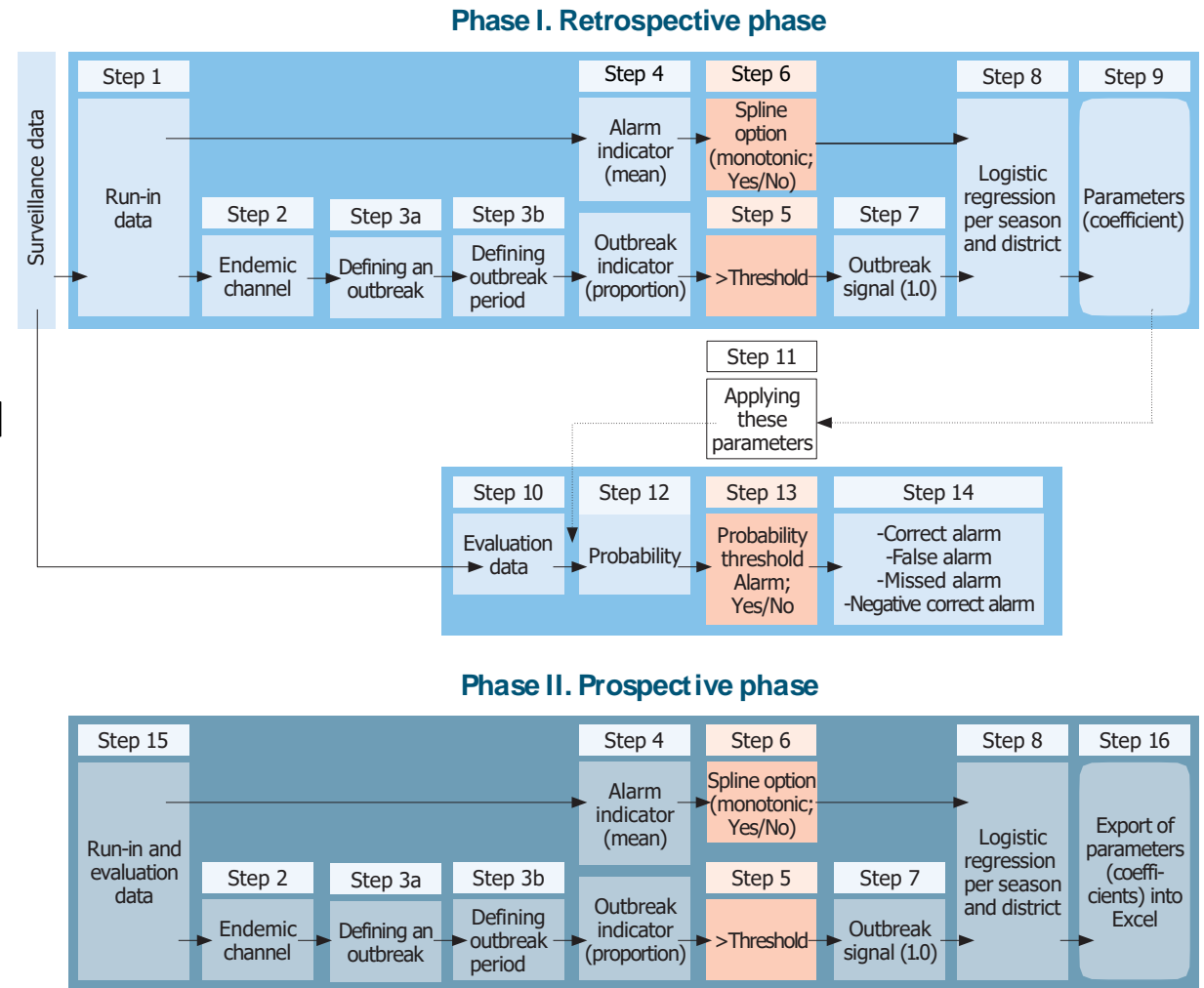
### Evidence

- *Evidence of climate impacts on the disease (to inform the development of risk forecasting models)*
- *Evidence generated through operational research on the implementation and performance of similar systems (to design the operational model for the application of the EWS)*



# How-to guide: Designing and delivering EWS

- Step 1.** Initial problem characterisation
- Step 2.** Health sensitivity review and analysis
- Step 3.** Feasibility assessment
- Step 4.** Developing integrated risk forecasting and monitoring
- Step 5.** Designing warnings and response plans
- Step 6.** Establishing a communication mechanism with communities
- Step 7.** Pilot-testing and application of EWS
- Step 8.** Monitoring, evaluation, and iterative improvement



Block diagram illustrating the process and steps of the retrospective and prospective phases to build a health EWS



# Requirements of climate-informed health EWS development:

## Initial problem characterisation

*This step aims at identifying the disease, geographical areas, and vulnerable populations for which EWS would provide added value*

### Key questions to guide problem characterisation

- What are the most common climate hazards in the country?  
How often and where do they occur?  
Is their frequency increasing or decreasing over time?
- What are the climate zones in the country? Are there any zones with special, varying climates?
- What are the climate-sensitive diseases of the highest burden? Where is the highest incidence seen? Are there seasonal variations? Have changes in the seasonal or spatial distribution of these diseases been observed in the last year?
- Is there evidence of the association of these diseases with climate hazards? Are they suspected to be associated with any climate hazards or climate variations?
- Have disease outbreaks been observed following certain climatic events? Where?
- Are there any emerging diseases suspected to be introduced due to changes in climatic conditions?
- What types of vulnerable groups exist in the country? Where are they located?



These questions may have already been assessed in a climate change and health Vulnerability and Adaptation assessment of your country/region/city.



# Requirements of climate-informed health EWS development:

## Health sensitivity review and analysis

*This step aims at reviewing and generating new knowledge on associations between climate and health to inform the production of risk forecasting models*

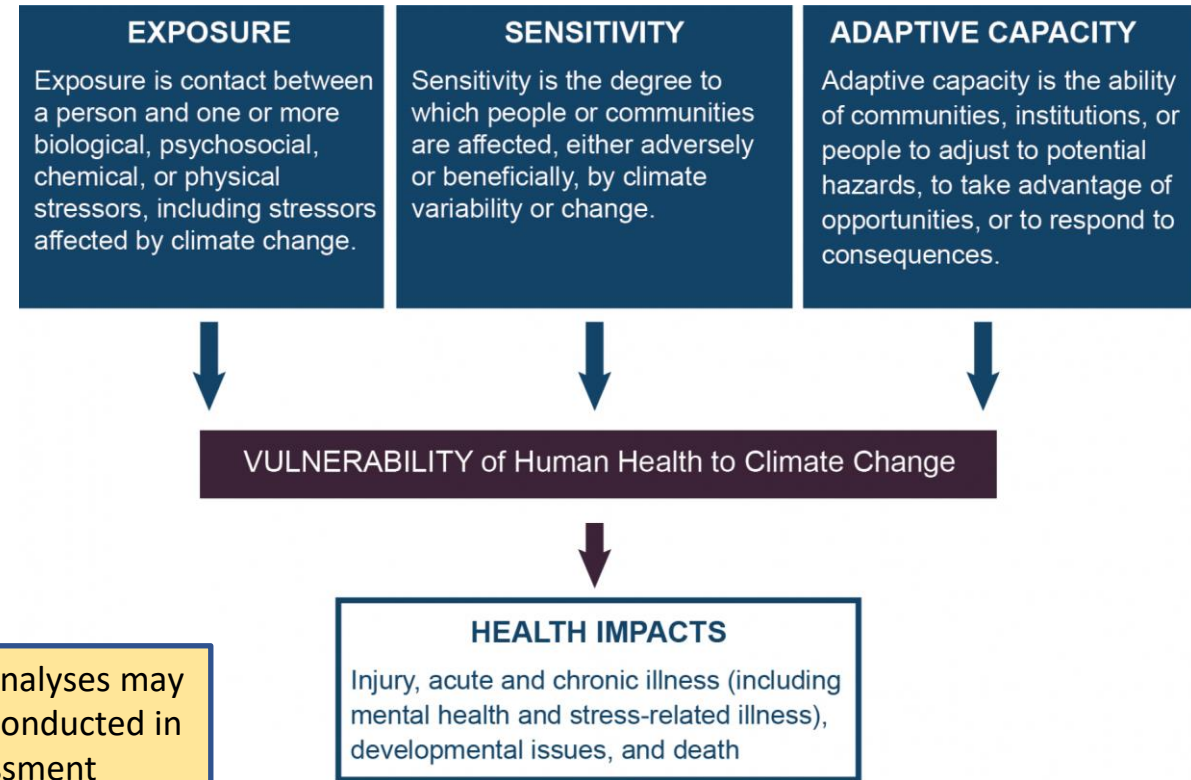
### Evidence review

- What type of analysis was conducted?
- What period does it cover?
- What are the geographical areas covered?
- Was the analysis conducted for the entire population or for a sub-population? (e.g., children under 5, elderly, etc.)

### Defining sensitivity analysis

Sensitivity -> the degree to which climate determines the occurrence and spatial distribution of health outcomes

- Commonly, spatiotemporal analysis is done. However, the type of analysis depends on the spatiotemporal resolution and the length of the datasets



Sensitivity analyses may have been conducted in a V&A assessment

Turner et al. 2003, PNAS



World Health Organization

# Requirements of climate-informed health EWS development:

## Health sensitivity review and analysis

### Data needs, availability, and access (Examples)

- Historical morbidity or mortality data
- Historical climate data and extreme weather events
- Data on predominant and suspected health risk factors
- Maps of national environmental, land use, or ecological zones
- Historical records of climate extreme impacts on health (mortality and morbidity)
- Socioeconomic data to characterise vulnerable populations



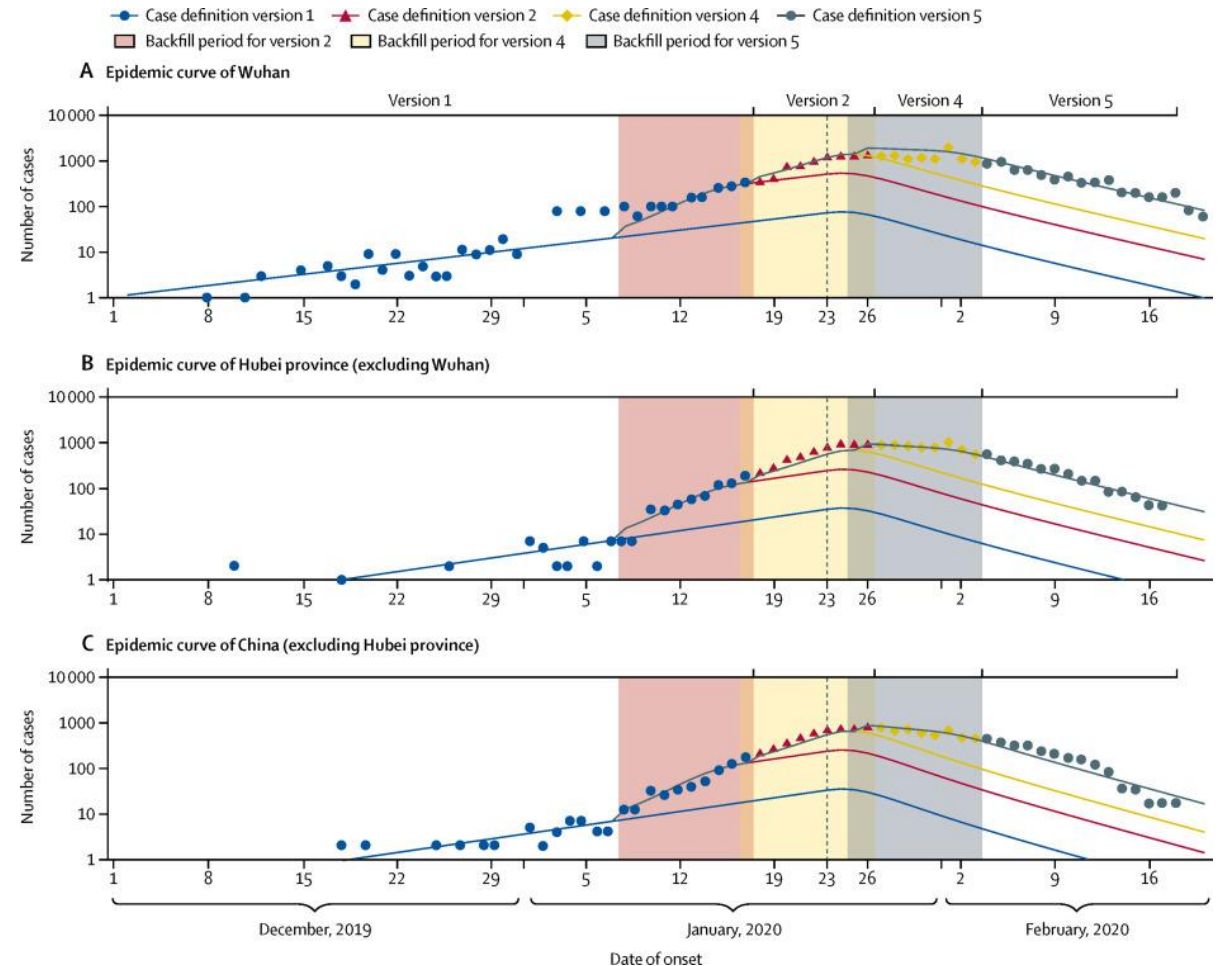
# Requirements of climate-informed health EWS development:

## Health sensitivity review and analysis

### Preparing data for analysis

- Have the variable definitions changed over time (e.g., case definitions)?
- Have reporting systems changed over time (e.g., from paper to electronic base)?
- Has the frequency of data collection changed? (e.g., from weekly accumulated disease cases to daily incidences)?
- Have the catchment areas changed over time (e.g., adding new health facilities might reduce the catchment area of the individual facilities)?
- Has the size and geographic distribution of populations changed over time (e.g., increased immigration will increase the number of patients per health facility)?

Source: *Lancet Public Health* (2020)



Reported COVID-19 cases by date of onset and the modelled exponential growth of daily numbers of cases by application of different versions of case definitions (Tsang, 2020)



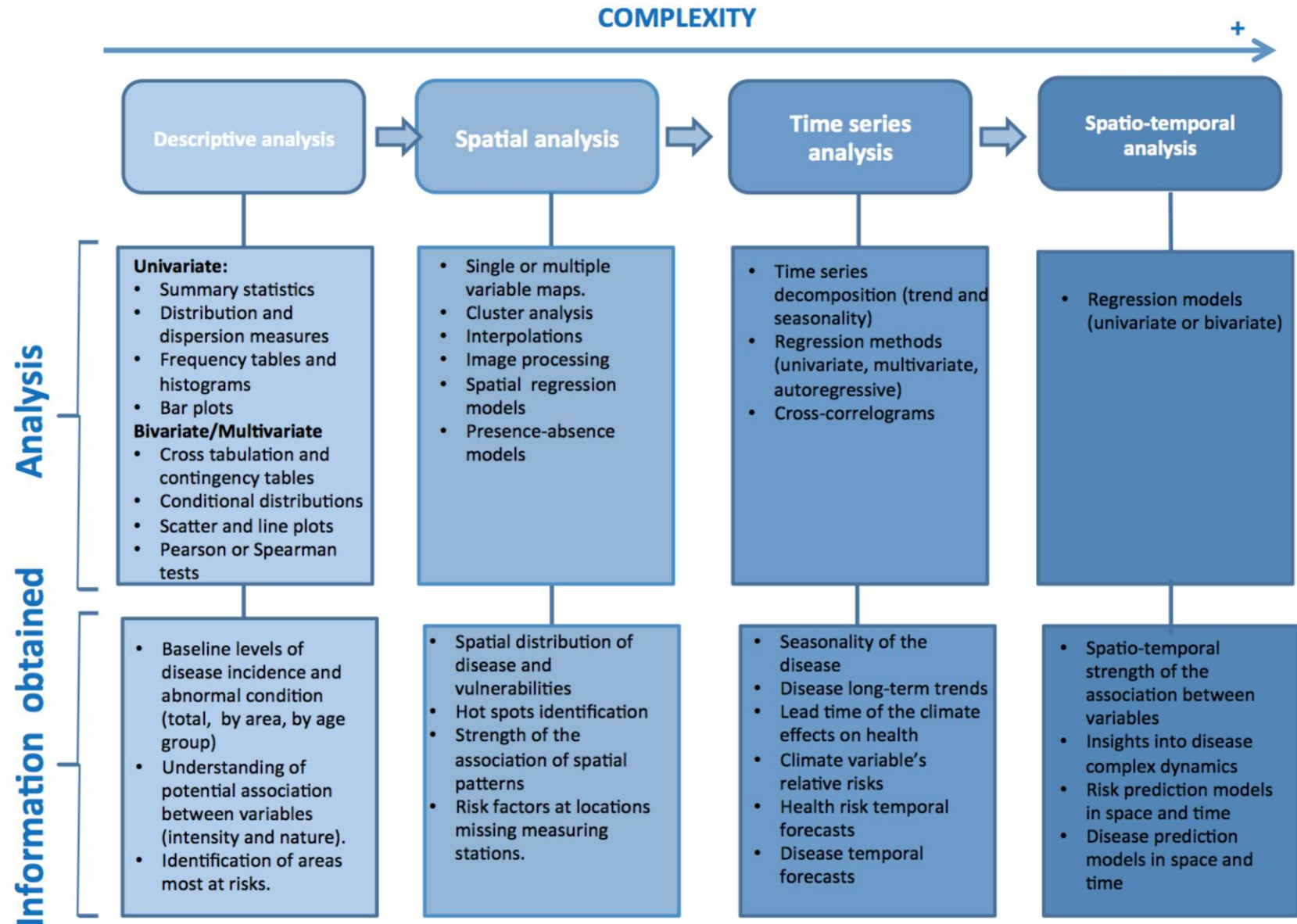
World Health Organization

# Requirements of climate-informed health EWS development:

## Health sensitivity review and analysis

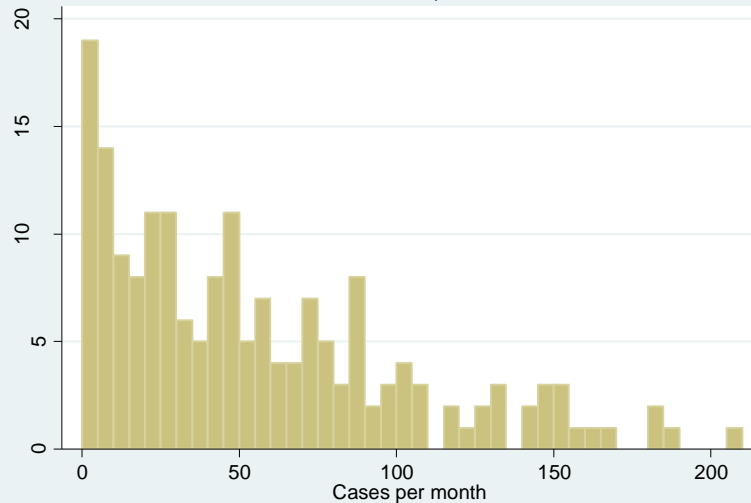
### Data analysis

- Descriptive analysis
- Spatial analysis
- Time series analysis
- Spatiotemporal analysis



## Descriptive analysis

Diarrhoea in Ba, 1995-2009

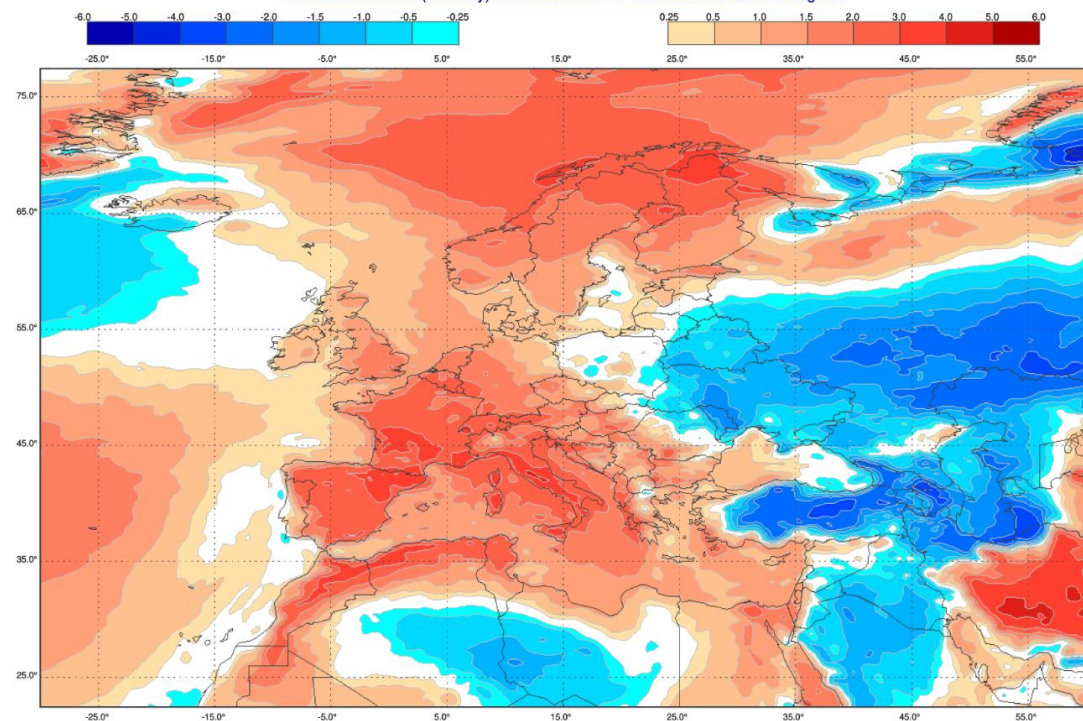


Histogram of diarrhoea cases in Fiji. Substantial numbers of cases of diarrhoea were reported in all twelve months of the year. The lowest overall rates occurred in November and December (total 570 and 524 cases, respectively, over 15 years) and the highest in February (1088 cases).

## Spatial analysis (of risk factors)

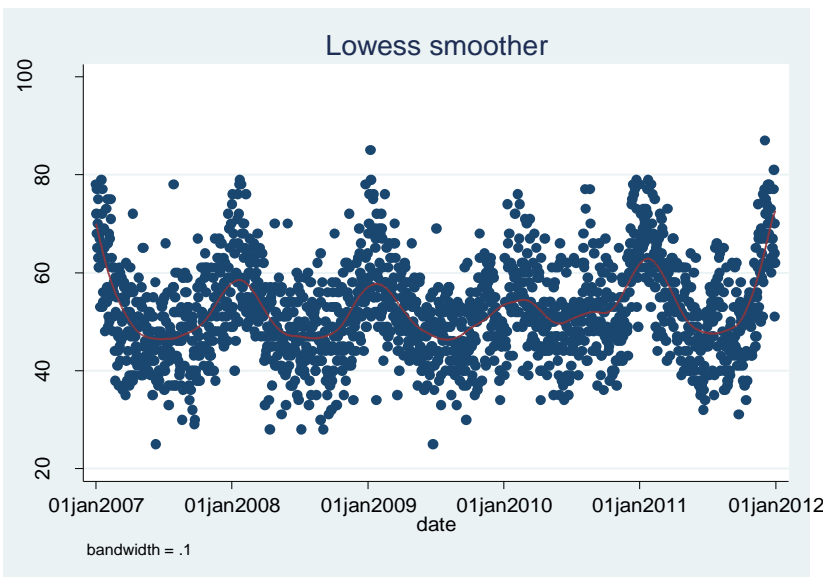
Monthly Temperature (T2m) Anomalies valid for week: from 29 July to 04 August 2024

Map processed by EFFIS System based on ECMWF Monthly Forecast System initiated on 25 July 2024  
Estimated deviation (anomaly) of the mean from model climate in Celsius degrees

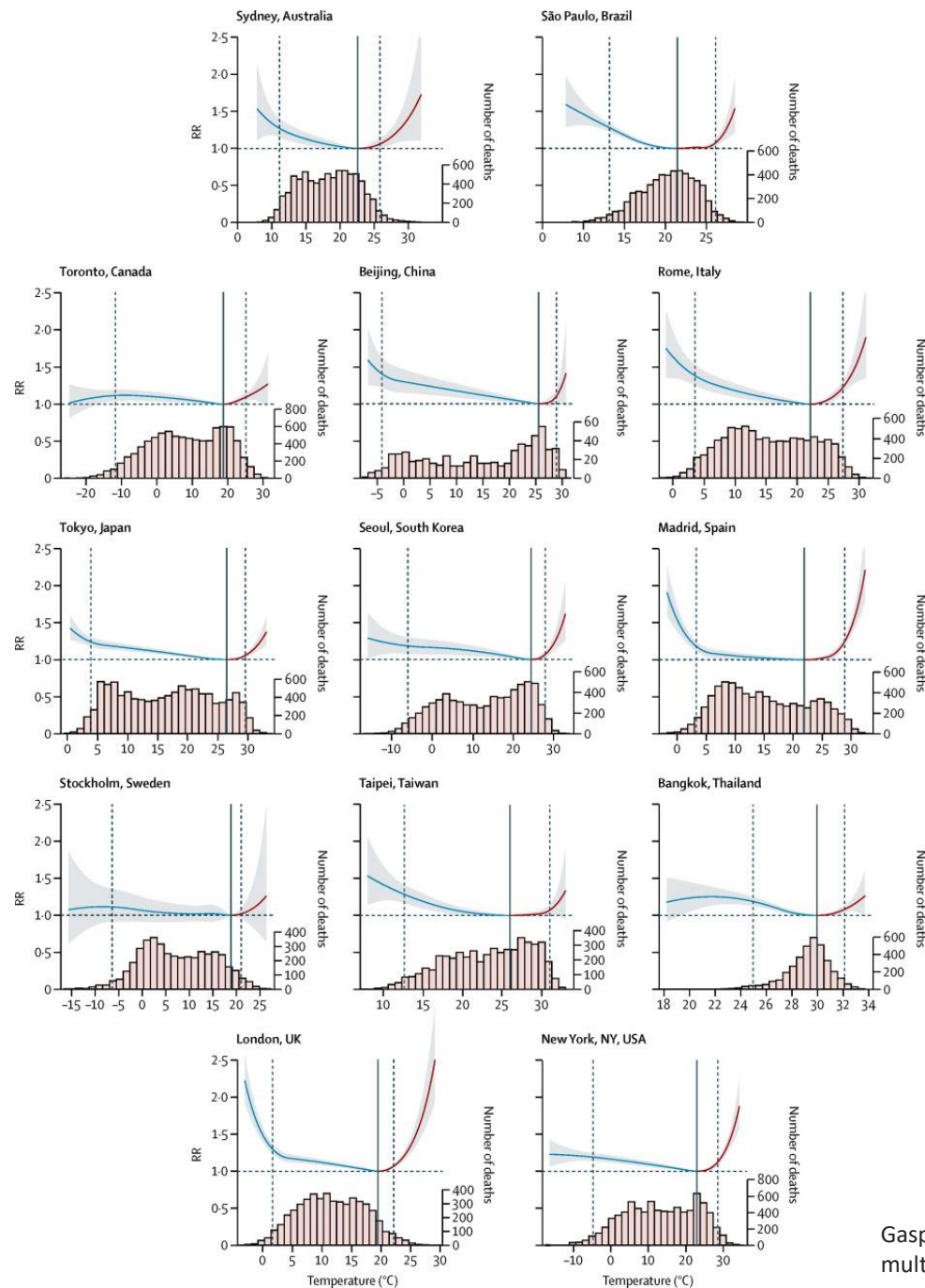


Long-term monthly forecast of temperature and rainfall anomalies (Source: <https://effis.jrc.ec.europa.eu/>)

## Time series analysis



Mortality data in Jordan. From the plot, it can be seen that mortality presents a seasonal variation. Hence, this data might be suitable for time series analysis.



## Spatio-temporal analysis

Overall cumulative exposure–response associations in 13 cities.

Exposure–response associations as best linear unbiased predictions (with 95% empirical CIs, shaded grey) in representative cities across the 13 countries, with corresponding temperature distributions.

Solid grey lines are minimum mortality temperatures, and dashed grey lines are the 2.5th and 97.5th percentiles. RR=relative risk.

Gasparrini A, et al. "Mortality risk attributable to high and low ambient temperature: a multicountry observational study." *The Lancet* (2015) 386: 369-375.

# Requirements of climate-informed health EWS development:

## Feasibility of risk forecasting

*The results of the previous analysis will serve as the basis for constructing the risk-forecasting model. At this stage, these results should be evaluated to determine the feasibility of the EWS*

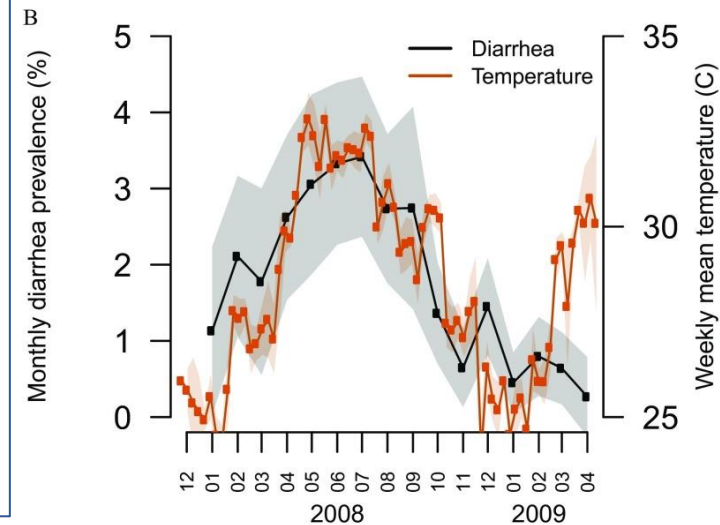
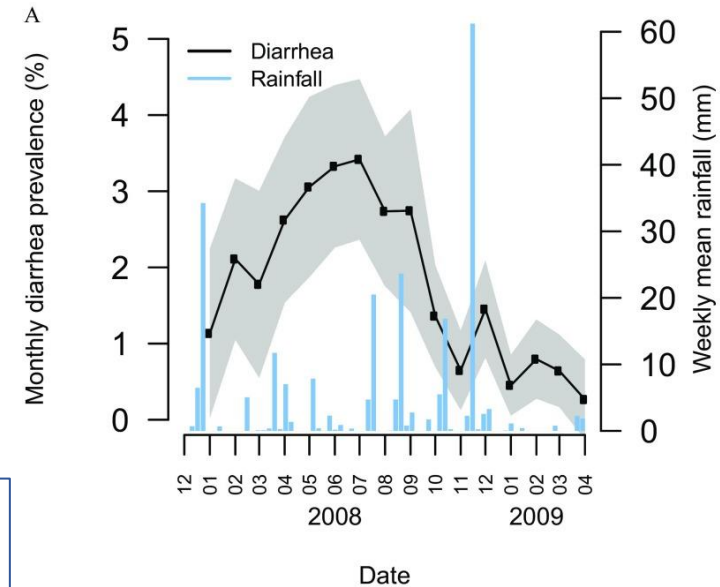
## Feasibility of the EWS

- Have associations between the disease and certain climate variables been identified?
- What is the strength of the association? What is the level of uncertainty in the association?
- Are the associations biologically plausible?
- Is data available on a regular basis for the risk factors that were found to be associated with the disease?
- Does the lag time of the association found to allow for the building of risk models that forecast risk with sufficient time in advance to allow for response?

Source: Open-access article (P111C0785227).

Temperature shows a close correlation with diarrhoea. However, the rainfall trend is poorly correlated to diarrhoea. How would you explain this with good “**biological plausibility**”?

The results suggest that in rural Tamil Nadu, heavy rainfall may wash pathogens that accumulate during dry weather into contact with children. Higher temperatures were positively associated with diarrhoea 1–3 weeks later. These findings suggest that diarrhoea morbidity could worsen under climate change without interventions to reduce enteric pathogen transmission through multiple pathways.



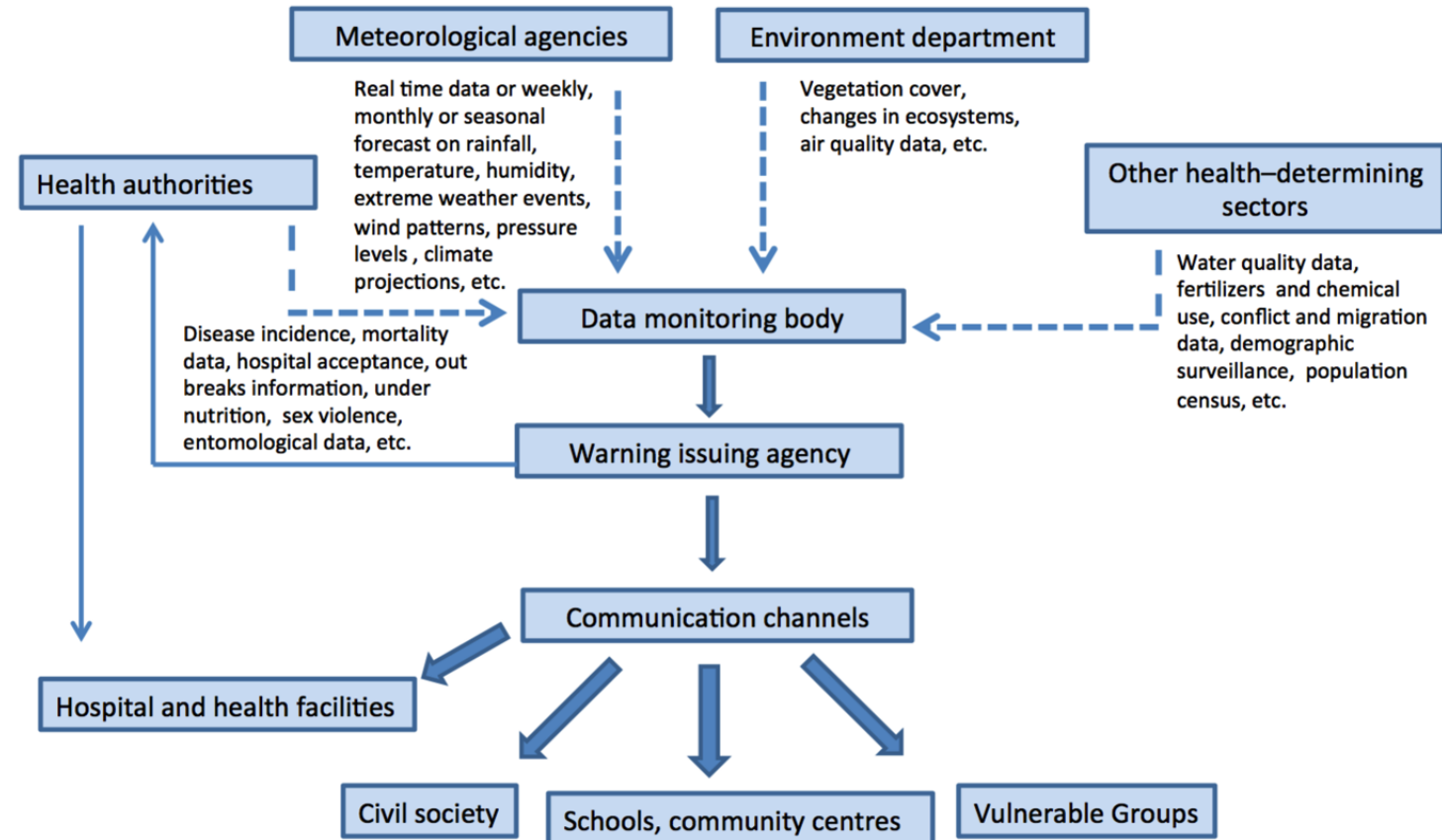
Mean 7-d prevalence of diarrhoea during each month and weekly rainfall and mean temperature (Mertens, et. al., EHP, 2019)

# Requirements of climate-informed health EWS development:

## Information Flow Chart

### Integrated risk monitoring

- Real-time or near-real-time data availability for continuous risk monitoring
- Policies and agreements on data sharing
- Data compatibility for integration
- Programmed data transformation to feed into the risk forecasting models
- Standard Operating Procedures for a consistent data management process



### Example: In Uzbekistan, weather, health, and map data were integrated in a web interface:

In Uzbekistan, earlier stages of the EWS process had developed correlations between meteorological conditions and a range of health outcomes. Data from ECMWF and GFS were used to generate warnings of adverse weather conditions. A function was developed to automatically distribute warnings from the EWS website to 10 email addresses of officials appointed by the MOH to be responsible for information exchange at the local level and for implementing predefined Protocols of Response to adverse weather conditions.

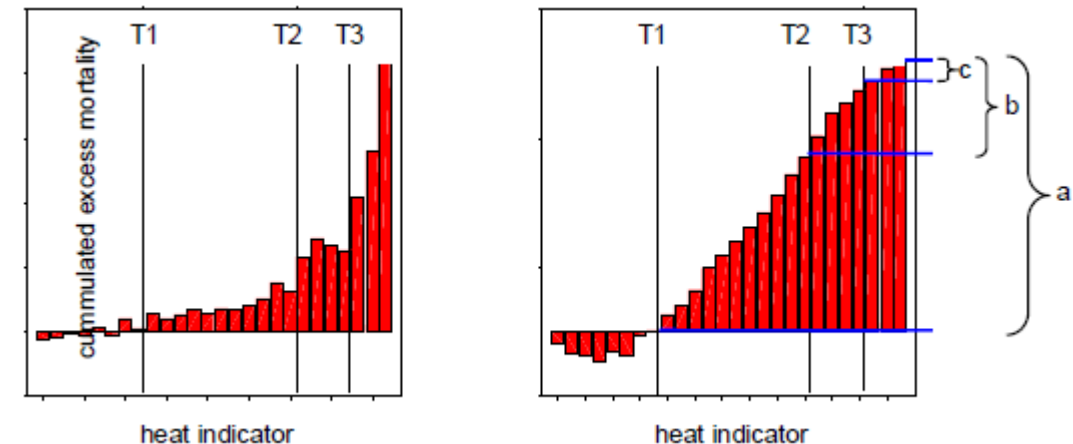
# Requirements of climate-informed health EWS development:

## Setting thresholds

- Different types of risk and risk levels will require different types of responses
- Thresholds can simply be based on the status of a certain climate variable (e.g., 95th percentile of summer maximum temperature)
- More complex thresholds will depend on the state of several risk factors and require modelling to quantify the level of risk (e.g., combined use of temperature, rainfall, and humidity values to evaluate malaria risk)
- Continuous update of risk-forecasting models is needed, thresholds also need to be updated over time to account for changes in sensitivities

	Examples of nomenclature	Description
Pre-alert levels (temporal)	Seasonal vigilance	Activated during the whole summer season, though no heat event is forecast.
	Outlook	A heat event is expected during the next 3–5 days.
	Watch (warning)	A heat event is expected within the next 24–48 hours.
Alert level (severity)	Heat alert Heat advisory Warning Severe weather warning	Moderate heat event occurring or imminent
	Excessive heat warning Extreme heat alert Heat emergency Maximum mobilization Extreme weather warning	Significant heat event occurring or imminent

Heat–Health Warning System levels based on the time until the event or magnitude during the event



Example of the relationship between temperature and excess mortality during summer (left) and cumulative excess mortality (right): T1–T3 thresholds; a, b, c – amount of mortality that can be prevented when applying the different thresholds in case of a 100 per cent effective Heat–Health Warning System.

Source: WMO & WHO 2015 - Heatwaves and Health: Guidance on Warning-System Development



# Establishing communication mechanism with communities:

*Warnings are tailored messages issued when risk thresholds are exceeded and are intended to trigger response action or protective behaviour at different levels*

## Core steps towards defining a community communication strategy

- Map the existing community communication channels and tools
- Evaluate the coverage of them considering the identified vulnerable groups
- Assess community preferences and customs
- Understand how the community uses the communication systems
- Select the best one by balancing between the capacity to deliver information and popularity among community members
- Formulate early warning messages that are:
  - *Concise, Consistent, Actionable, Adapted to local languages and culture*
- Make sure that communities know:
  - *Which message will be issued, how to interpret them, and how to respond*
- Define an information flow protocol, identifying roles and responsibilities within the agencies or organisations responsible for issuing the warning



© WHO

# Pilot-testing and application of EWS:

*Before full implementation, EWS needs to be pilot tested. Practical implementation will allow for the identification of problems and situations that might compromise the optimal performance of EWS.*

## Checklist: Process evaluation of EWS pilot tests

Question	Answer	Proposed action
Is a warning being used for the emergency?	No	<ul style="list-style-type: none"><li>• Revise data collection and data sharing protocols</li><li>• Revise monitoring systems</li><li>• Revise climate sensitivity</li></ul>
Did the warning issued correspond to a real emergency?	No	<ul style="list-style-type: none"><li>• Revise climate sensitivity</li></ul>
Were the thresholds and/or triggering criteria accurately set to issue a timely warning?	No	<ul style="list-style-type: none"><li>• Set higher or lower thresholds or develop more sensitive criteria</li></ul>
Was the information properly shared across different responsible parties?	No	<ul style="list-style-type: none"><li>• Revise roles and responsibilities</li><li>• Track information blockages</li></ul>
Did the warning messages reach the targeted audience in a timely manner and were they understood?	No	<ul style="list-style-type: none"><li>• Revise roles and responsibilities</li><li>• Revise message content</li><li>• Revise communication channels</li></ul>
Has the community responded to the warning?	No	<ul style="list-style-type: none"><li>• Revise response protocol, plans, and roles</li></ul>
Have the expenses exceeded the calculated budget?	No	<ul style="list-style-type: none"><li>• Identify elements causing excess expenses</li><li>• Identify additional funding sources</li></ul>

## Section 4.2:

# Forecasting models: climate driven dengue early warning systems

**Learning objective:** Introduce data and timeframes required to produce real-time disease risk forecasts. Provide examples of communicating and visualising probabilistic forecasts. Discuss forecast validation and evaluation techniques.

### Case study:

Dengue outlook for the World Cup in Brazil: an early warning model framework driven by real-time seasonal climate forecasts

### Resources:

- The BUGS (Bayesian inference Using Gibbs Sampling) project <https://www.mrc-bsu.cam.ac.uk/software/bugs/>
- The R-INLA project: Bayesian computing using integrated nested Laplace approximations <http://www.r-inla.org>
- Forecast Verification: a practitioner's guide <https://leseprobe.buch.de/images-adb/13/86/1386a538-a631-47b7-8e4b-12ea9ca873ee.pdf>
- R Verification package [www.cran.r-project.org/web/packages/verification.index.html](http://www.cran.r-project.org/web/packages/verification.index.html)
- Seasonal forecasting and health impact models: challenges and opportunities <https://researchonline.lshtm.ac.uk/3783976/> (open access version)





# Section 4.2

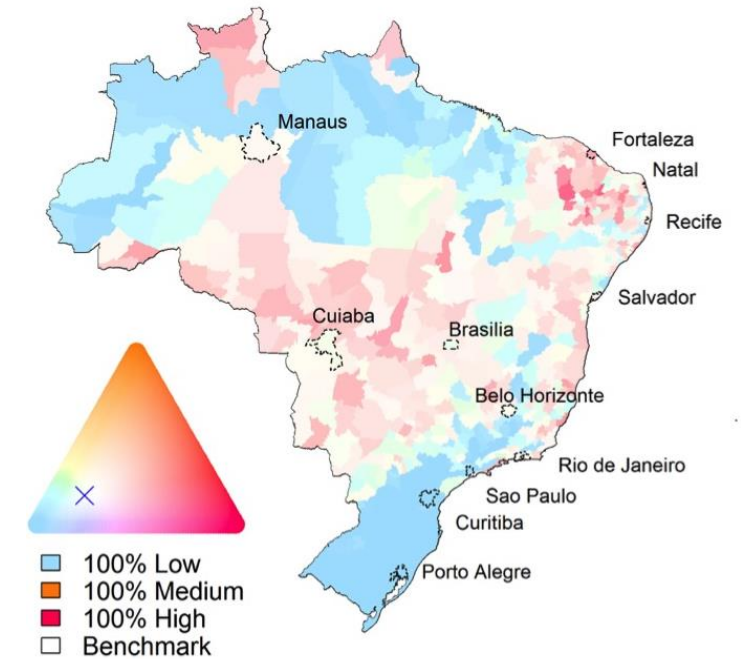
Forecasting models: climate driven dengue early warning systems

Dr Rachel Lowe

London School of Hygiene and Tropical Medicine

# LEARNING OBJECTIVES

- Introduce data and timeframes required to produce real-time disease risk forecasts.
- Provide examples of communicating and visualising probabilistic forecasts.
- Discuss forecast validation and evaluation techniques.



Lowe et al., 2014, *Lancet Infect Dis*

# INTENDED LEARNING OUTCOMES

By the end of the module, you will be able to:

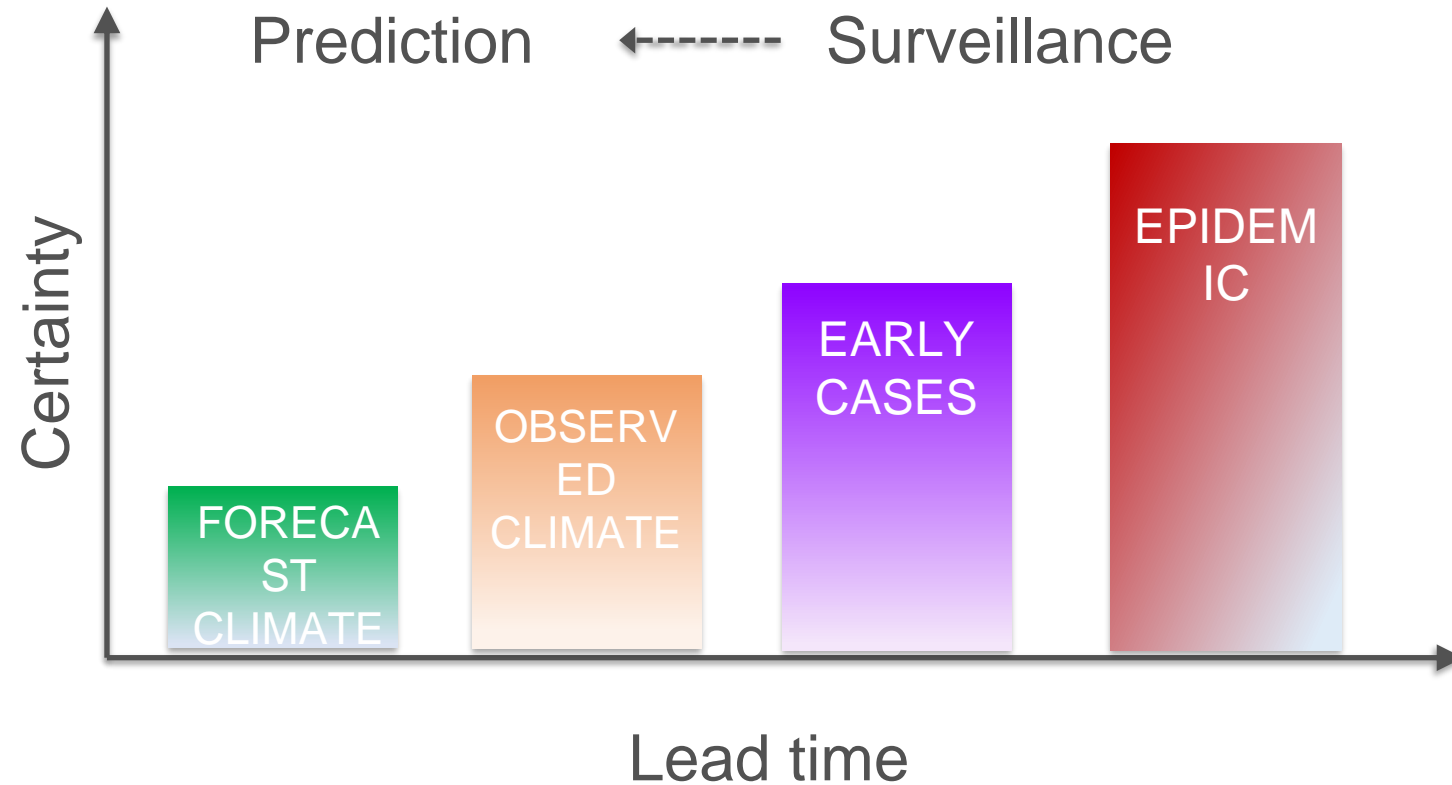
- Understand data and methods needed to produce and communicate real-time probabilistic disease risk forecasts.
- Select and critique appropriate forecast validation and evaluation techniques
- Recognise the challenges in implementing sustainable epidemic early warning systems.

# CLIMATE-INFORMED EARLY WARNING SYSTEMS

**Early warning systems** that account for multiple disease risk factors can help to implement timely control measures.

**Seasonal climate forecasts** provide an opportunity to anticipate epidemics several months in advance.

**Bayesian model framework** used to make probabilistic statements about future disease risk (e.g., probability of an epidemic during a mass gathering or extreme climatic event)?



The increased predictive lead time comes at the cost of increased uncertainty, which needs to be carefully communicated to public health decision makers



# WHY DO WE NEED EARLY WARNING SYSTEMS?

- Prepare for mass gatherings
  - Example: dengue and the World Cup in Brazil
- Build resilience against hydrometeorological extremes
  - Example: El Niño and flooding in southern coastal Ecuador
  - Example: drought and water storage in Barbados
- Strengthen operational dengue surveillance and control
  - Example: dengue early warning in Vietnam

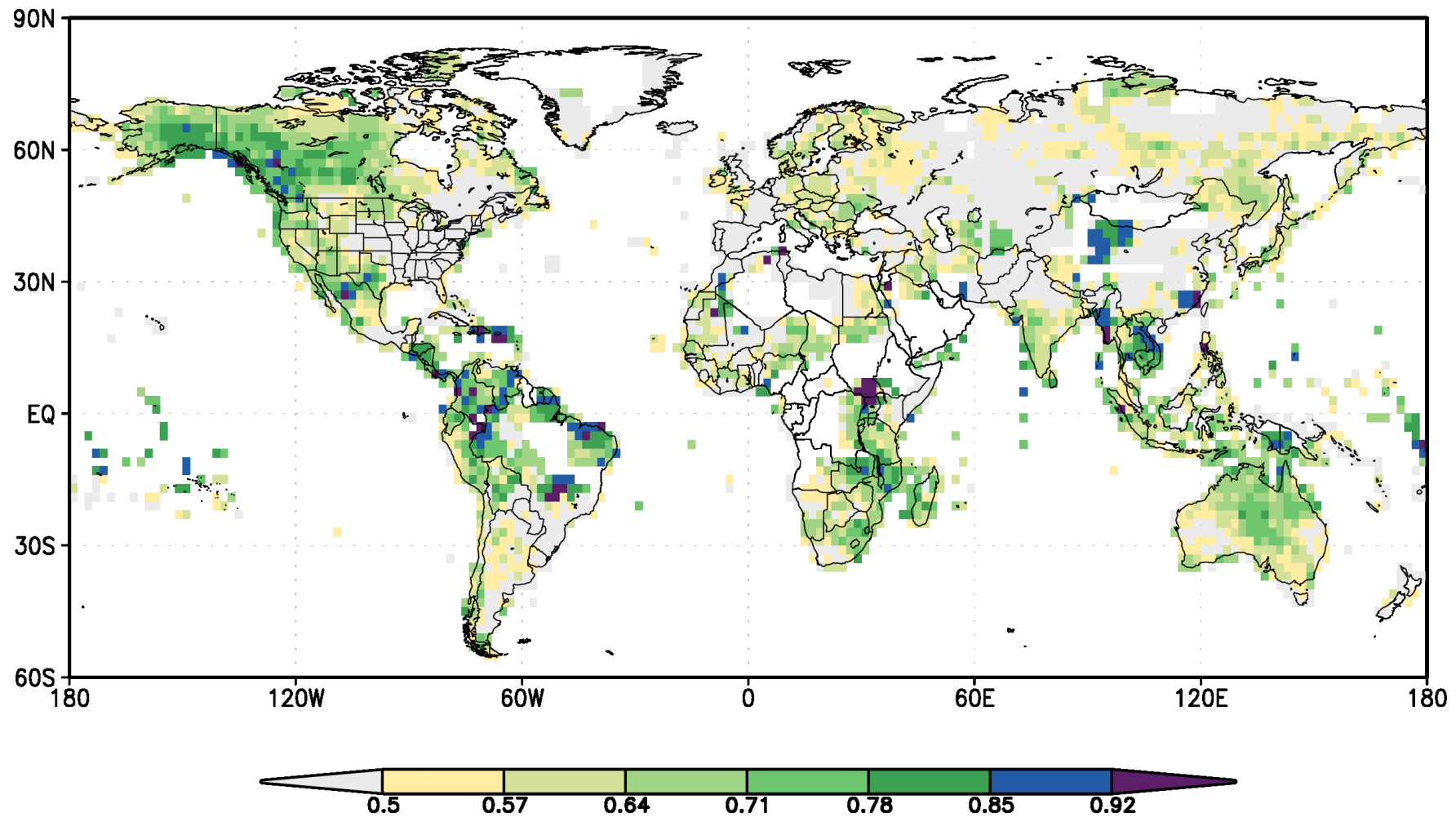




Link early warnings to early action

Photo: Danny Krom

# WINDOW OF OPPORTUNITY

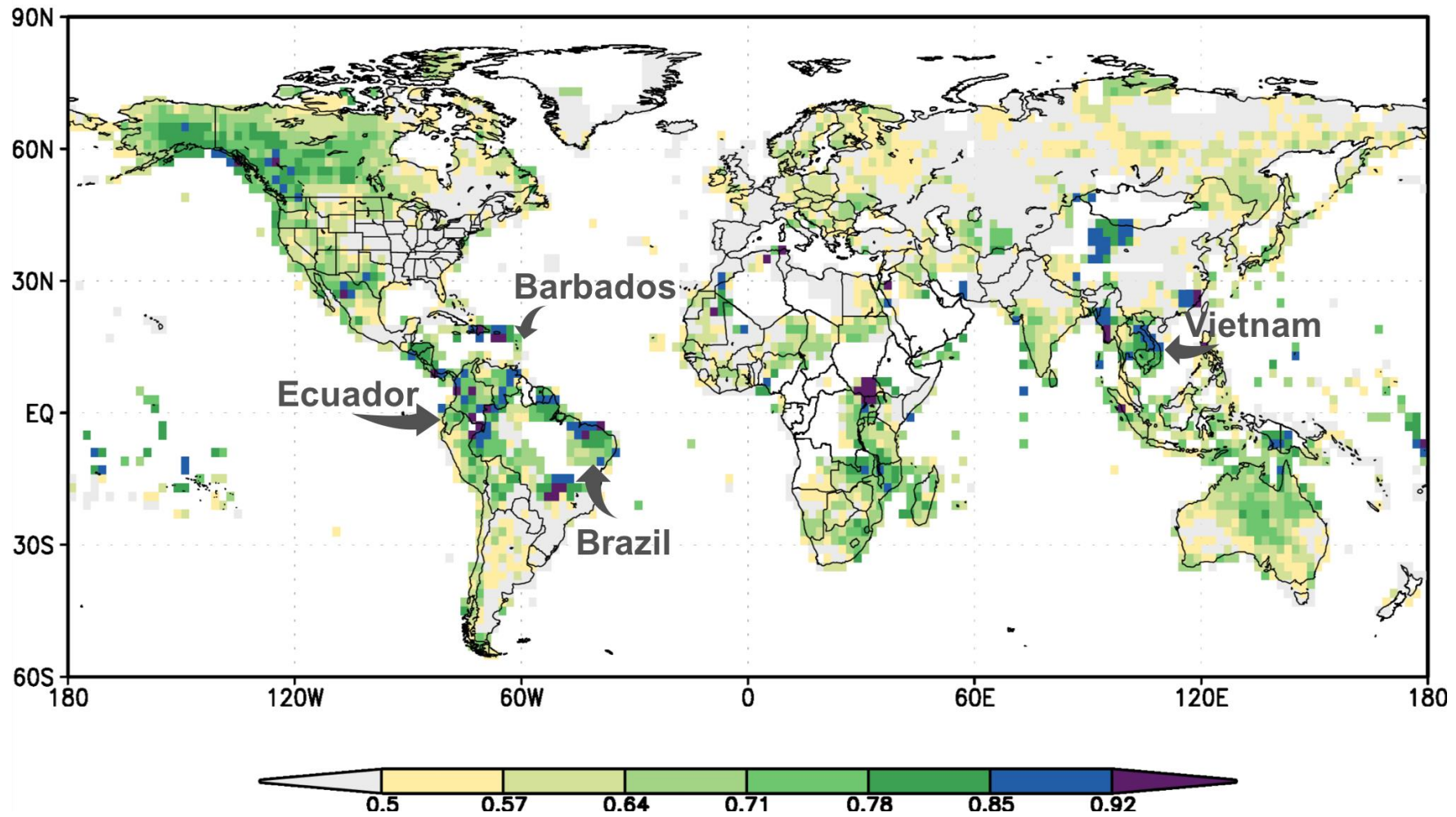


This map shows the skill of March-May temperature forecasts with a 3-month lead time, with green to purple colours showing areas where forecasts perform better, for example, in parts of South America and South-East Asia. We can use this type of information to identify areas where climate-driven early warning systems are most likely to succeed.

Source: Colon-Gonzalez et al. (2021), *Lancet Planetary Health*.



# CASE STUDIES



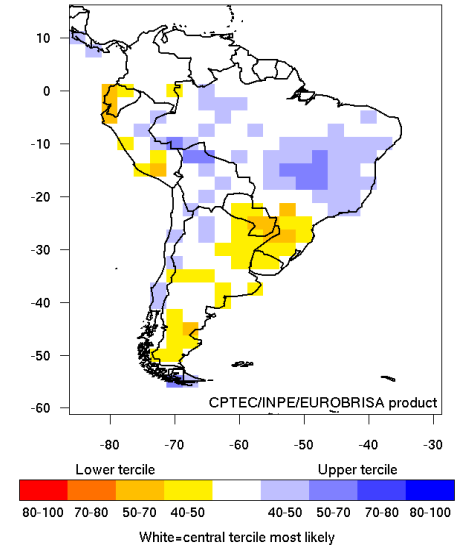
Source: Colon-Gonzalez et al. (2021), *Lancet Planetary Health*.



# DENGUE MODEL CO-DESIGN

- **Model** framework developed in collaboration with European-Brazilian **climate** and **health** institutions.
- **Data** (dengue, climate, cartographic, demographic, socio-economic) to formulate a model, produce probabilistic dengue predictions for >550 microregions.
- Optimum **trigger alert thresholds** determined for scenarios of medium-risk and high-risk of dengue, according to incidence **alert levels** defined by the Ministry of Health.

Integrated: Prob. of most likely precip. tercile (%)  
 Issued: Feb 2014 Valid for MAM 2014



# MODEL FORMULA

Counts of cases in space and time

Negative binomial probability distribution for count data; allows for variance > mean

$$y_{st} \sim \text{NegBin}(\mu_{st}, \kappa)$$

Random intercept for ecological zone

Spatially (un)structured random effects

$$\log(\mu_{st}) = \log(e_{st}) + \alpha + \alpha_{s'(s)} + \sum \beta_j x_{jst} + \sum \gamma_j w_{jst} + \delta z_{st} + \phi_s + u_s + \omega_{t'(t)} + \omega_{t'(t),s'(s)}$$

Offset: expected cases

Climate and non-climate effects

Current cases

Random month effects by ecological zone

To account for the underlying population in each area

Various fixed effects: Temperature, precipitation, proportion of population living in urban areas, altitude

To account for dependency between neighbouring regions and additional overdispersion related to socio-economic disparities, population immunity or variations in control measures, for which data is not available

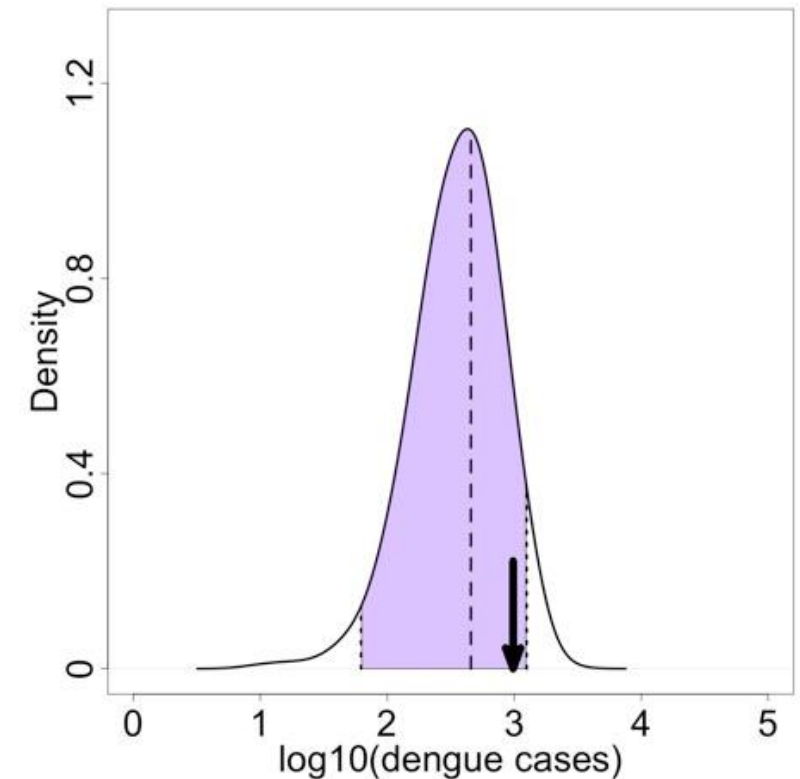
Spatially structured random effects allow for correlated heterogeneity between areas. A typical choice for a spatially structured prior is a conditional intrinsic Gaussian autoregressive (CAR) model. When undertaking CAR modelling of spatial data, it is necessary to define an adjacency matrix that characterises the neighbourhood structure of the data under analysis.

**Problem** lack of data to model disease system

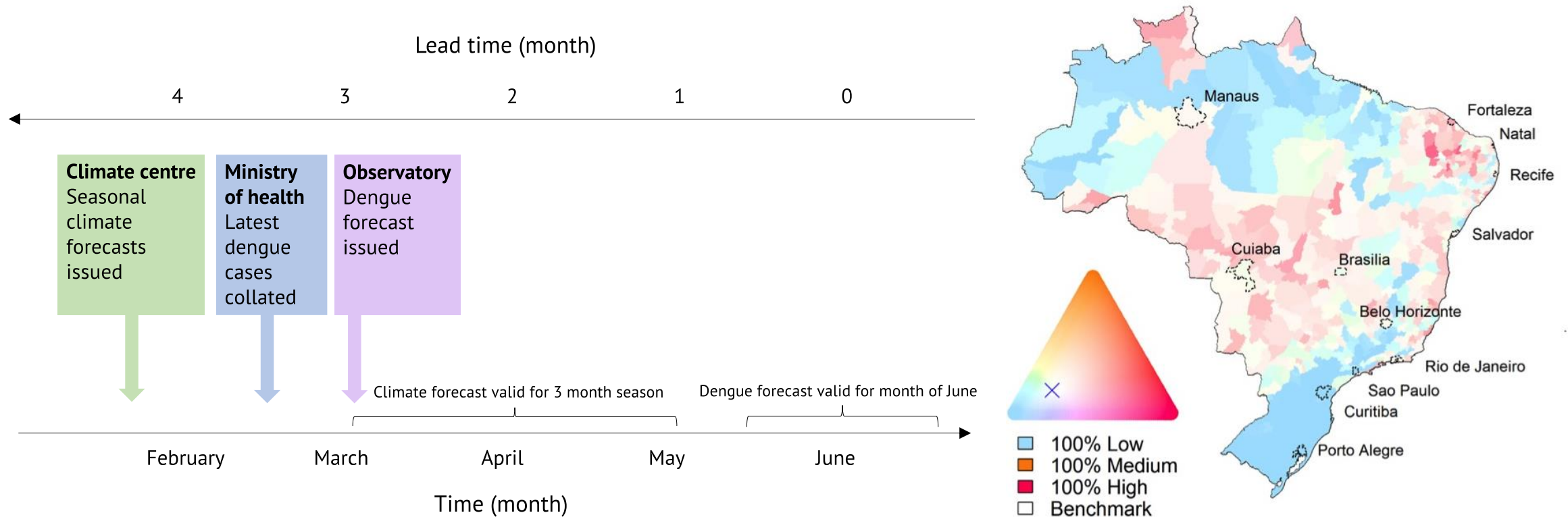
**Solution** Bayesian hierarchical mixed model - add extra level uncertainty

# QUANTIFYING UNCERTAINTY

- Random effects account for unmeasured factors in space and time.
  - Help better quantify the risk attributable to explanatory factors (e.g., climate variation).
- Posterior predictive distributions, by using the outputs of the model to simulate from the probability distribution for the count data
  - allow for uncertainty in the response given model parameters.
- Ensemble forecasting
  - E.g, an ensemble of rainfall forecasts to account for uncertainty in the explanatory variables
  - E.g, an ensemble of dengue models to capture model variations
- Make probabilistic statements about future disease risk:
  - What is the probability of exceeding epidemic thresholds of dengue during a major event (e.g., mass gathering or natural disaster)?
- Evaluate the model compared to a null model/baseline model (corresponding to current practice) to understand whether the EWS has added value
  - Current practice may be using seasonal averages or the endemic curve



# EARLY WARNING 3 MONTHS AHEAD

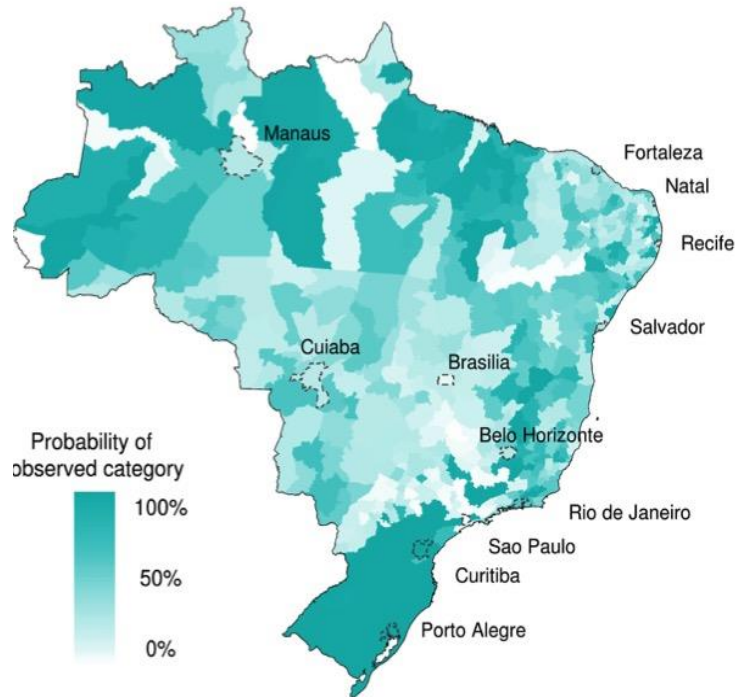


- Early warning framework applied to predict dengue risk for the World Cup in Brazil.
- Category boundaries: 100 and 300 cases per 100,000 inhabitants.

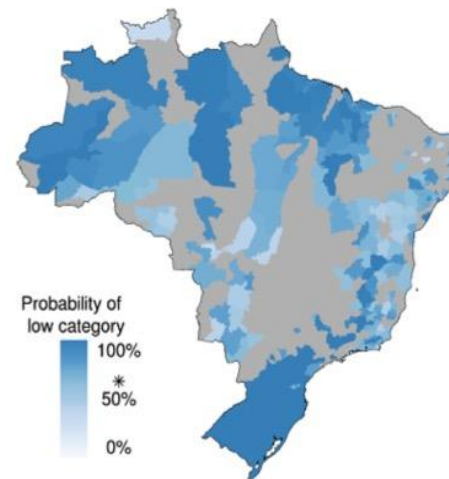
Lowe *et al.*, 2014, *Lancet Infect Dis*

# PROBABILITY OF OBSERVING CORRECT CATEGORY

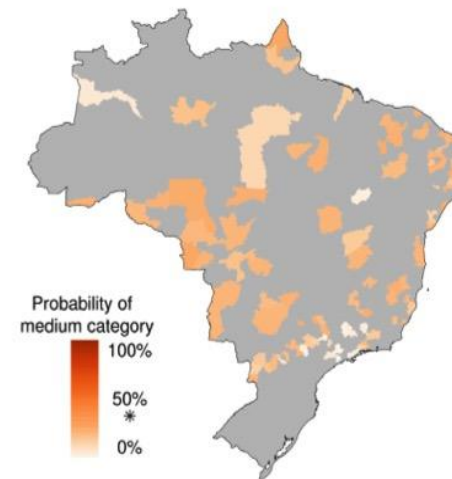
Validation of the forecast post-event using observed cases



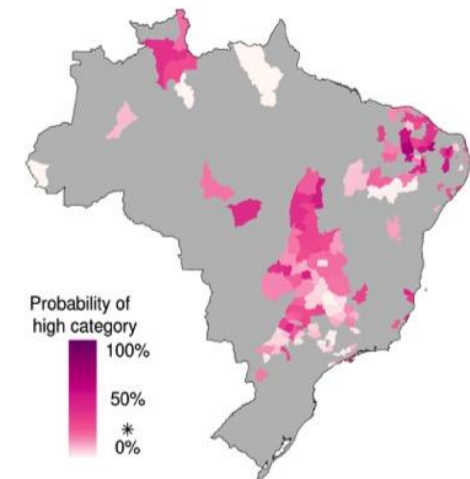
Low



High



Medium



Predicted probability of the observed category with intense shades of green indicating where the model performed better

Low risk was defined as fewer than 100 cases per 100,000 inhabitants, medium risk as between 100 and 300 cases per 100,000 inhabitants, and high risk as greater than 300 cases per 100,000 inhabitants.

Lowe *et al.*, 2016, *eLife*



World Health Organization

# POSSIBLE OUTCOMES FOR CATEGORICAL FORECASTS OF A BINARY EVENT

		Event observed		Total
		Yes	No	
Forecast warning issued	Yes	Hit ( $a$ )	False alarm ( $b$ )	$a+b$
	No	Miss ( $c$ )	Correct rejection ( $d$ )	$c+d$
	Total	$a+c$	$b+d$	$a+b+c+d=n$

DOI: [10.7554/eLife.11285.011](https://doi.org/10.7554/eLife.11285.011)

# ROC ANALYSIS

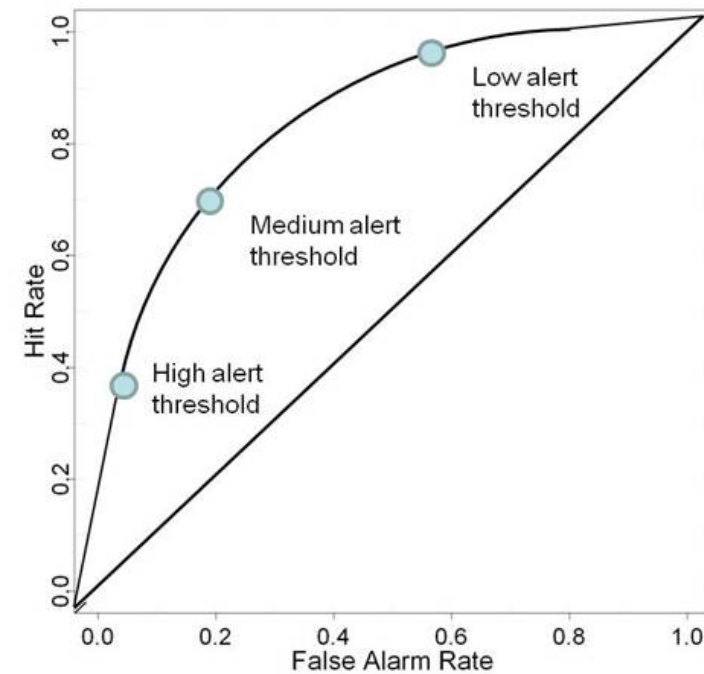
true positive rate = sensitivity = recall = hit rate =  $a / (a + c)$

false positive rate =  $(1 - \text{specificity}) = \text{false alarm rate} = b / (b + d)$

proportion correct = accuracy =  $(a + d) / n$

		Event observed		Total
		Yes	No	
Forecast warning issued	Yes	Hit (a)	False alarm (b)	$a+b$
	No	Miss (c)	Correct rejection (d)	$c+d$
	Total	$a+c$	$b+d$	$a+b+c+d=n$

DOI: [10.7554/eLife.11285.011](https://doi.org/10.7554/eLife.11285.011)



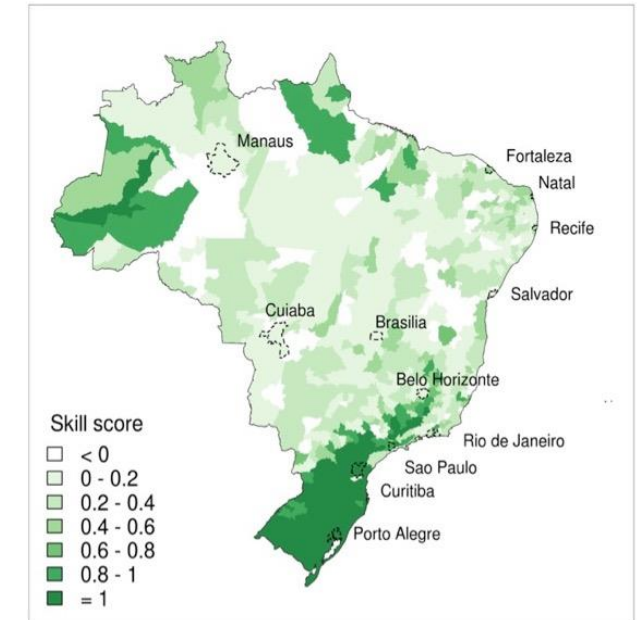
The Receiver Operating Characteristic (ROC) curve shows the hit rate against the false alarm rate for different decision thresholds.

# VALIDATION OF PAST PERFORMANCE

- The rank probability score (RPS) was calculated
  - How well does the probability forecasting system predict the category that the observations fell into?
  - RPS penalises forecasts less severely when their probability are close to the true outcome
- Rank probability skill score (RPSS) calculated using past observations and **out-of-sample** retrospective dengue forecasts, June 2000–13.

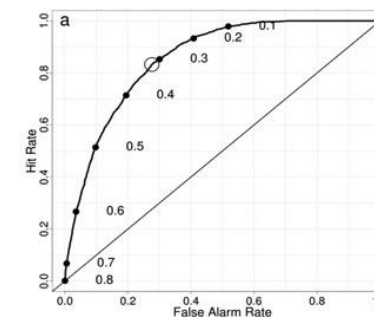
$$RPSS = 1 - \frac{RPS}{RPS_{benchmark}}$$

- The RPSS takes the value one for a perfect forecast.
- A ROC analysis is conducted as the next step
  - To define the optimum trigger thresholds for warnings in the low, medium, and high-risk categories
  - These were defined as the point on the curve closest to the point of perfect discrimination (0, 1), the point that maximizes hits and minimizes false alarms

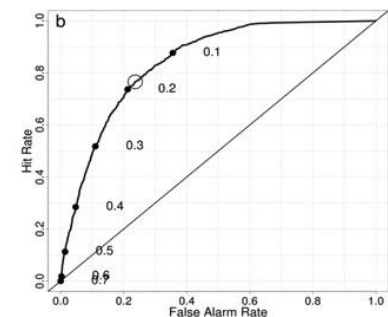


The RPSS quantifies forecast skill relative to a benchmark forecast for each microregion. This map shows where the forecasting has worked well (and not so well).

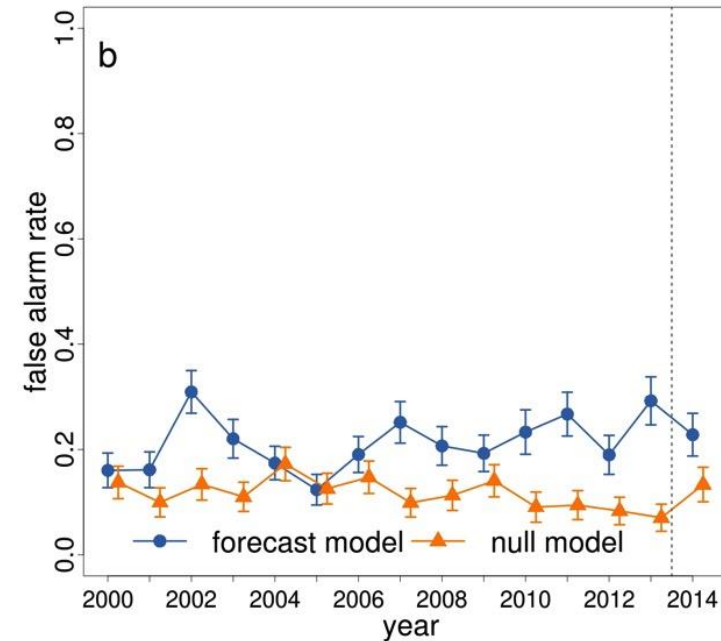
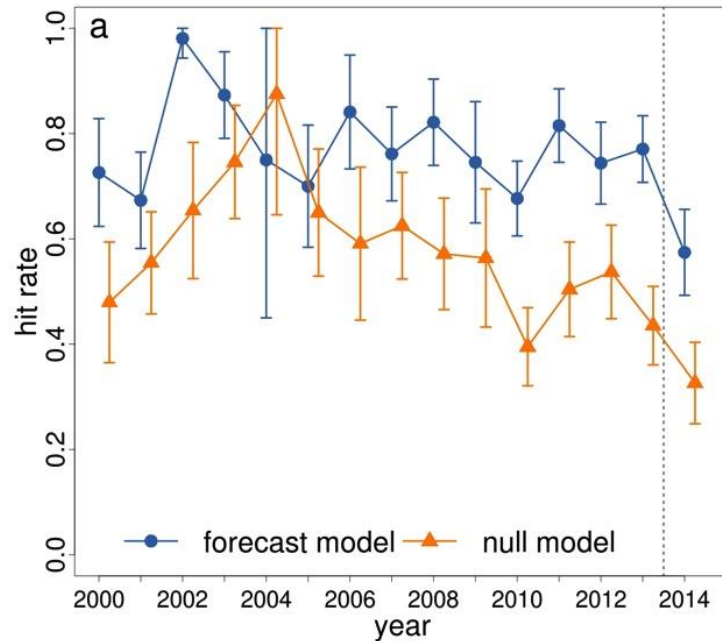
**MEDIUM**



**HIGH**



# COMPARISON OF FORECAST TO NULL MODEL



Comparison of hit rate and false alarm rate for forecast model (blue) and seasonal average null model (orange) for June 2000-2014.

<i>2014 event</i>	<i>Forecast model</i>	<i>Null model</i>
hit rate:	57%	33%
false alarm rate (type I error rate):	23%	13%
miss rate (type II error rate):	43%	67%

# FROM EVIDENCE TO APPLICATION TO EVALUATION



Formulate

Spatio-temporal modelling of climate-sensitive disease risk: Towards an early warning system for dengue in Brazil

Rachel Lowe<sup>a,\*</sup>, Trevor C. Bailey<sup>a</sup>, David B. Stephenson<sup>a</sup>, Marilia Sá Carvalho<sup>d</sup>, Christovam Barcellos<sup>d</sup>

Statistics  
in Medicine

Research Article

Received 22 August 2011, Accepted 3 July 2012, Published online 24 August 2012 in Wiley Online Library  
(wileyonlinelibrary.com) DOI: 10.1002/sim.5549

**The development of an early warning system for climate-sensitive disease risk with a focus on dengue epidemics in Southeast Brazil<sup>‡</sup>**

Rachel Lowe,<sup>a,\*</sup> Trevor C. Bailey,<sup>a</sup> Tim E. Jupp,<sup>b</sup> Richard J. Graham,<sup>c</sup> Marilia Sá Carvalho<sup>d</sup>

**Dengue outlook for the World Cup in Brazil: an early warning model framework driven by real-time seasonal climate forecasts**

Rachel Lowe, Christovam Barcellos, Caio A S Coelho, Trevor C Bailey, Giovanini Evel Marilia Sá Carvalho, David B Stephenson, Xavier Rodó



Evaluate



Develop

Apply

**Evaluating probabilistic dengue risk forecasts from a prototype early warning system for Brazil**

Rachel Lowe<sup>1\*</sup>, Caio AS Coelho<sup>2</sup>, Christovam Barcellos<sup>3</sup>, Marilia Sá Carvalho<sup>3</sup>, Rafael De Castro Catão<sup>1,4</sup>, Giovanini E Coelho<sup>5</sup>, Walter Massa Ramalho<sup>6</sup>, Trevor C Bailey<sup>7</sup>, David B Stephenson<sup>7</sup>, Xavier Rodó<sup>1,8</sup>



# EL NIÑO-INDUCED COASTAL FLOODING & DENGUE

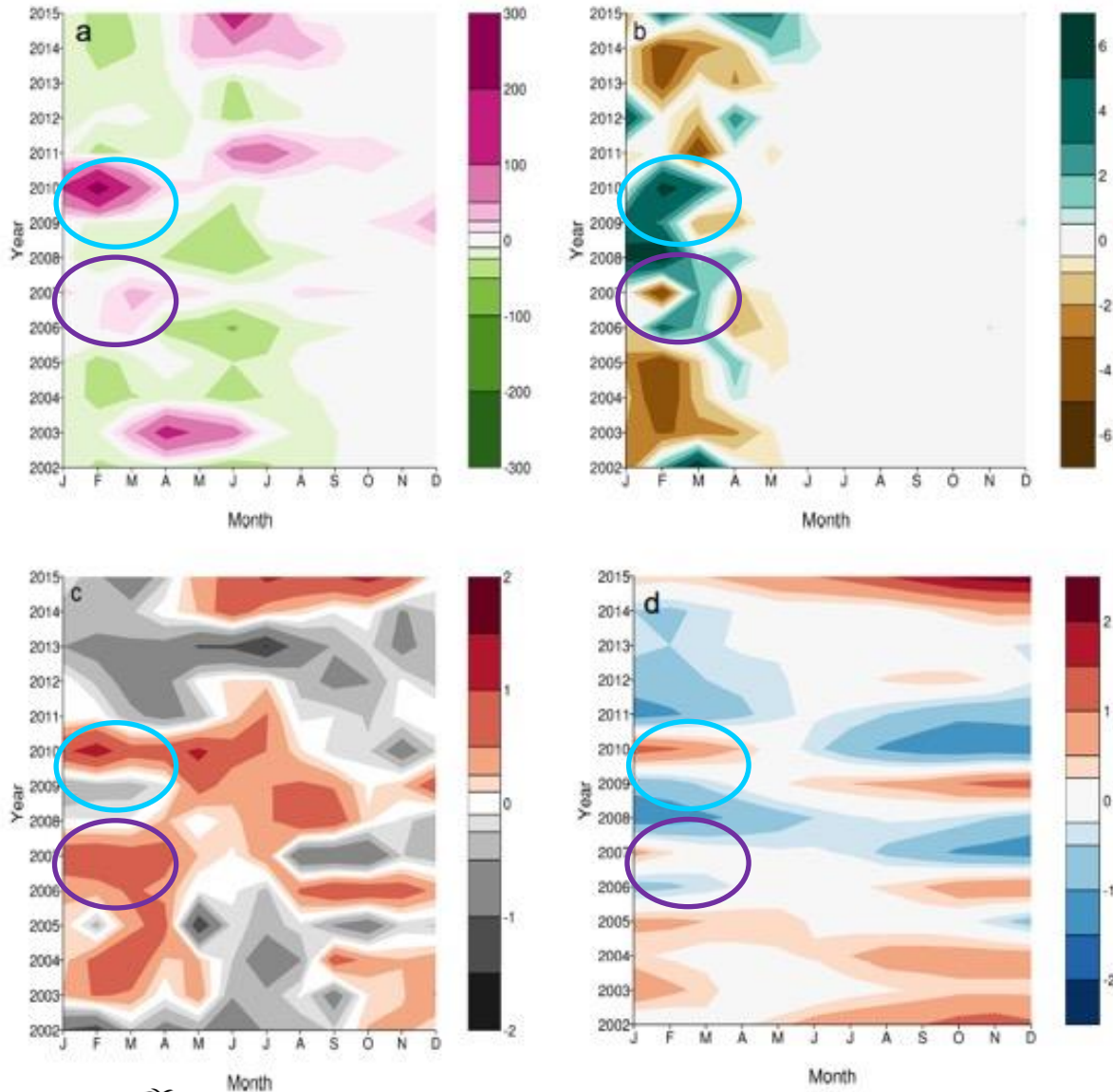




In February 2016, following a large El Niño event, intense rainfall combined with high tides caused the worst flooding in Machala, Ecuador, since the 1998 El Niño, creating ideal conditions for disease outbreaks.

Photo: Danny Krom

# CLIMATE & DENGUE VARIATION



- Cooler and drier than usual → less dengue
- Warmer and wetter than usual → more dengue

## Bayesian hierarchical model

$$y_t \sim \text{NegBin}(\mu_t, \kappa)$$

$$\log(\mu_t) = \log(p) + \log(r_t)$$

$$\log(r_t) = \underbrace{\alpha}_{\text{Dengue incidence rate}} + \underbrace{f(\beta_{t'(t)})}_{\text{Annual cycle}} + \underbrace{\sum \gamma_j x_{jt}}_{\text{Climate variables}} + \underbrace{\delta_{T'(t)}}_{\text{Inter-annual variation}}$$

Dengue incidence rate

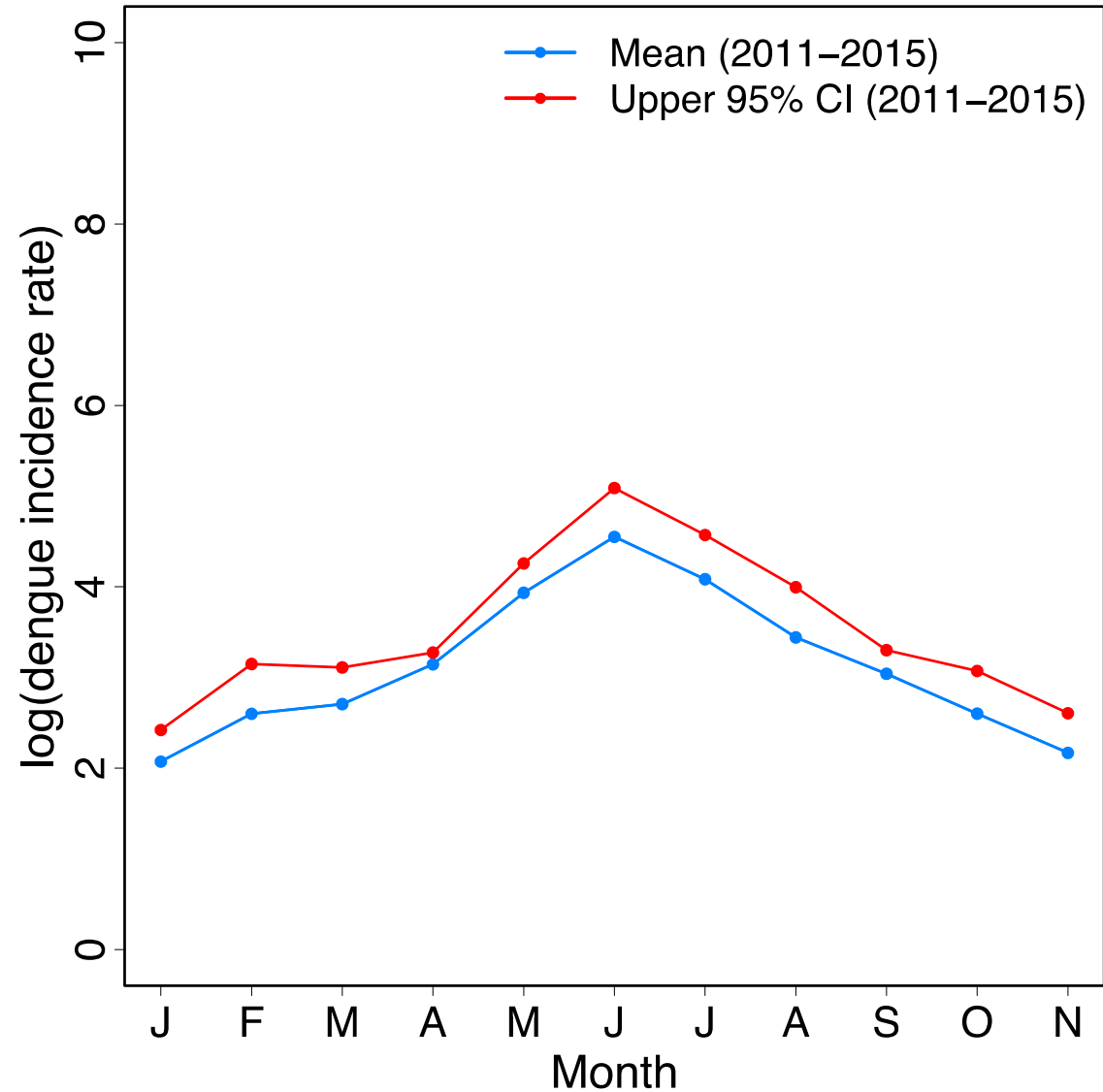
Annual cycle

Climate variables

Inter-annual variation



# CURRENT PRACTICE

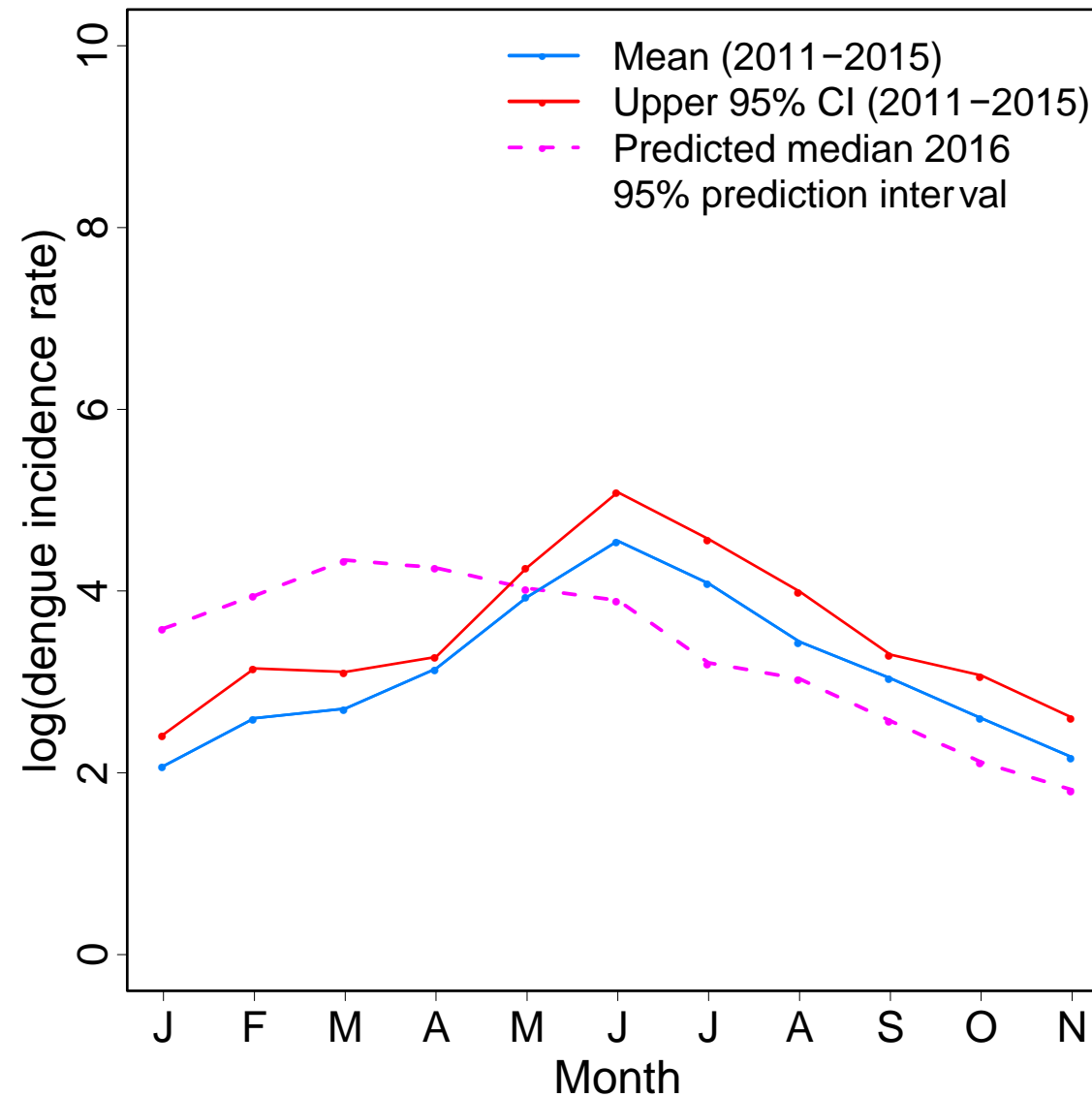


Each local health district monitors dengue behaviour using the endemic curve, calculated from retrospective dengue case reports over the last five years.

According to the data from 2011 to 2015, for the 2016 dengue season, we would have expected dengue to peak in June 2016.



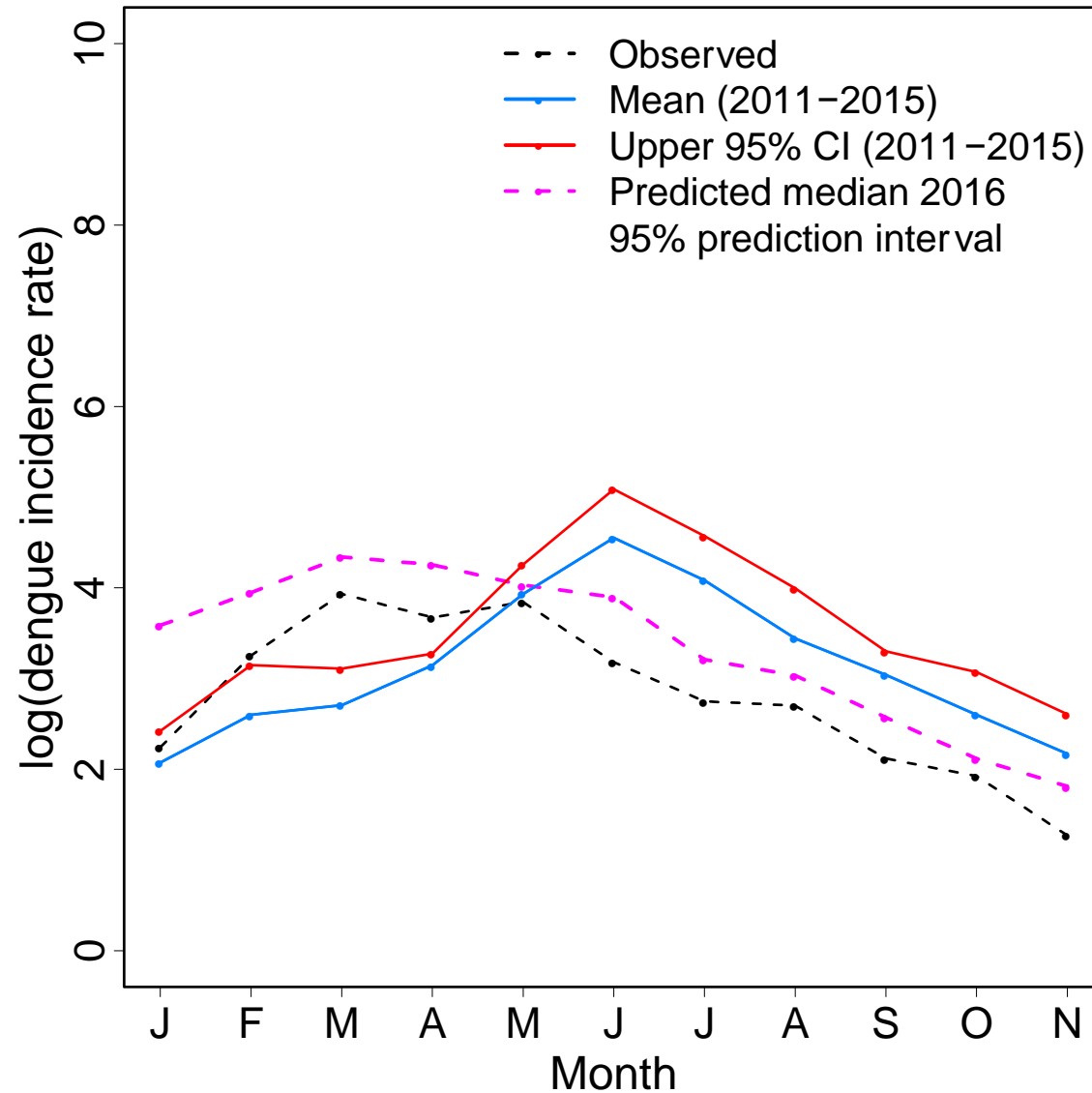
# CLIMATE-DRIVEN DENGUE PREDICTION



By combining seasonal climate forecasts with our dengue prediction model, we forecast an early peak in dengue in March 2016, with a probability of exceeding the upper limit of 85%.



# EARLY PEAK PREDICTED USING CLIMATE FORECAST



The peak in dengue did, in fact, occur in March, three months earlier than would have been expected using the average epidemiological curve alone.

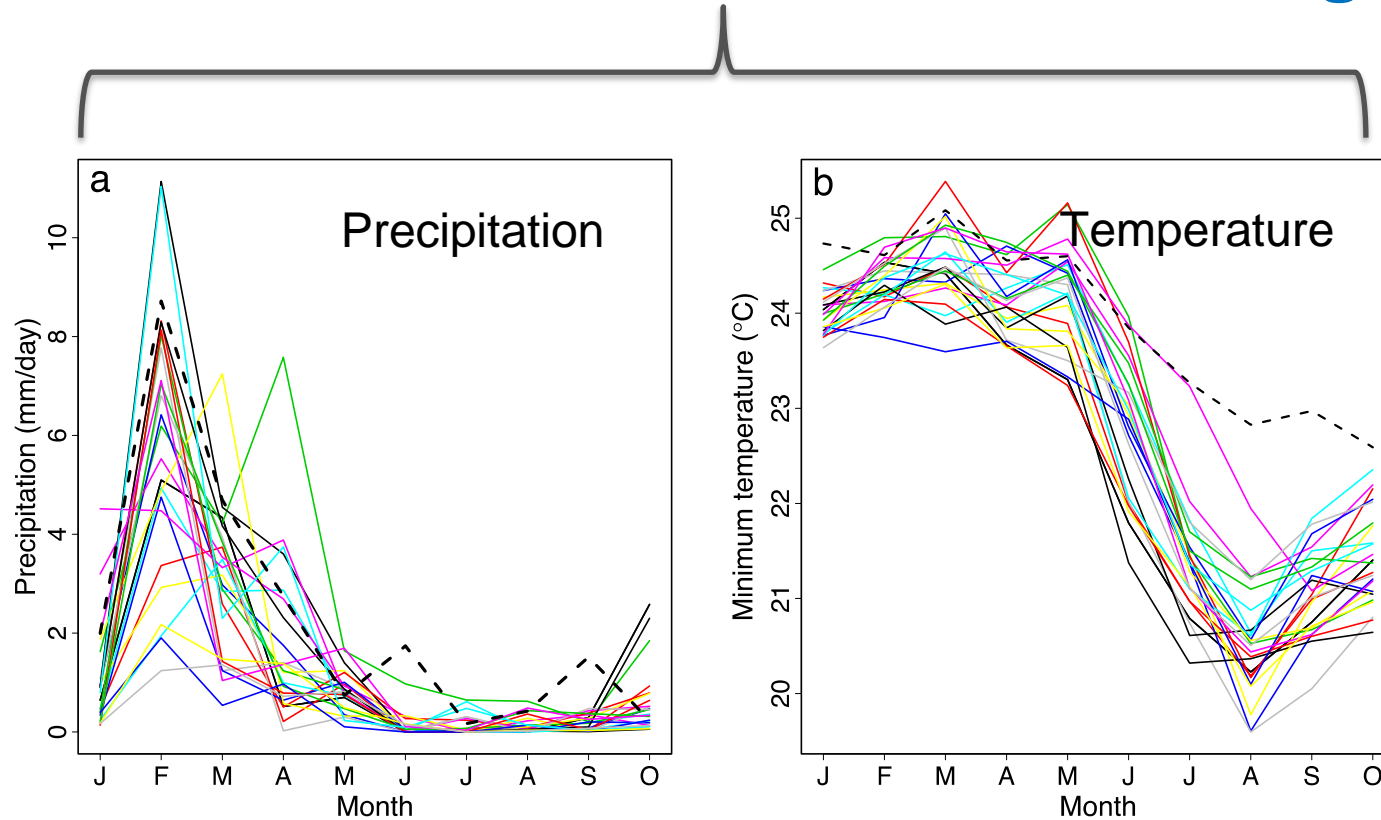
This sort of early warning can facilitate timely preventive public health interventions, such as intensive vector control measures and educational campaigns to inform local communities and travellers about risk prevention.

Lowe *et al.*, 2017  
*Lancet Planet Health*

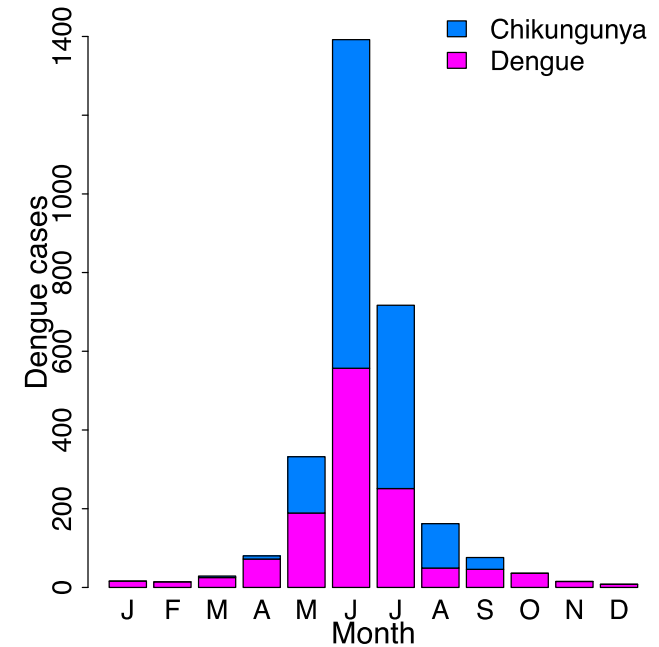


# SOURCES OF PREDICTABILITY

## Timing



## Magnitude



## Seasonal climate forecasts Active surveillance

Information source 1:

The El Niño event of 2015, with its accurate forecasts of heavy rains and high temperatures in February

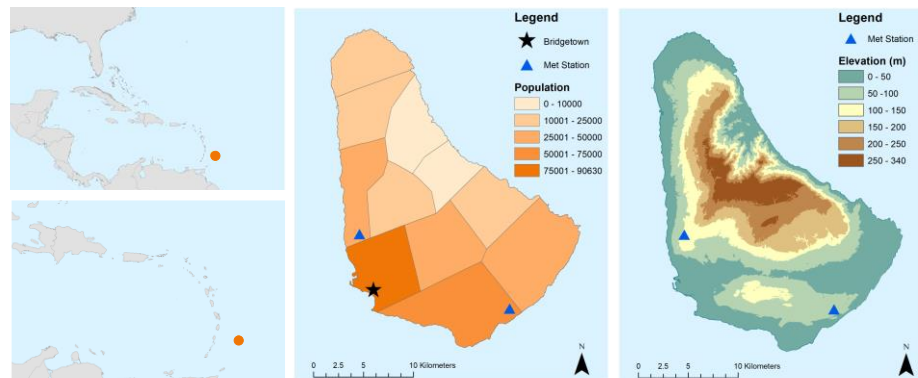
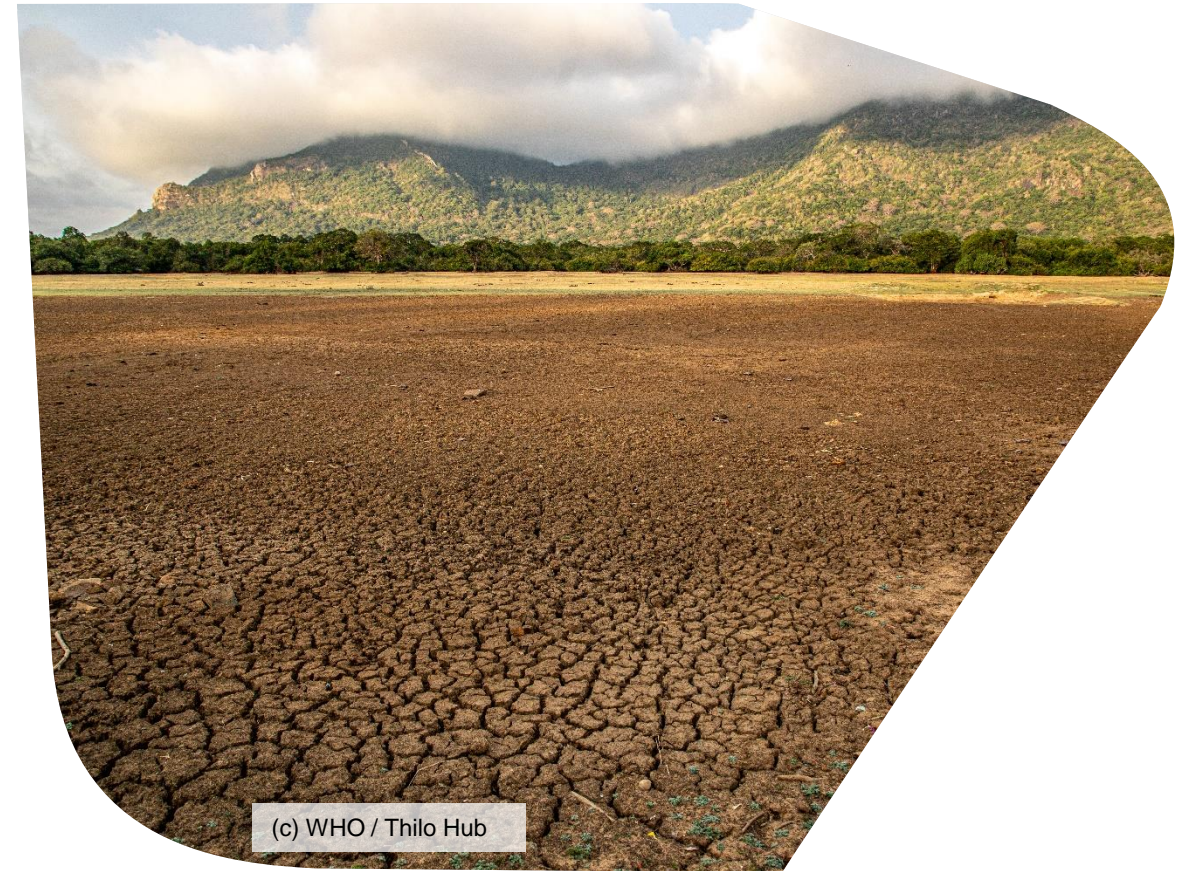
Information source 2:

Thanks to a serological study, clinically diagnosed dengue cases (later confirmed as chikungunya) were removed from the passive surveillance dataset before fitting the model.



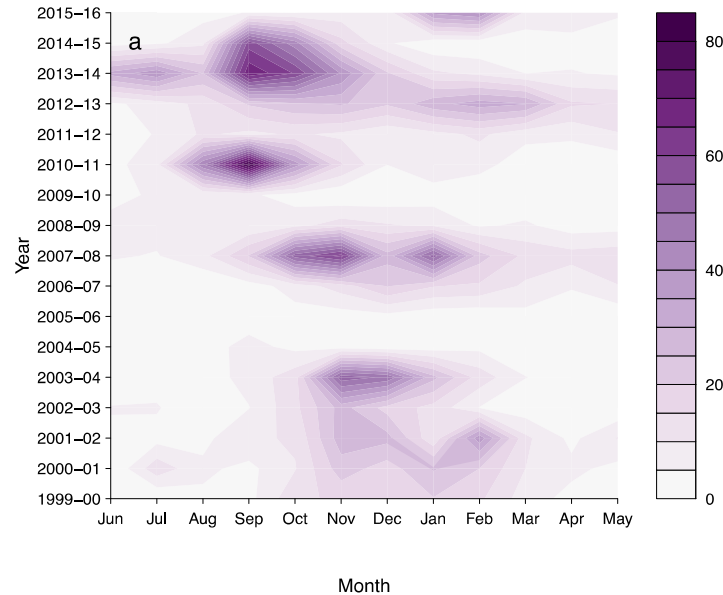
# DROUGHT & DENGUE

- The Caribbean region is facing a major crisis of co-occurring epidemics of **dengue**, chikungunya and Zika viruses.
- An increased incidence of dengue suspected in **Barbados** following **drought** events.

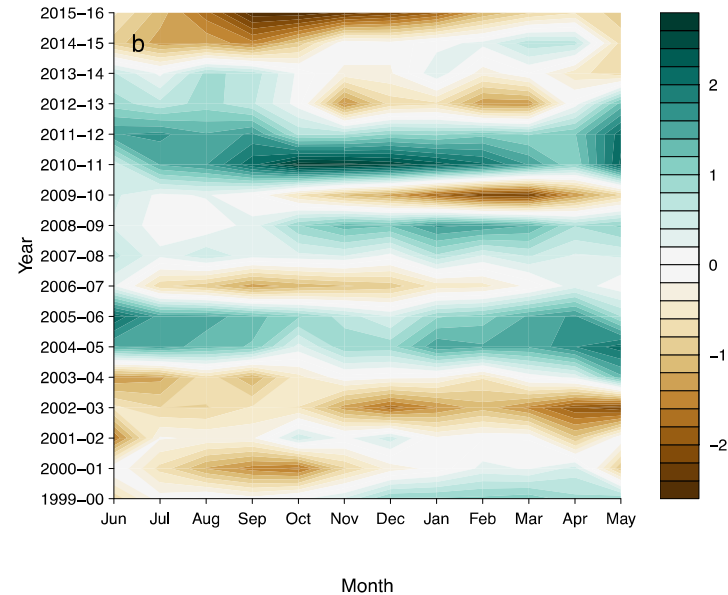


Source: Lowe et al. (2018), PLOS Medicine.

# COMBINED IMPACT OF DRY & WET CONDITIONS

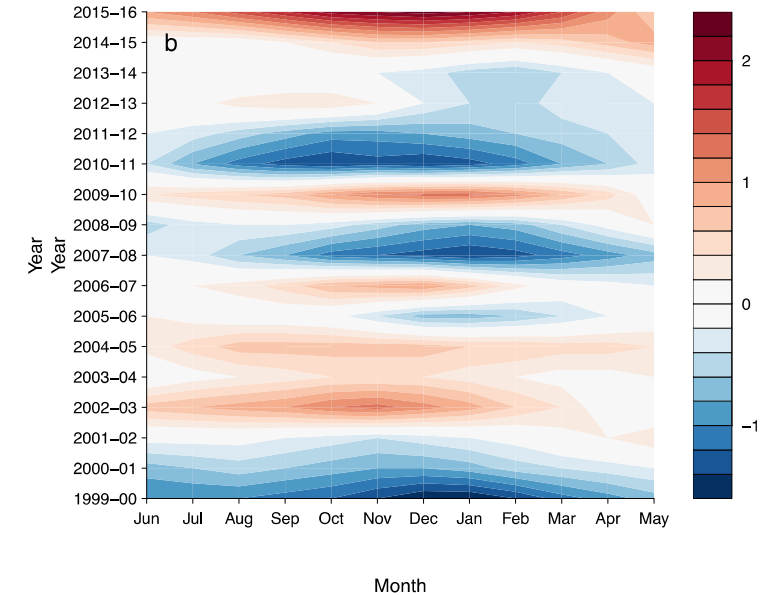


Dengue incidence rate in Barbados (per 100,000 population)



Standardised precipitation index

The standardised precipitation index is a metric for monitoring drought.



Oceanic Niño index

We can see an association between El Niño events (in red) and dry periods (in brown).

- We used **distributed lag non-linear models** (Gasparrini, 2013) coupled with a **Bayesian hierarchal model** (Lowe et al, 2017) to understand exposure-lag response associations between dengue, temperature, drought and rainfall.
- The model could account for both dry and wet periods in the months prior to a potential dengue outbreak.

# MODELLING EXPOSURE LAG RESPONSE ASSOCIATIONS

Dengue incidence rate per 100,000 inhabitants

$$y_t | \mu_t \sim \text{NegBin}(\mu_t = \overbrace{p_{T'(t)} \rho_t}, \kappa)$$

$$\log(\mu_t) = \log(p_{T'(t)}) + \log(\rho_t)$$

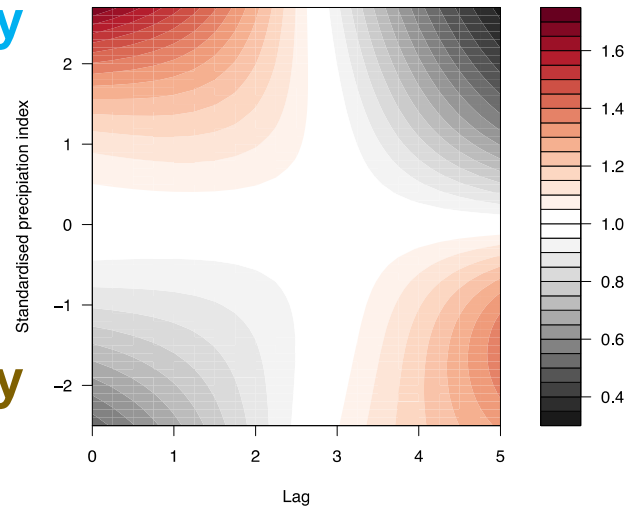
$$\log(\rho_t) = \alpha + \underbrace{\beta_{t'(t)}}_{\text{Annual cycle}} + \underbrace{\gamma_{T'(t)}}_{\text{Interannual variation}} + \underbrace{f.w(x_{1t}, l) + f.w(x_{2t}, l)}_{\text{Exposure-lag-response functions SPI-6 \& Tmin}}$$

- A Bayesian model was used to understand variations in the dengue incidence rate, accounting for the annual cycle and interannual variations.
- We then tested different combinations of climate variables with linear and nonlinear functions to select the best-fitting model.
- We could then extract dengue relative risk at different exposure-lag combinations for the standardised precipitation index (better predictor than precipitation) and minimum temperature (better predictor than mean or max temperature).

# MODELLING EXPOSURE LAG RESPONSE ASSOCIATIONS

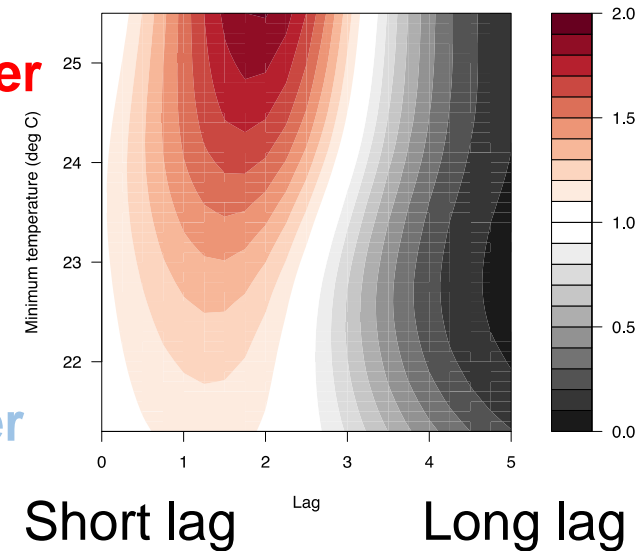
Exceptionally  
wet

Exceptionally  
dry



Warmer

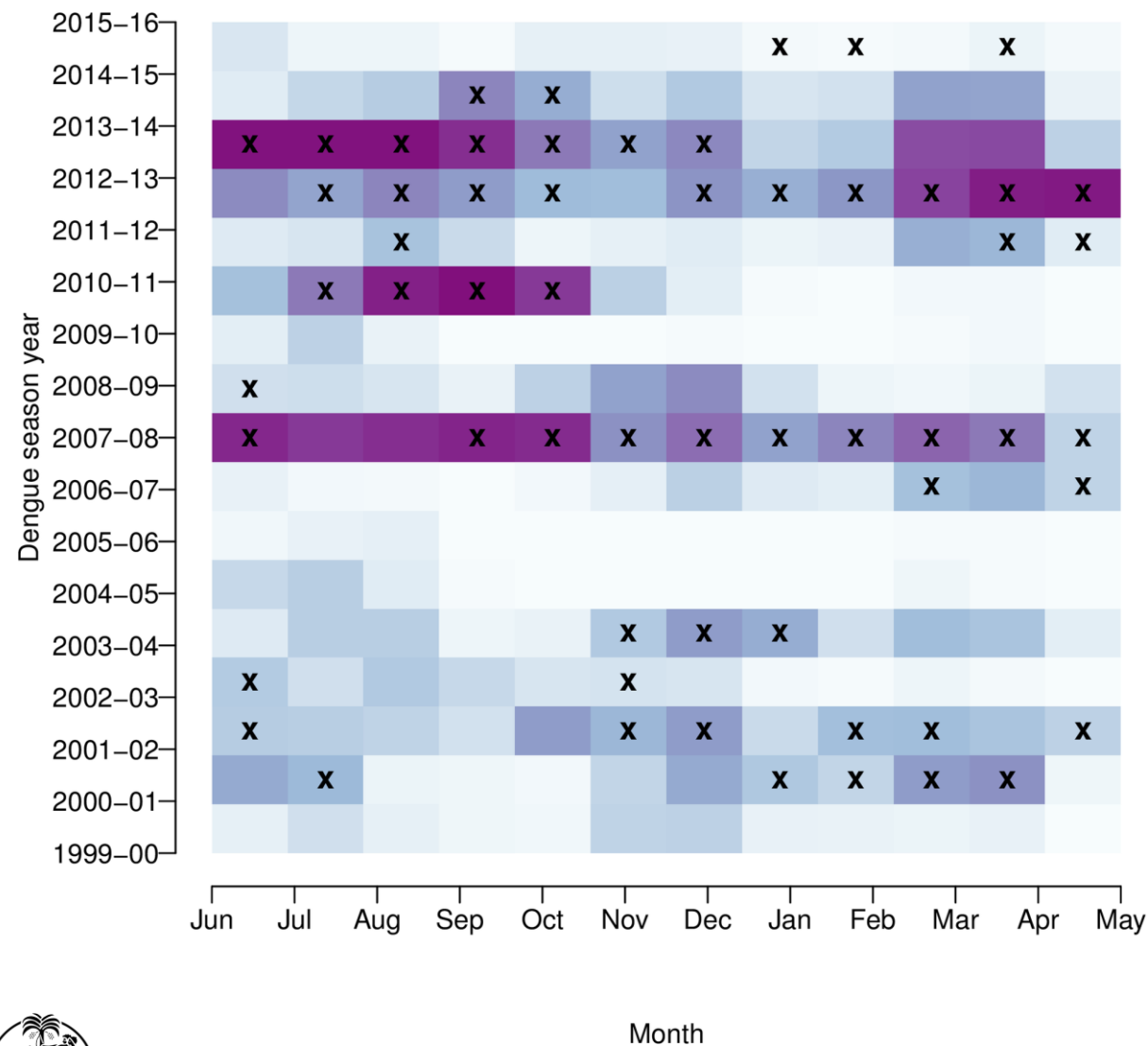
Cooler



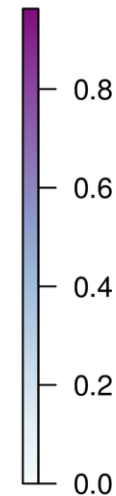
- We found the effect of excess rainfall and drought on dengue risk operated at different time scales, with drought followed by warm and wet conditions 3-4 months later providing optimum conditions for dengue outbreaks in Barbados.
- Drought is a slow-onset climate hazard. As households become aware of water scarcity, they store water in containers around the home, which can increase the availability of larval habitat for *Aedes aegypti*.
- However, following a rainfall event, the availability of larval habitat increases and within a few weeks (depending on the temperature), eggs hatch and adult mosquito densities increase.

Lowe *et al.*, 2018, *PLOS Medicine*

# PROBABILITY OF EXCEEDING OUTBREAK THRESHOLD



x outbreak occurred



Probability trigger threshold of 30%

The model correctly predicted a low probability of outbreaks in 2004-2006 and outbreaks in 2007, 2010 and 2013, but missed the late-season outbreak in 2015-2016.

This was likely complicated by the introduction of chikungunya and Zika viruses on the island.



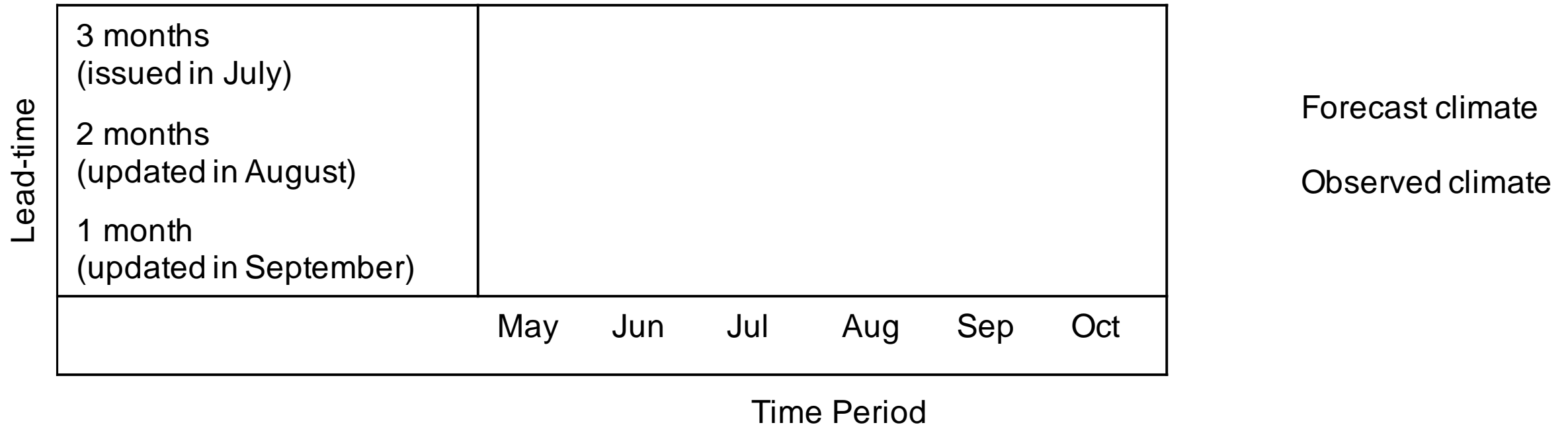
# SENSITIVITY & SPECIFICITY OF EXCEEDING THRESHOLD

Performance measures	Final model	Baseline model
Area under ROC curve	0.9 (0.85, 0.94)	0.75 (0.71, 0.79)
Probability trigger threshold	0.3	0.27
Hit rate	0.9 (0.82, 0.97)	0.79 (0.69, 0.9)
False alarm rate	0.31 (0.22, 0.39)	0.57 (0.51, 0.63)
Proportion correct	0.86 (0.81, 0.91)	0.64 (0.58, 0.71)

The selected model produced **more hits** and **fewer false alarms** than a null model accounting only for seasonality, with a hit rate of 90% (compared to 79% for the baseline) and a false alarm rate of 31% (compared to 57% for the baseline).



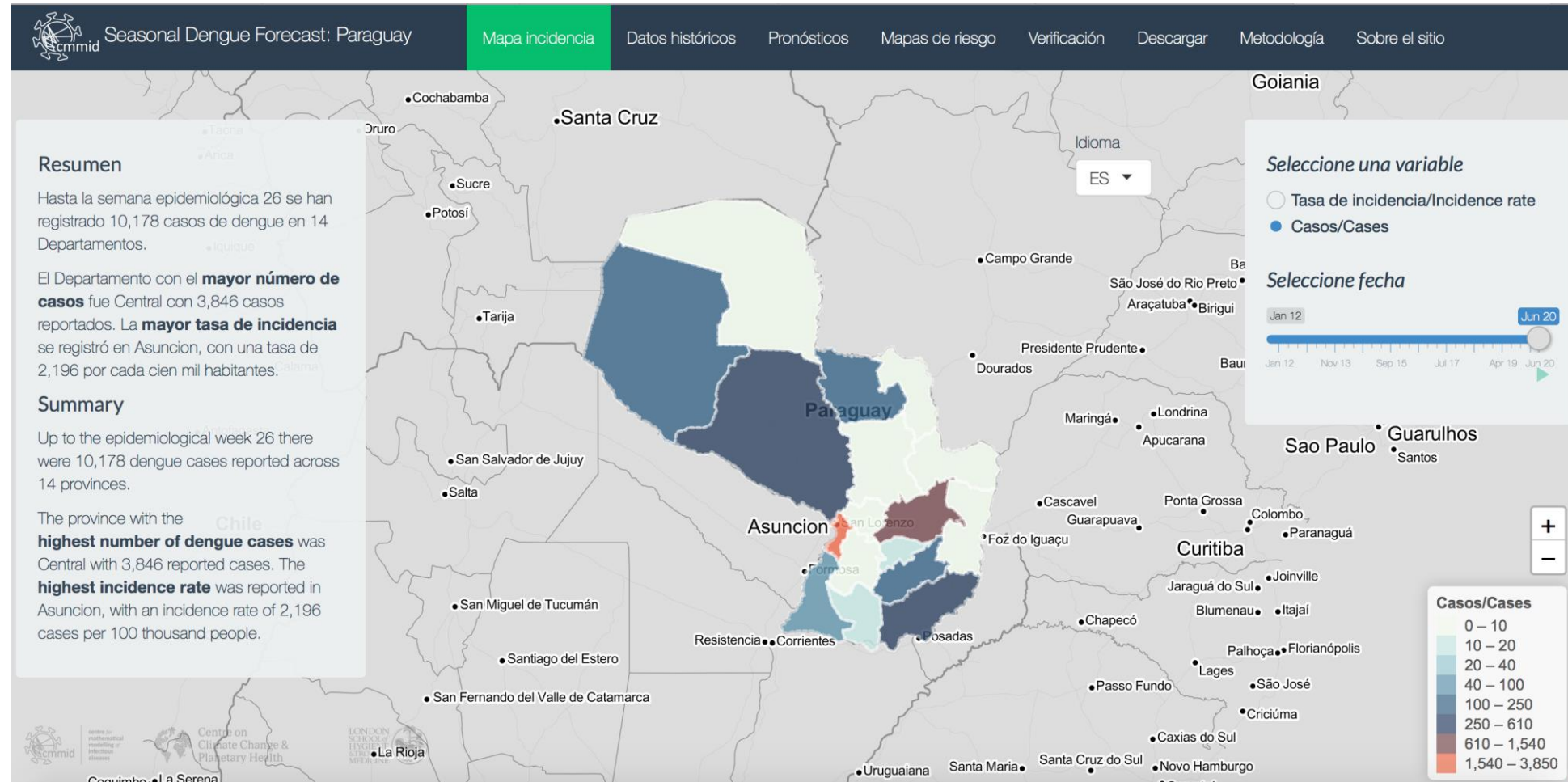
# APPROACHING A TARGET: MULTIPLE LAG & LEADS



Schematic showing the type of climate information needed to produce a dengue forecast for a target month of October

SPI forecasts are typically issued with a 3-month lead time. Therefore, in July, a combination of observed and forecast climate information could be used to predict dengue. As the target month approaches, the forecast could be updated, incorporating new observations and revised forecasts, and so on. The idea would be to have overlapping, iterative forecasts for each month up to 3 months ahead.

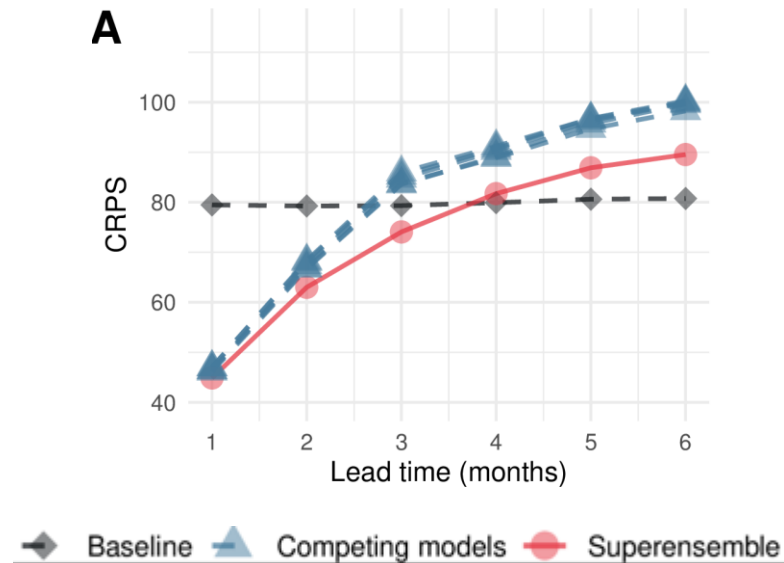
# FROM THEORETICAL TO OPERATIONAL



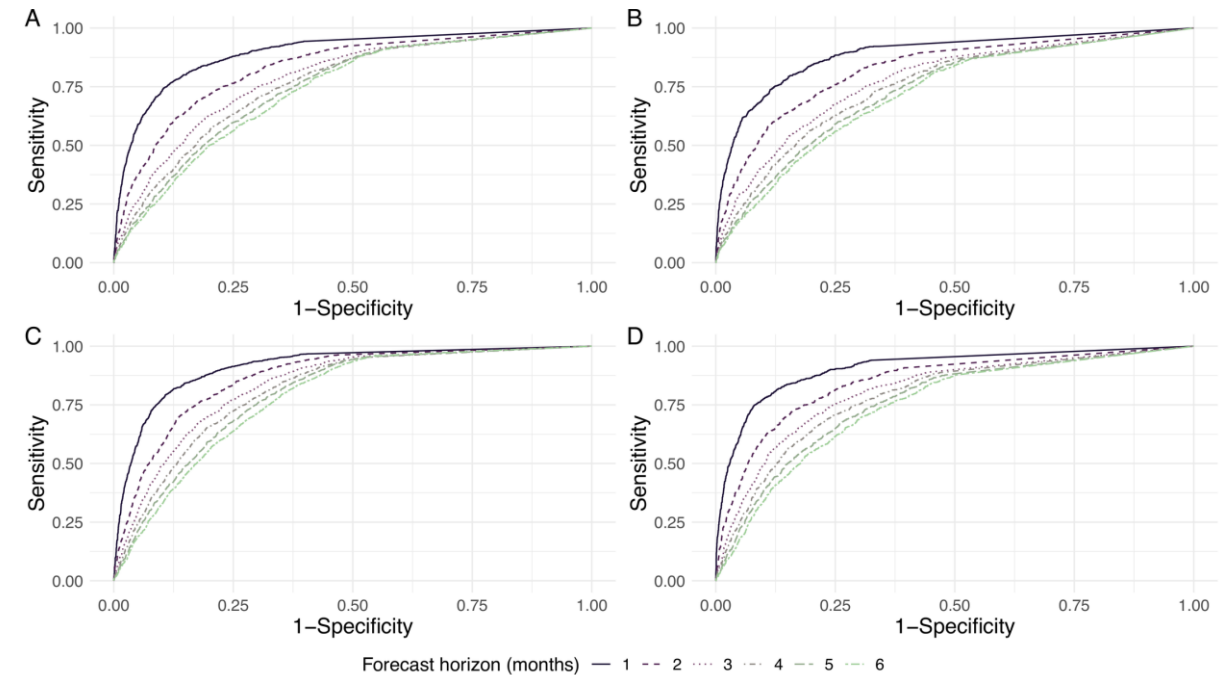
Example of an operational dengue early warning system for Paraguay, using interactive and open source visualisation platforms

# EVALUATING MULTI-LEAD DENGUE FORECASTS IN VIETNAM

- We are evaluating the skill of the model in any given month for a range of predictive lead times (from 1-6 months) to see how the skill varies throughout the dengue season and as lead time increases
- The Continuous Ranked Probability Score (CRPS; similar to the RPSS presented earlier) is used to evaluate the performance of probabilistic forecasts by comparing them against observations.
- Generally, the lower the CRPS, the better the model's performance.



The graph shows that predictions generated one month ahead have consistently lower CRPS values than those generated at longer time leads.



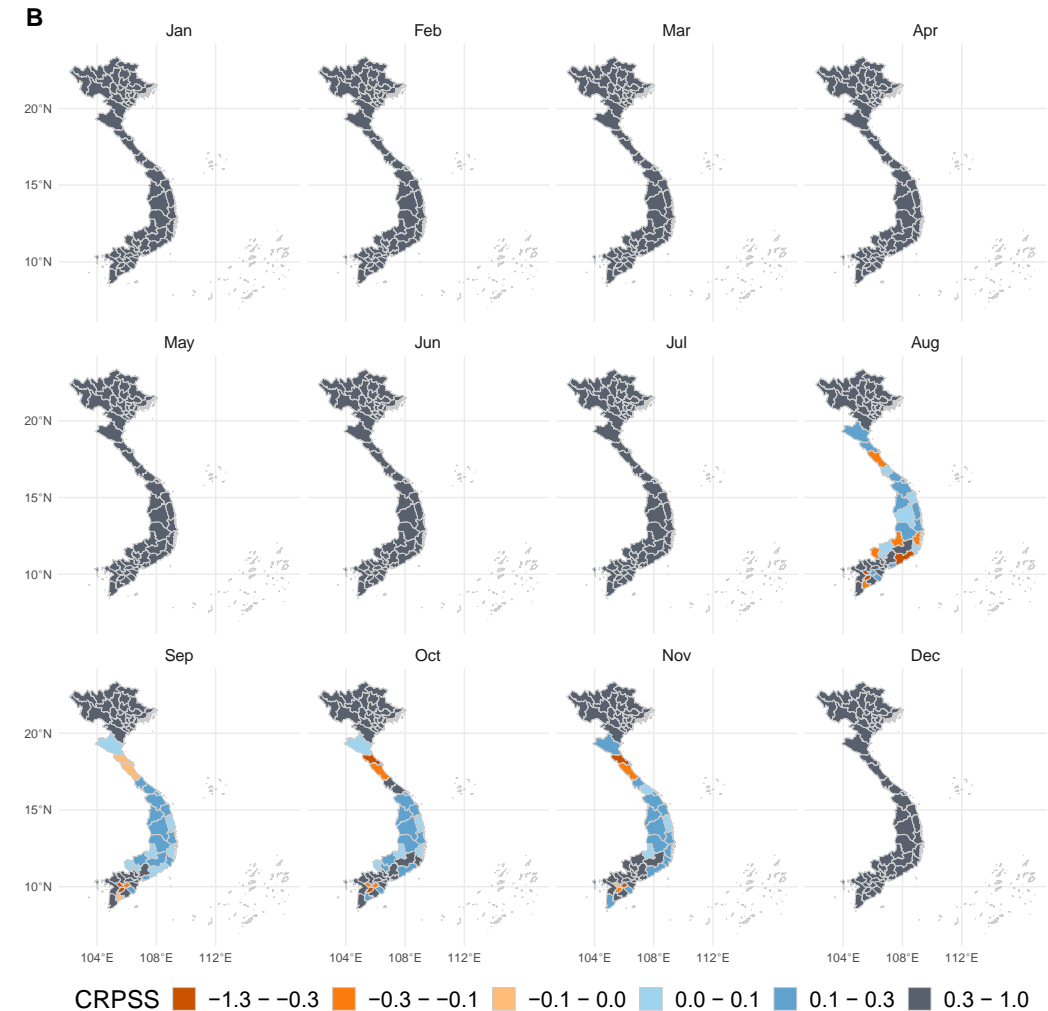
# EVALUATING MULTI-LEAD DENGUE FORECASTS IN VIETNAM

- Compared to a baseline model with no climate information, our early warning system performed consistently better across the whole country for the period December to July.
- From August to November, however, the skill of our model is lower for some provinces characterised by large variability in dengue incidence.

CRPSS = Continuous rank probability score

$$CRPSS = 1 - \frac{CRPS_f}{CRPS_b}$$

- We can also assess the ability of the system to discriminate outbreaks, using the ROC analysis, which shows how the overall skill decreases with increasing lead time, suggesting there is a compromise between outbreak detection and lead-time/time to intervene.



# CHALLENGES & REQUIREMENTS

- Long-term disease datasets (e.g. dengue cases)
- Data on the structure of human, vector (and host) populations
- Social, demographic and economic indicators
- Environmental data and local meteorological records
- Access to climate forecasts and hindcasts (to evaluate past performance)
- Background knowledge of local idiosyncrasies
- Real-time data stream for prediction
- Iterative evaluation of model assumptions and predictive performance
- Strong partnerships between public health stakeholders, climate and health researchers, data managers, and climate service providers



© WHO/Anna Kari

# REFERENCES & RESOURCES

## Reading

- Dengue outlook for the World Cup in Brazil: an early warning model framework driven by real-time seasonal climate forecasts ([http://www.thelancet.com/pdfs/journals/laninf/PIIS1473-3099\(14\)70781-9.pdf](http://www.thelancet.com/pdfs/journals/laninf/PIIS1473-3099(14)70781-9.pdf))
- Evaluating probabilistic dengue risk forecasts from a prototype early warning system for Brazil (<https://elifesciences.org/articles/11285>)
- Climate services for health: predicting the evolution of the 2016 dengue season in Machala, Ecuador ([http://www.thelancet.com/pdfs/journals/lanplh/PIIS2542-5196\(17\)30064-5.pdf](http://www.thelancet.com/pdfs/journals/lanplh/PIIS2542-5196(17)30064-5.pdf))
- Nonlinear and delayed impacts of climate on dengue risk in Barbados: A modelling study (<https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1002613>)
- Probabilistic seasonal dengue forecasting in Vietnam using super ensembles (<https://doi.org/10.1371/journal.pmed.1003542>)

## Resources

- The BUGS (Bayesian inference Using Gibbs Sampling) project (<https://www.mrc-bsu.cam.ac.uk/software/bugs/>)
- The R-INLA project: Bayesian computing using integrated nested Laplace approximations (<http://www.r-inla.org>)
- Forecast Verification: a practitioner's guide (<https://onlinelibrary.wiley.com/doi/book/10.1002/9781119960003>)
- R Verification package ([www.cran.r-project.org/web/packages/verification.index.html](http://www.cran.r-project.org/web/packages/verification.index.html))

## Section 4.3:

# Using climate/weather-health associations

## Projection of future health outcomes

**Learning objective:** Gain a basic understanding of how to develop a pathway to linking exposures/environmental hazards to health outcome(s).

### Resources:

- [Gosling, McGregor & Páldy \(2007\). Climate change and heat-related mortality in six cities, Part 1. Int J Biometeorol 51:525–540.](#)
- [Gasparrini & Leone \(2014\). Attributable risk from distributed lag models. BMC Med Res Methodol 14:55.](#)
- [Phalkey et al. \(2015\). Systematic review of efforts to quantify the impacts of climate change on undernutrition. PNAS.](#)
- [Mesa-Frias, Chalabi & Foss \(2014\). Quantifying uncertainty in health impact assessment. Environment International 62:95–103.](#)
- Confalonieri & Tong (2014). Climate change and human health: issues for teacher and classroom. In: Teaching Epidemiology, 4th ed., Oxford University Press.



# **4.3 Using climate/weather-health associations**

Projection of future health outcomes

Dr Lawrence Kazembe

# Learning objective

A common theme in epidemiology and public health is measuring changes in a defined health outcome or impact and attributing these trends to changes in a directly related risk factor. In studying the health effects of climate change, an integrated approach in which disease and climatic factors are analysed together is required, but often missing. As climate varies naturally over time (and is one of many determinants of disease rates), modelling is required to identify the climate-attributable part of disease and the long-term trends.

## General Objective:

- Provide a general framework for identifying climate-attributable health impacts, and gain awareness of projecting future burden of disease for climate-sensitive health outcomes.

## Specific Objectives:

- Introduction to the selection of health issues and exposure-response relationships;

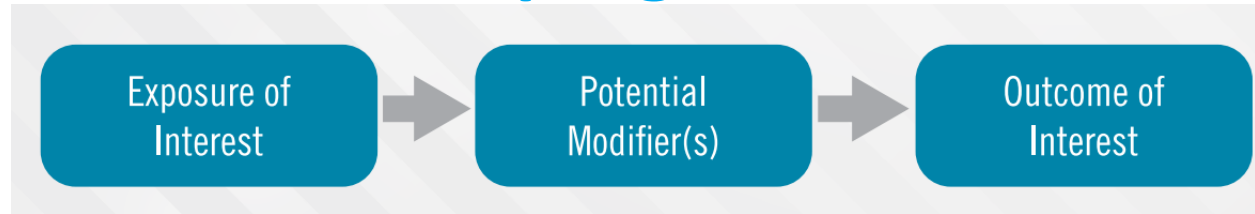


# Steps in examining future health burdens

- **STEP 1: Develop Causal Pathways** - how to develop a pathway to link exposures/environmental hazards to health outcome(s).
- **STEP 2: Assemble Data Elements** - gathering data for baseline climate-disease relationships, and climate change projections
- **STEP 3: Exposure-Outcome function** - selecting the relationship between exposure (climate) and response (disease)
- **STEP 4: Project health burden** - an approach to examine health burden in the future
- **STEP 5: Perform Uncertainty Analysis** - common sources of uncertainty and how to ascertain them.



# STEP 1: Developing Causal Pathways



- Causal pathways linking a climate-sensitive exposure to health outcome(s) of interest are central to climate change disease burden projections.
- Causal pathways (also known as exposure pathways or causal process diagrams) are schematic representations of how an exposure affects health outcomes (Figure above).
- Causal pathways outline and show the steps between an exposure and its health outcome.
- In the case of climate-sensitive health outcomes, causal pathways link an environmental hazard or other environmental exposure to a change in the incidence of specific adverse health outcomes.
- They can be elaborated with varying degrees of complexity by adding potential modifiers and can be static or dynamic, and are particularly useful for identifying and assembling the data elements that will be needed to pursue the modelling effort.
- The complexity of these pathways is likely to increase with the inclusion of intermediate factors that modify the hypothesised association, and this has implications for modelling the association.

# Purpose of Causal Pathways

The pathways will serve several purposes:

1. Characterisation of the health outcome's climate sensitivity.
  2. Identification of important underlying drivers and potential effect modifiers.
  3. Development of an inventory of variables to include in the exposure-outcome model.
  4. Identification of data needs for the modelling effort.
  5. Characterisation of knowledge gaps and significant areas of uncertainty.
- The causal pathways should be tailored to a particular area and must be defined for each climate-related hazard.
  - These pathways should be developed with attention to scope and scale, both of which should be matched to the area of interest.

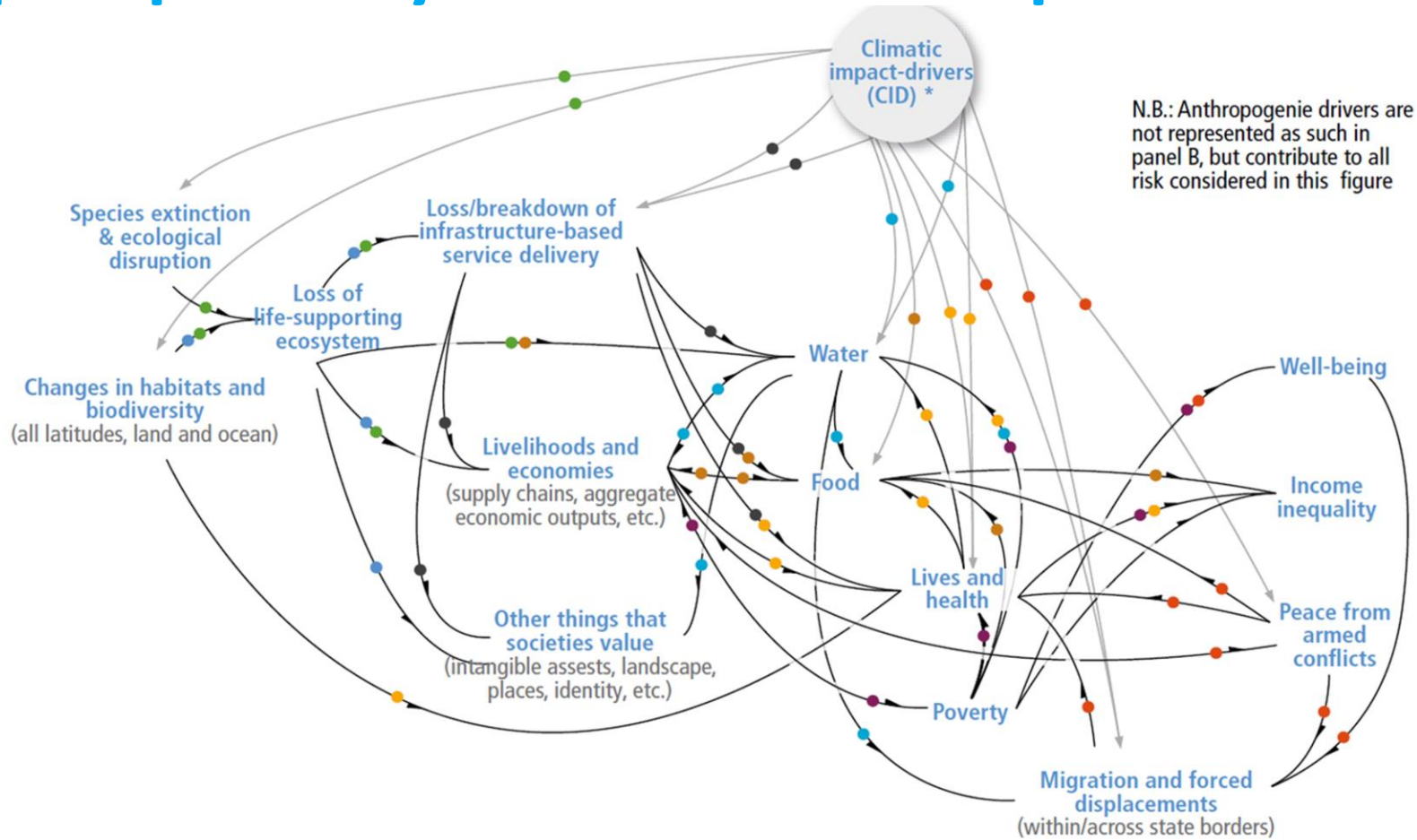


# Guiding questions when developing a causal pathway

- Questions to consider...
  - Have there been epidemiological studies in your geographic location relevant to this causal pathway?
  - Is there more than one route of exposure?
  - If there are multiple modifiers in the causal pathway, how will you decide which to include in your disease burden projection?
- The links in a causal pathway may be hypothesised, such that:
  - Are consistent with current understanding of the exposure and disease pathogenesis.
  - Are consistent with current understanding of the social determinants of health (a range of socio-economic, ecological, infrastructural, etc. );
  - Other types of factors should be included if there is reason to believe that these factors may modify the association between the exposure and health outcome.
  - Make pathways easy to map and model, capturing both direct and indirect paths



# Risk Cascades of Representative Key Risks: Complex pathways from climate impact drivers to health impacts



[IPCC AR6 Report, Chapter 16: Key Risks across Sectors and Regions | Climate Change 2022: Impacts, Adaptation and Vulnerability](#)

## Risk cascades \*\*

-  Across key risks
-  Climate-driven

## Representative Key Risks

-  A (Low-lying coasts)
-  B (Ecosystems)
-  C (Infrastructure)
-  D (Living standards)
-  E (Human health)
-  F (Food security)
-  G (Water security)
-  H (Peace and human mobility)

\*\* Illustrative rather than comprehensive, and qualitative rather than quantitative, as suggested across the RKR assessments in this report.

## Examples of direct and indirect pathways linking climate-related exposures and health outcomes

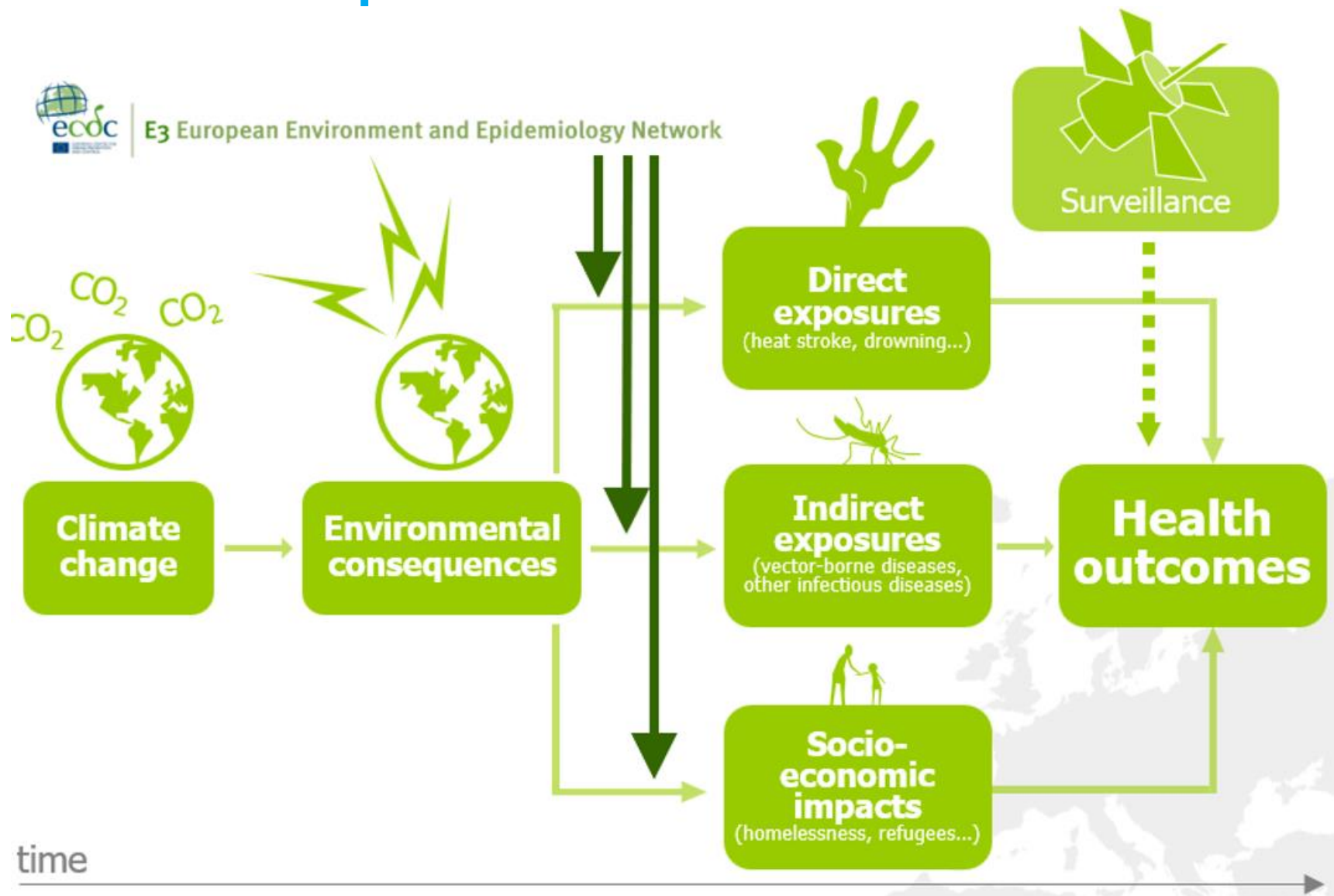
EXPOSURE	HEALTH OUTCOME	NOTES	CITATION
Extreme heat, Temperature variability, Social disruption	Human Health (general)	Contains direct and indirect pathways between environmental systems and human health	McMichael, A.J., <i>Globalization, Climate Change, and Human Health</i> . New England Journal of Medicine, 2013. 368(14): p. 1335-1343.
Extreme heat	Heat-related adverse health outcome	Proximal racial and social determinants of heat vulnerability	Gronlund, C., Racial and Socioeconomic Disparities in Heat-Related Health Effects and Their Mechanisms: a Review. <i>Current Epidemiology Reports</i> , 2014. 1(3): p. 165-173.
Extreme heat	Mortality	Illustrates how ozone could modify and/or confound heat-related mortality	Reid, C.E., et al., <i>The role of ambient ozone in epidemiologic studies of heat-related mortality</i> . <i>Environmental Health Perspectives</i> , 2012. 120(12): p. 1627-1630.
Bacterial pathogens	Diarrhea incidence	Demonstrates the complexities of transmission cycle of waterborne pathogens, including magnitude and direction of impacts	Moors, E., et al., <i>Climate change and waterborne diarrhoea in northern India: Impacts and adaptation strategies</i> . <i>Science of The Total Environment</i> , 2013. 468-469, Supplement(0): p. S139-S151.
Temperature, precipitation	Infectious disease	Exhibits the impacts of both temperature and precipitation on the transmission of infectious diseases	McMichael, A.J. and E. Lindgren, <i>Climate change: present and future risks to health, and necessary responses</i> . <i>Journal of Internal Medicine</i> , 2011. 270(5): p. 401-413.

Source: CDC, *Projecting Climate-Related Disease Burden*.



World Health Organization

# Examples of direct and indirect pathways linking climate-related exposures and health outcomes



Source: IJERPH (2015) 12(6):6333, MDPI.

## STEP 2: Acquiring, organizing, and managing the data elements



- Once a causal pathway has been developed, the next step is to assemble the necessary data.
- The causal pathway can be used to develop an inventory of the data needed to model future disease burden.
- Specifically, we may require: baseline disease burden; exposure-outcome “dose-response” relationship; baseline climate data; projections of future climate, population and possibly disease burden.

## Data Element: Climate Data

- Climate data from the past is linked with retrospective health data in epidemiological analyses to assess how climate-sensitive morbidity and mortality are affected by changes in environmental exposures (see Section 4)
- GCMs project future climate states using scenarios, sets of assumptions about the trajectories of major climate drivers (also known as forcings), including greenhouse gas emissions.
- Several GCMs can be used together to produce groups of projections (termed “ensembles”) that can help reduce uncertainty by providing a range of projected outcomes. Example: Climate Model Intercomparison Project (CMIP).
- These ensembles can provide projections of near-term (through 2035) and long-term (2100 and beyond) climate.



# Uncertainty in GCM projections

- The three important categories of uncertainty in GCM projections are:
  - 1) that deriving from different approaches to modelling,
  - 2) that deriving from natural climate variability, and
  - 3) that derive from different emissions scenarios.
- The uncertainty associated with different approaches to modelling can, to some degree, be addressed through the use of projections from multiple GCMs.
- The uncertainty associated with natural climate variability can best be managed by increasing the number of model runs included and using the average of each GCM's runs.
- Societal uncertainty is represented by the emissions scenarios (RCPs)
- Climate change health impact projections should use GCM outputs based on two or more RCPs for projections beyond 2050.
- Typically, GCMs produce gridded outputs that operate on the coarse scale of hundreds of kilometres. Statistical or weather modelling techniques can downscale temperature and precipitation simulations to finer scales for such applications.



# Data Elements: Baseline Disease Burden

- Another important data element is baseline health data, as projections of health outcomes require a baseline from which to start
- There are three primary elements to this activity:
  1. Determine the scale at which estimation and projections are required
  2. Choose an indicator of disease burden
  3. Determine the population group
- **Determine the Scale of the Effort:** There are two areas in which the scale of the effort needs to be specified: geographical (spatial) and temporal
- **Choose an Indicator of Disease Burden:** Various data sources and indicators can be used to measure, track, and describe current and future disease burden
- These are typically in the form of a disease prevalence or incidence (e.g., annual rates of emergency department visits for heat stroke)
- **Focus population group:** Determine the group you are interested in, as these react differently to different health outcomes. For example, the elderly during heatwaves, and children under five in malaria-endemic regions.



# Data Elements: Population Data

- In addition to the baseline rate, it is important to know details related to the baseline population demographics, as these can affect exposure and disease susceptibility and significantly affect projected disease estimates
- Given the important role that population-level characteristics play in many climate and health outcome relationships, it is critical to capture demographic and other information related to the setting from which the estimate was derived and assess for potential biases.
- Comparisons between current and projected populations can be important, particularly in areas where large changes in population demographics (e.g., ageing or migration) are expected in the coming decades.
- These factors are important to consider with regard to both their role in the association between the exposure and outcome under consideration and with regard to baseline health status.



# STEP 3: Exposure-Outcome Response Function

## Exposure Outcome Response Function ( $\alpha$ )

### Data Sources

Analog or  
Location-Specific  
Epidemiologic Studies

### Model Types

Time Series  
Case Crossover

- An exposure-outcome function describes how the likelihood of an adverse health effect (example outcome: death) is related to an environmental hazard (example exposure: extreme heat).
- In different disciplinary settings, these may also be referred to as 'dose-response' or 'concentration-response' functions.
- In the context of climate change, the exposures of interest could directly be weather-related, like ambient temperature, precipitation, extreme weather events, or weather-mediated factors, like pollen levels or factors affecting the environmental presence of water-borne or vector-borne pathogens.
- A specific exposure could affect multiple health outcomes (e.g., heat can cause exacerbations of a range of diseases leading to morbidity and mortality), and specific health outcomes can have several environmental drivers (e.g., water-borne disease outbreaks may be associated with both temperature and precipitation).
- A standard practice in deriving exposure-outcome functions in environmental epidemiology involves linking health and exposure data through common spatial (such as county, city, or other administrative boundaries) and temporal (such as day or month) variables.

# STEP 3: Exposure-Outcome Response Function

## Exposure Outcome Response Function ( $\alpha$ )

### Data Sources

Analog or  
Location-Specific  
Epidemiologic Studies

### Model Types

Time Series  
Case Crossover

- Data availability is an important consideration for selecting an exposure-outcome function
- An example of a health impact linked to environmental exposure is air pollution, where daily health data can be linked to daily weather data at a specific city or jurisdiction
- Examining air pollution, changing temperatures and health outcomes requires the establishment of retrospective datasets. From these, time-series statistical models can be used to estimate the change in health outcome attributable to changes in temperature. This allows the production of odds ratios and relative risk estimates for the health outcome of interest
- This approach may not be feasible if data is unavailable. Alternative approaches can use estimates from the literature with careful consideration of their appropriateness. Qualitative estimates may also be an option

# STEP 4: Components for projecting future disease burden



- Once all data elements are assembled, they are combined using a modeling approach that captures the relationships among them. The modelled present burden is then used to project the health burden in the future.
- As shown above, this requires four elements:
  - climate projection, baseline disease prevalence, exposure-response function, and population characteristics
- Model outputs may be:
  - **Health impacts** such as: deaths, disability-adjusted life years or DALYs, all-cause or cause-specific visits to the emergency department, laboratory-confirmed cases of a specific disease diagnosis, etc.
  - or
  - **Risk factor** that is a determinant of future health impacts (such as temperature distribution or habitat suitability for vectors).
- Here we focus primarily on projections of disease impacts

# The Delta Method

- Most climate change disease burden projections have used what is referred to as ***“The delta method.”***
- The delta method changes parameters in climate models to produce estimates of an exposure of interest both in the current and future scenarios (e.g., current temperature compared to projected future temperature).
- The change, or delta, can be applied to exposure-outcome models to estimate future health burden. An overview of studies using the delta method was conducted by Gosling et al. (2007)
- The ***“damage function approach,”*** often used to estimate morbidity from air pollution from shifting energy sources, is an example of a method that can be applied to projecting health impacts from climate change.
- Essentially, this combines the different elements described above, projected change in exposure, baseline disease prevalence, the exposure-outcome functions and baseline population in a mathematical function to derive an estimate of the disease burden. This approach has been widely used in assessing the adverse health outcomes that could be avoided by improved air quality.



# Equation for the damage function approach for projecting health impacts

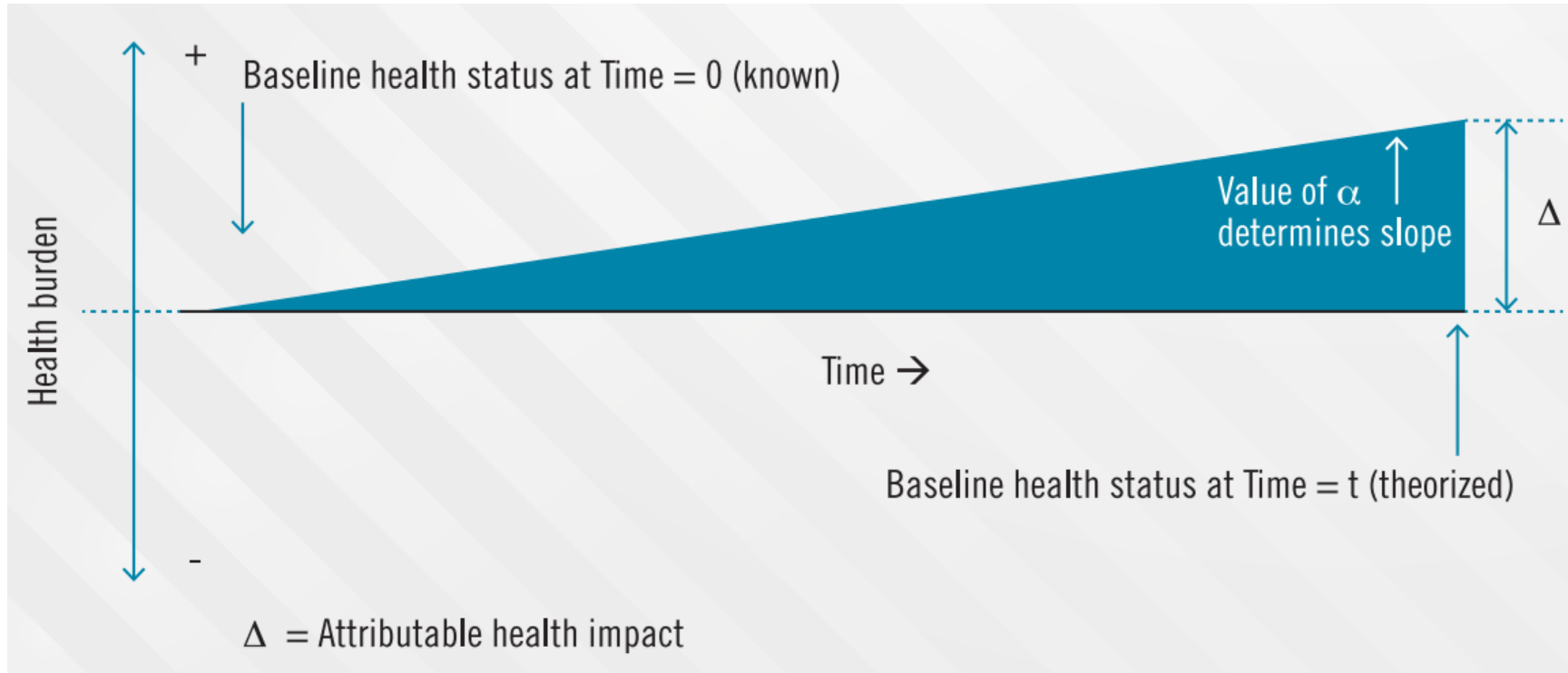
- A useful tool to use is the damaging function (based on delta method):

$$\Delta y = y_0(e^{\alpha\Delta x} - 1) * Pop$$

- where
- $\Delta y$  is the change in the health effect
- $y_0$  is the change in the baseline incidence rate
- $\alpha$  is a coefficient derived from the relative risk (RR) associated with a change in exposure
- $\Delta x$  is the estimated change in exposure (e.g. temperature between 2010 and 2050)
- $Pop$  is the exposed population



# Changing health status over time



- $\alpha$  is the coefficient associated with each of the climatic factors;
- Models have to be estimated for at least two Scenarios (e.g. RCP4.5 and RCP8.5);
- Both current and projected data are required to generate future burden;
- Negative impacts are also possible.

# Types of models for health impact projection

- Event-based
  - For example: heatwave, cyclone, flood
- Theoretical models
  - For example: climate suitability for vector-borne disease
- Empirical models
  - For example: Observed distribution and modelled risk of dengue in 2010

# STEP 5: Uncertainty Analysis

- Fundamentally, uncertainty relates to “imperfect knowledge,” the inability to fully know all of the factors affecting a particular process.
- There are many sources of uncertainty in climate change health burden projections, as expected in any modelling effort. Uncertainty is due:
  - model uncertainty (i.e. uncertainty resulting from simplification of complicated real-world processes) and
  - parameter uncertainty (i.e. uncertainty resulting from incomplete knowledge regarding the specifics of model parameters and their interactions in future).
- There are established methods for identifying and quantifying uncertainty in climate change disease burden projection efforts that will be discussed.
- The following steps are required:
  - identifying major sources,
  - attempting to characterise their impacts on the analysis, and
  - presenting sensitivity analyses with other findings.



# Identifying major sources of uncertainty

MAJOR CATEGORY OF UNCERTAINTY	SOME TREATMENT STRATEGIES
Lack of knowledge regarding future emissions	Include exposures derived from a range of emissions scenarios
Lack of knowledge related to exposure-outcome associations or $\alpha$	Evaluate values of $\alpha$ within a certain range, e.g., within the bounds of the 95% confidence interval for the original estimate(s)
Lack of knowledge related to future conditions, including adaptation and demographic trends	Evaluate different central assumptions related to future conditions and adaptation, e.g. socioeconomic development, migration, prevalence of mechanical air conditioning

- There are two major types of uncertainty:
- ***intrinsic***, which is inherent to the system being studied,
- and ***extrinsic***, which is related to the ways in which problems are conceptualised and data are collected and analysed.



# Uncertainty in Causal Pathways

- Addressing uncertainty starts in the process of framing and articulating causal pathways;
- It is important to identify where structural uncertainties may be located (e.g., whether nonlinearities, delays, or threshold dynamics may be major concerns) and where parametric uncertainties are present;
- Structural uncertainties are particularly common for vector-borne and zoonotic diseases, but can be seen with many different disease processes;
- Parametric uncertainties are common throughout environmental health.
- Examples of how uncertainty associated with framing assumptions might be treated have recently been introduced into the literature (Tate 2013, Mesa-Frias et al. 2013).



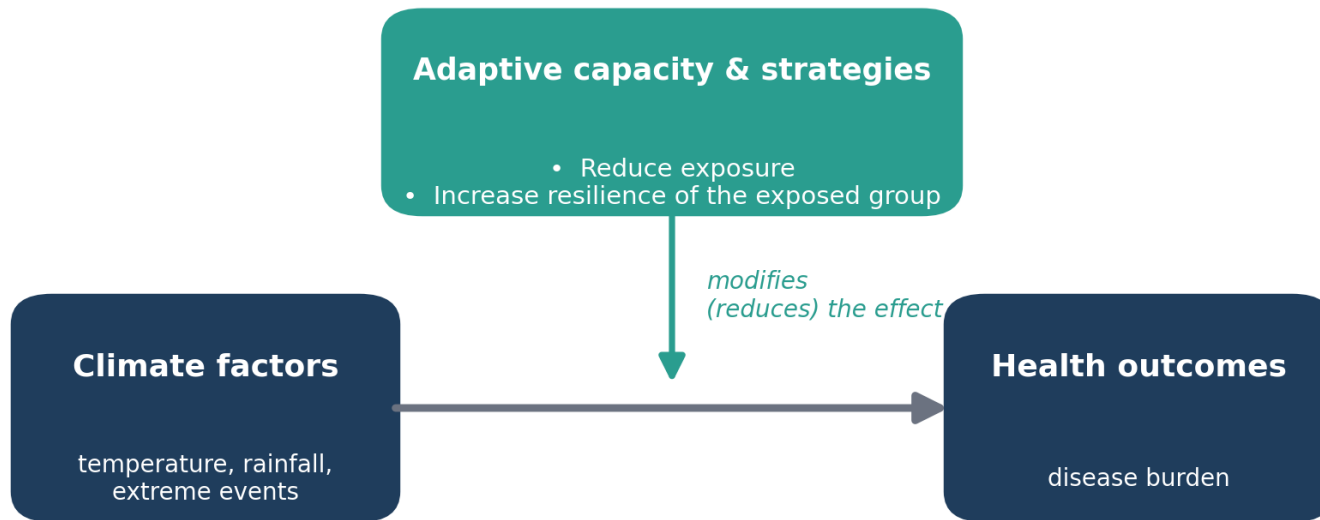
# Uncertainty in Analysis

- A host of strategies are available for identifying and treating uncertainty in analytic processes.
- To deal with structural uncertainties, it is important to use appropriate modelling approaches.
- Structural uncertainties identified in the causal pathway may have analytical implications, which will require fitting a number of plausible models and assessing the stability of parameters.
- This process of systematically evaluating the effect of variations in model parameters is sometimes referred to as uncertainty analysis and sometimes as sensitivity testing.



# Evaluating Uncertainty

## How adaptive capacity modifies the climate-health relationship



Failure to account for adaptation in disease-burden projections can bias estimates, typically overestimating the future effect.

- One significant source of uncertainty specific to climate change health impact projections is whether and how to model climate change adaptation, which has the potential to reduce climate change impacts, including those on public health.
- Failure to account for adaptation in disease burden projections can introduce a systematic bias that will likely result in overestimation of effect.
- This figure shows adaptive capacity and strategies that would modify the effect of climate factors on health outcomes.
- Strategies include those aimed at reducing exposure or increasing the resilience of the exposed group.

# BIBLIOGRAPHIC REFERENCES



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