Climate factors, climate change, and their health impacts

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Global Health Resilience group

Advanced Webinar Series on Spatiotemporal Modeling of Climate-Sensitive Diseases
21st of January 2026

About us

BSC Barcelona Supercomputing Center Centro Nacional de Supercomputación

Ania Kawiecki Peralta

I am a postdoc at the Global Health Resilience group at the BSC. My background is in Veterinary Medicine, and I have a PhD in Epidemiology studying dengue virus vector surveillance and control.

Currently I am working on developing R packages to facilitate disease risk modeling and prediction using Bayesian spatio-temporal models in INLA.

Carles Milà

I am a data scientist at the Global Health Resilience group at the BSC. My background is in statistics and geoinformatics, and I have a PhD in spatial modelling for exposure assessment.

I am currently working on developing R packages for climate-sensitive data processing and modelling.

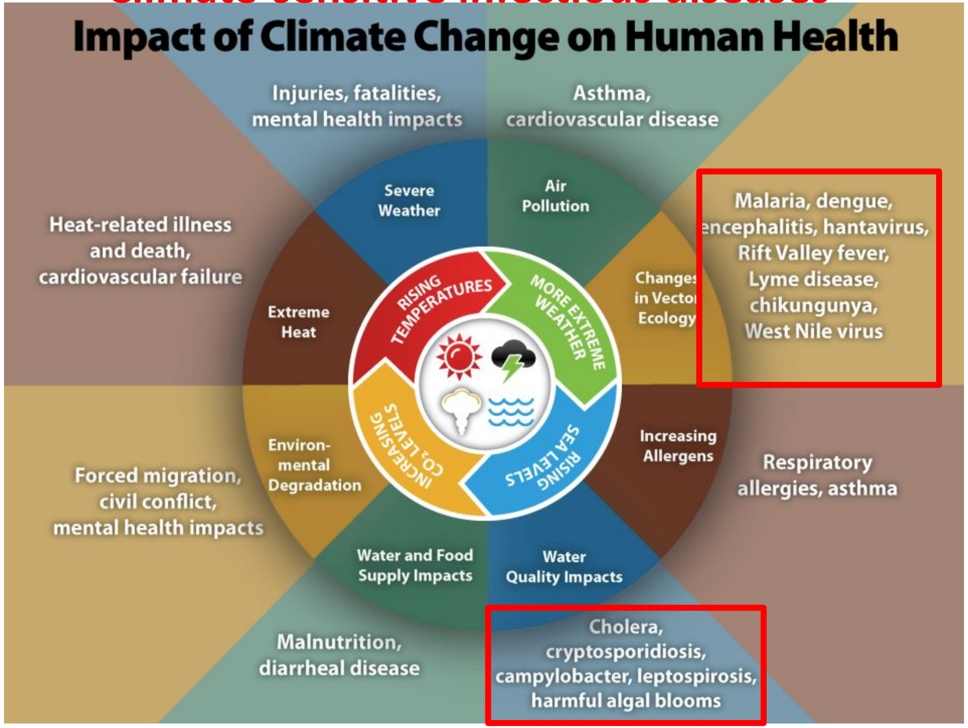
Webinar Outline

1. Climate sensitive-diseases.
2. Health impact of climatic variables and climate change.
3. Climate-informed early warning systems.
4. Data structure, pre-processing and exploration.
5. Questions at the end!

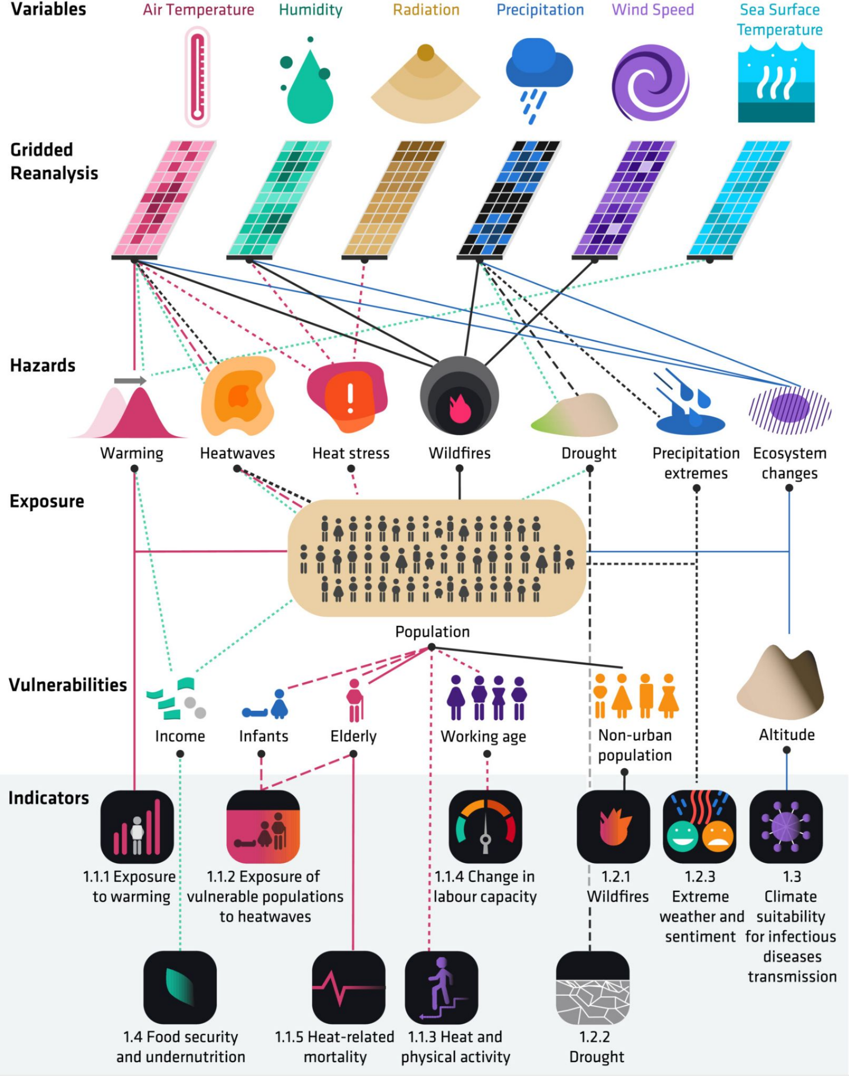
Climate-sensitive diseases

Health impacts of climate change

Climate-sensitive infectious diseases

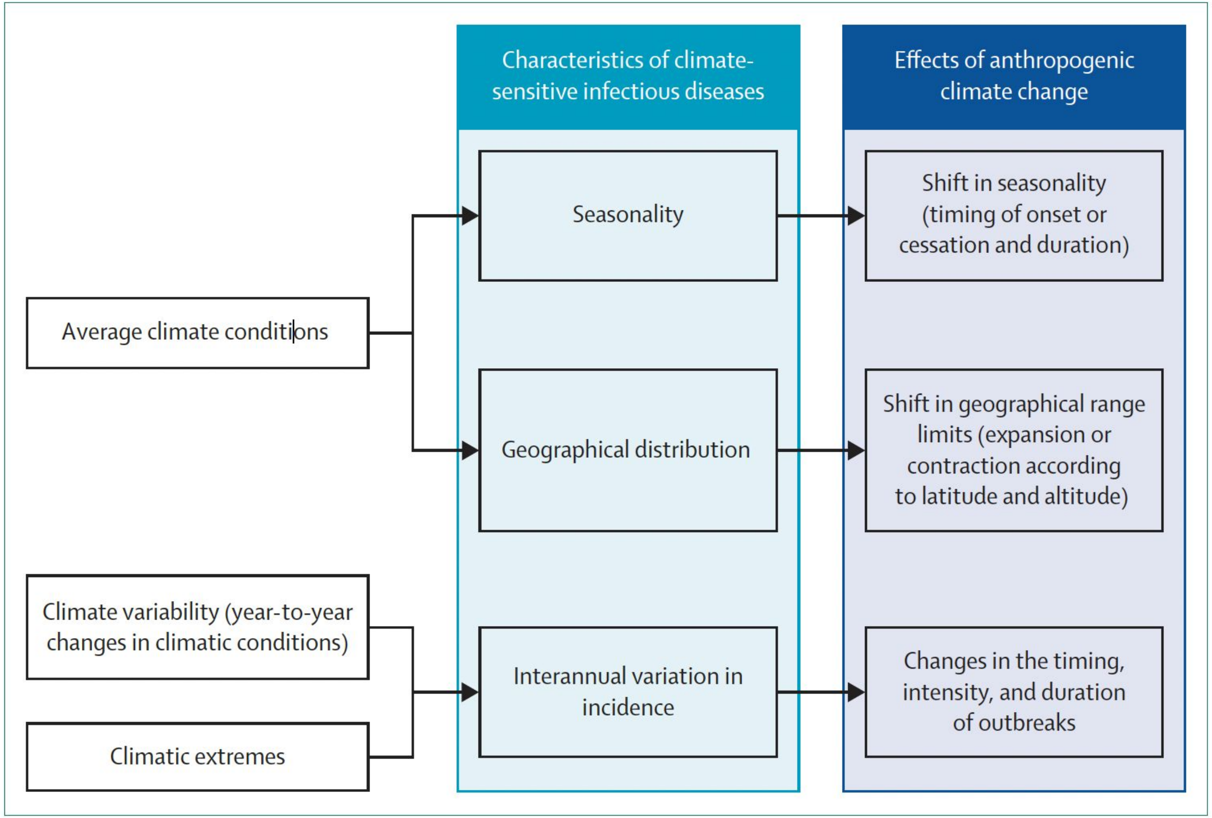


George Luber adapted from Patz *et al. et Nature* 2005



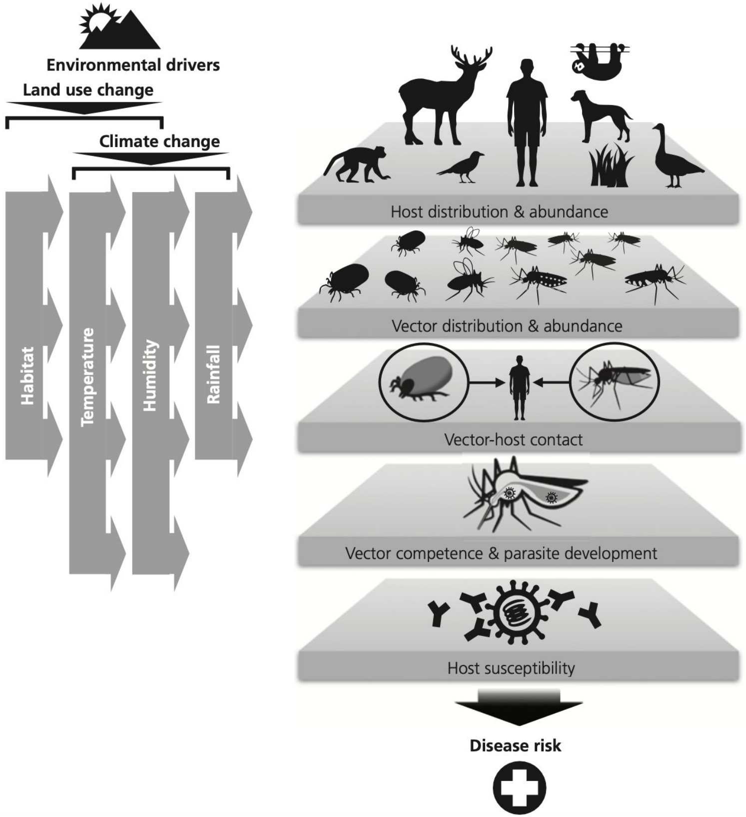
Di Napoli *et al. Meteorological Applications* 2022

Climate-sensitive infectious diseases

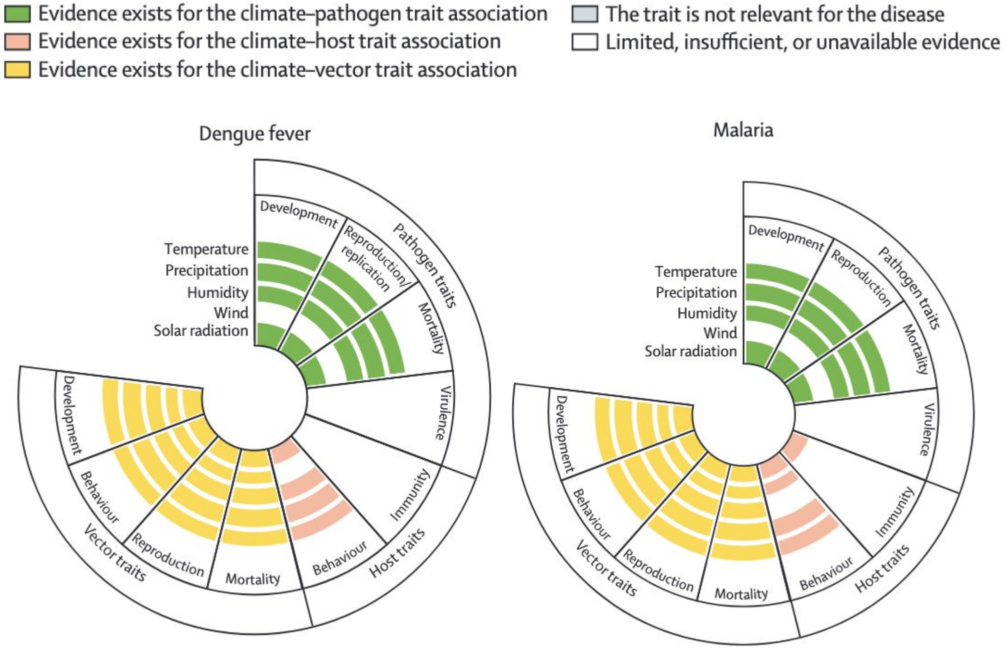


Alcayna *et al.*, *Lancet Planet Health* 2025

Climate-sensitive infectious diseases - vector-borne diseases

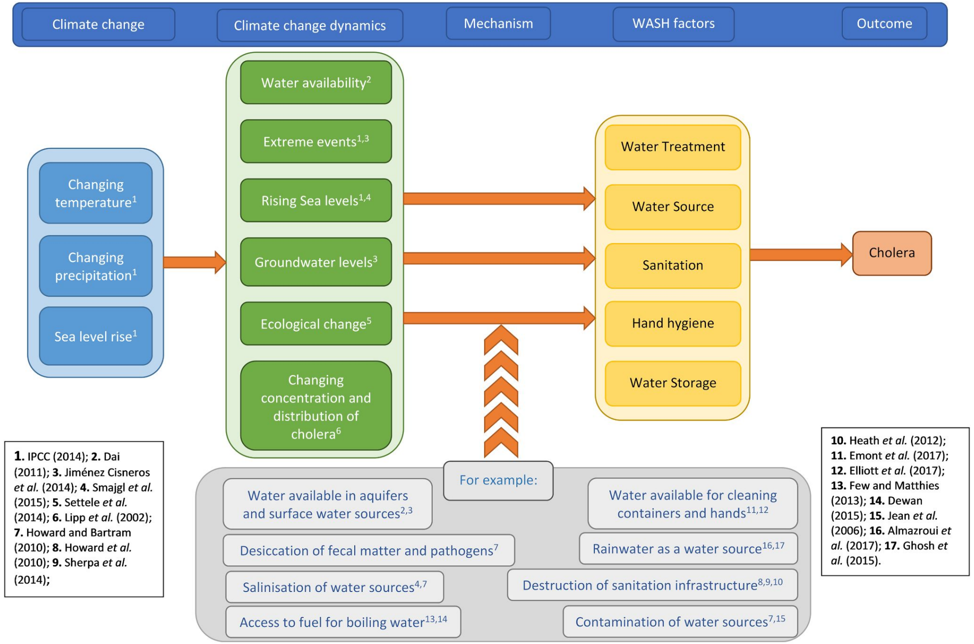


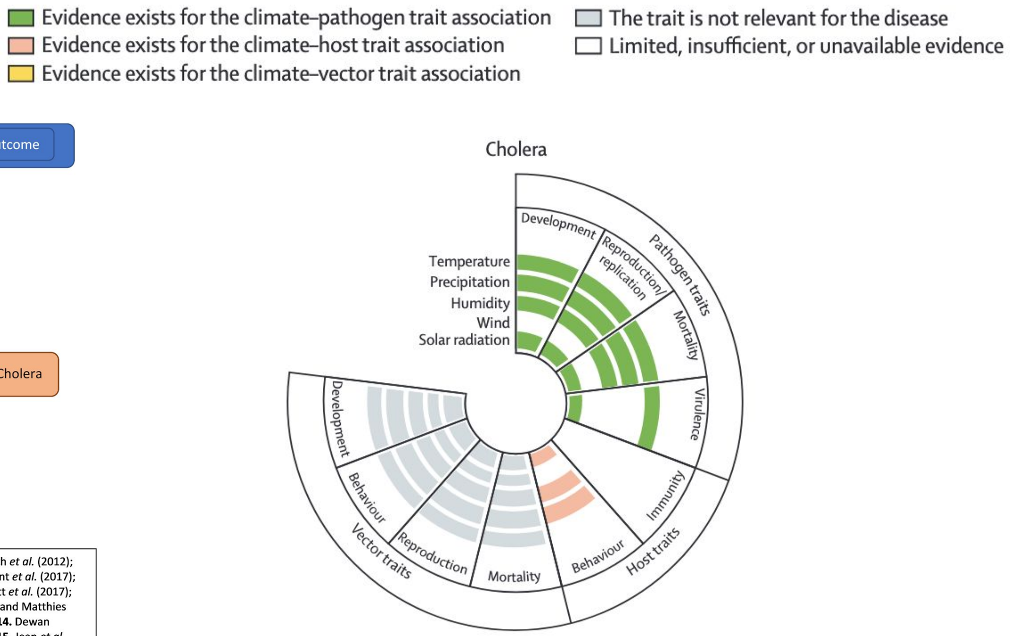
Shocket *et al.*, *Oxford University Press* 2020



Alcayna *et al.*, *Lancet Planet Health* 2025

Climate-sensitive infectious diseases - water-borne diseases



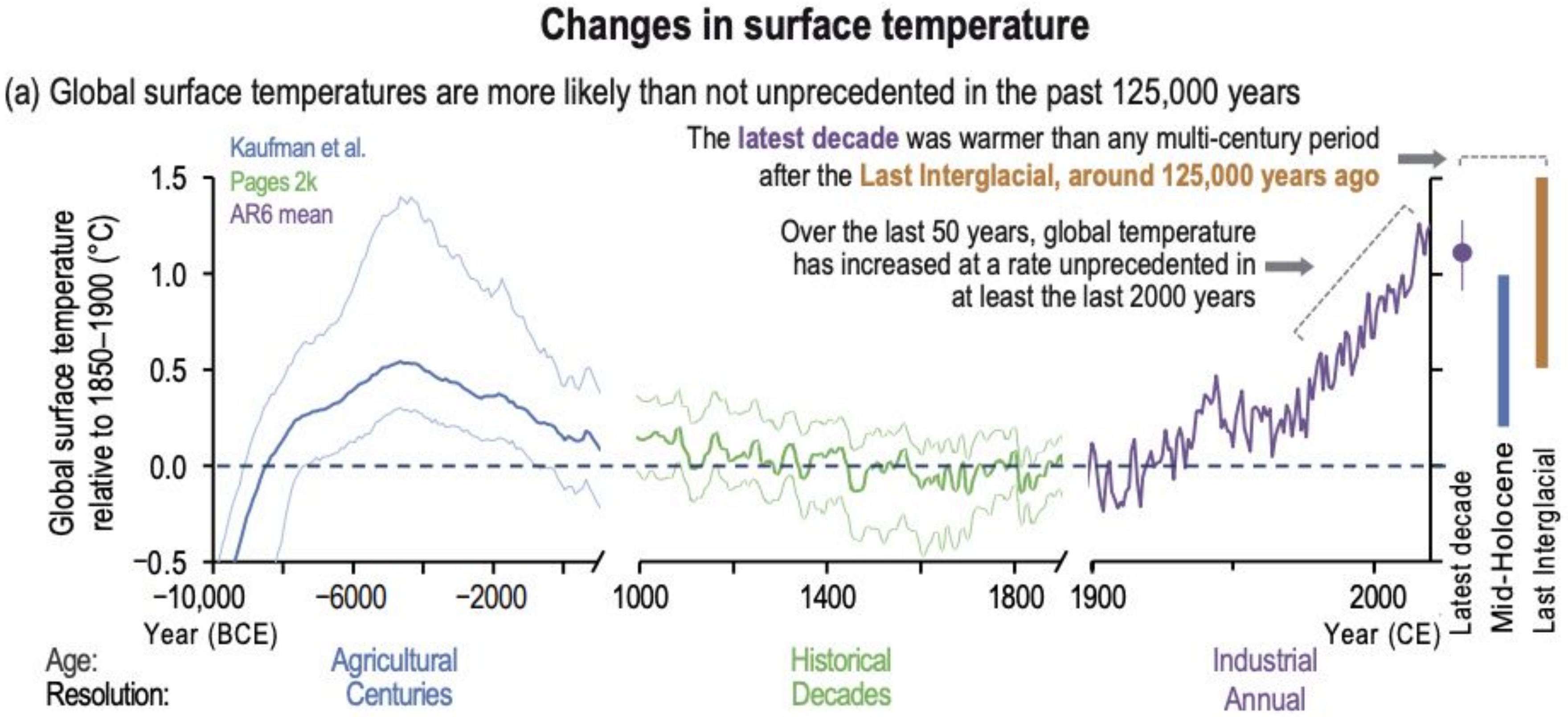


Jones *et al.*, *J Water Health* 2020

Alcayna *et al.*, *Lancet Planet Health* 2025

Health impact of climatic variables and climate change

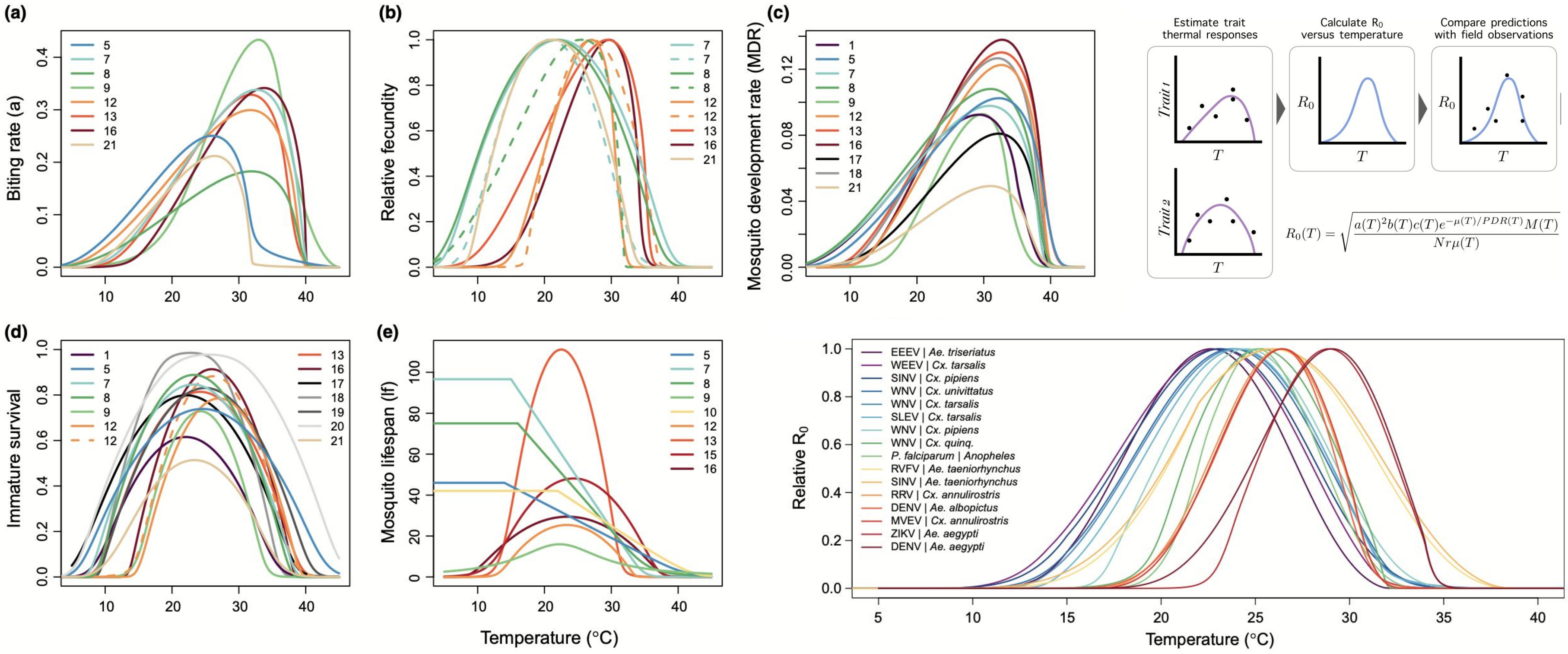
Temperature



IPCC 6th Assessment report, WG1, Technical Summary

Temperature

Effect on disease transmission-relevant vector traits



Mordecai *et al.*, *Ecology Letters* 2019

Temperature

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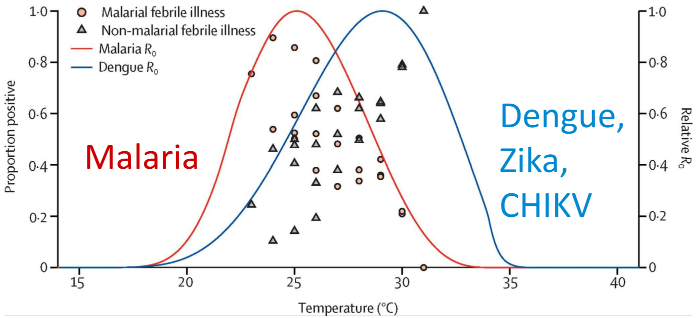
Shifts in geographical distribution of disease

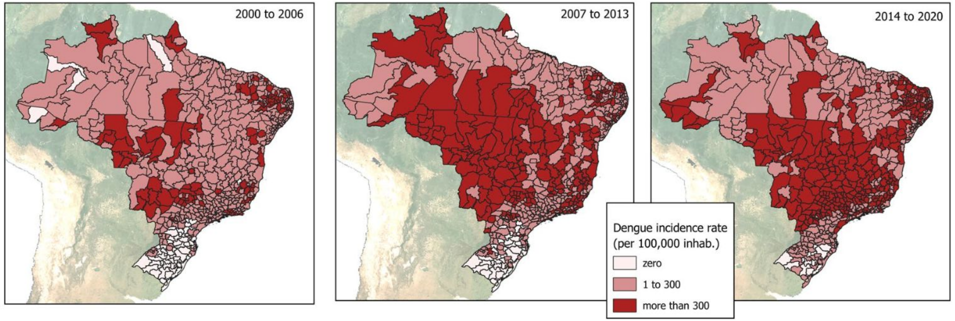
Observed

Kenyan children from 2014 to 2018



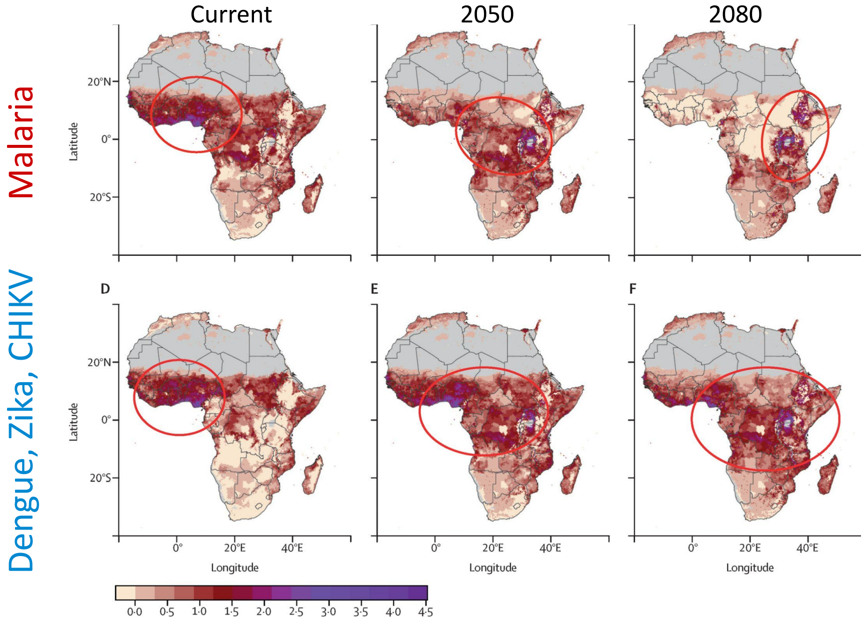
Mordecai *et al. Lancet Planetary Health* 2020

Brasil - dengue incidence



Barcellos *et al. Nature Scientific Reports* 2024

Projected



Mordecai *et al. Lancet Planetary Health* 2020

Extreme precipitation and drought

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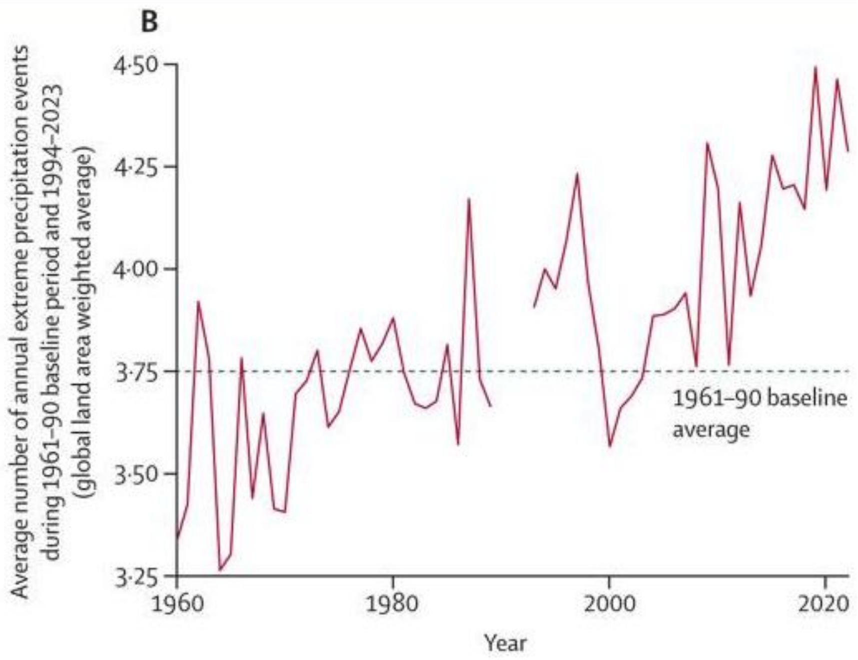
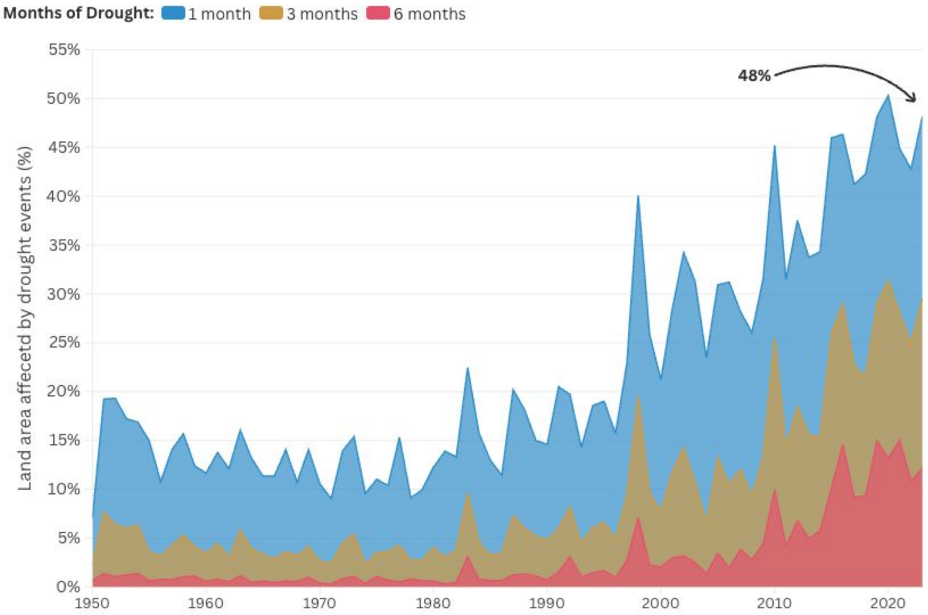
Extreme precipitation events over time

Average number of annual extreme precipitation events per 79 km2 average land area in baseline years (1961–90) and during the most recent 30-year period (1994–2023).



Land Affected by Extreme Droughts

Percentage of global land area affected by one, three, six or twelve months of extreme drought per year, from 1950-2023

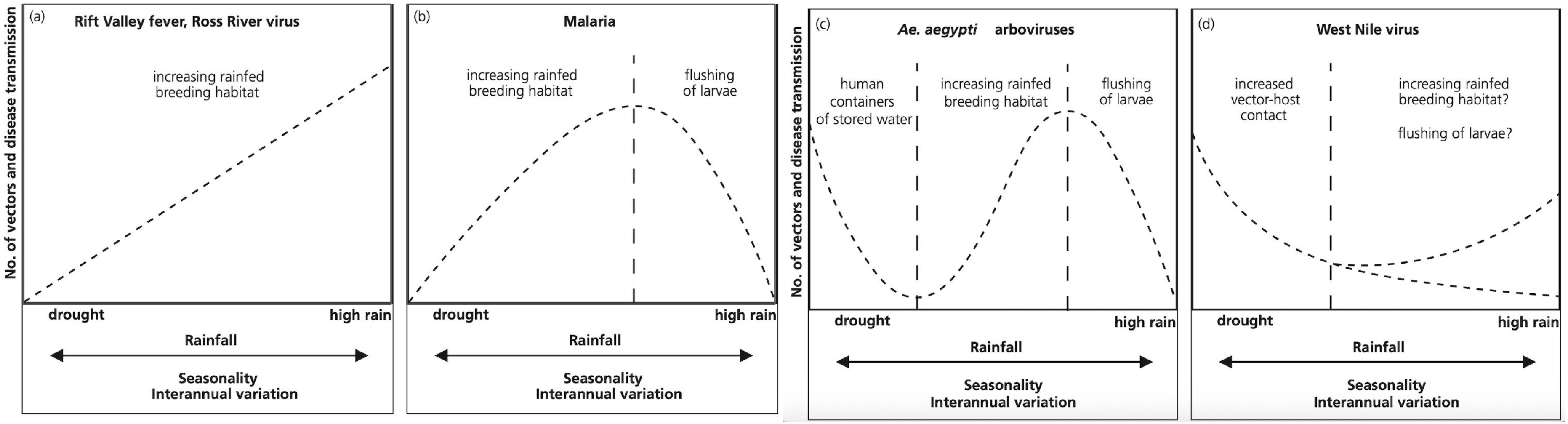


Please reference the 2024 Report of the Lancet Countdown if using this data •
For a full description of the indicator, see the 2024 report of the Lancet Countdown at lancetcountdown.org

Romanello *et al. Lancet* 2024

Extreme precipitation and drought

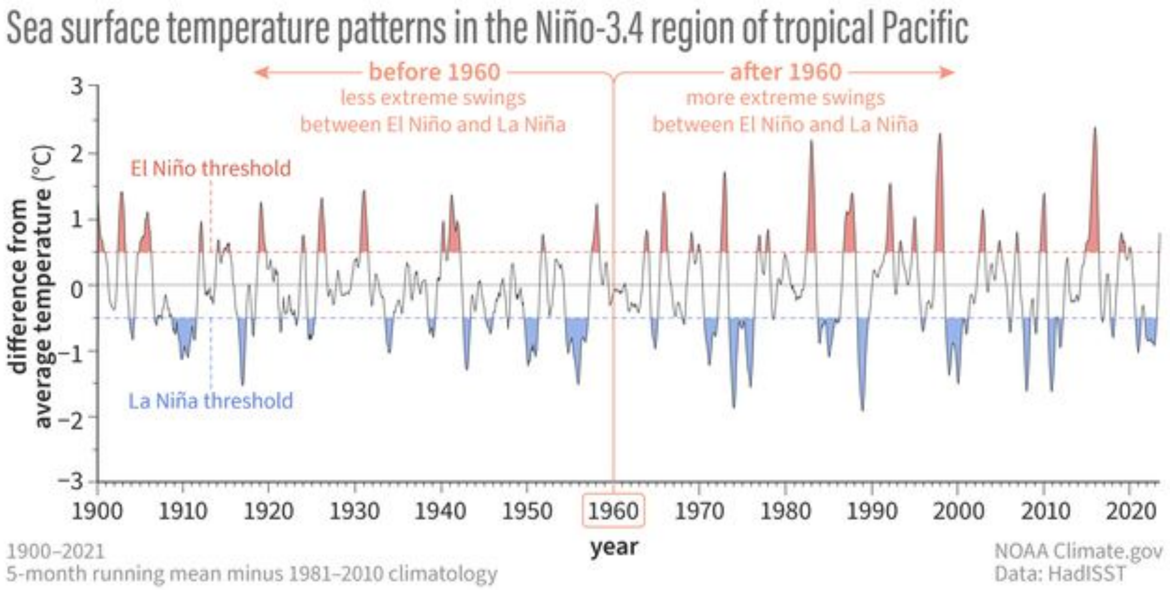
Effect on vector-borne diseases



Shocket *et al.*, *Oxford University Press* 2020

Oceanic indices

Climate change is expected to influence ENSO by changing ocean–atmosphere interactions in the tropical Pacific, potentially affecting its intensity, rainfall patterns, and global impacts, but there is still considerable uncertainty about how ENSO frequency and strength will change in the future (IPCC AR6 WGI, 2021)



Review Article | Published: 17 August 2021

Changing El Niño–Southern Oscillation in a warming climate

Wenju Cai, Agus Santoso, Matthew Collins, Boris Dewitte, Christina Karamperidou, Jong-Seong Kug, Matthieu Lengaigne, Michael J. McPhaden, Malte F. Stuecker, Andréa S. Taschetto, Axel Timmermann, Lixin Wu, Sang-Wook Yeh, Guojian Wang, Benjamin Ng, Fan Jia, Yun Yang, Jun Ying, Xiao-Tong Zheng, Tobias Bayr, Josephine R. Brown, Antonietta Capotondi, Kim M. Cobb, Bolan Gan, ... Wenxiu Zhong + Show authors

Nature Reviews Earth & Environment **2**, 628–644 (2021) | Cite this article

Perspective | Published: 18 May 2023

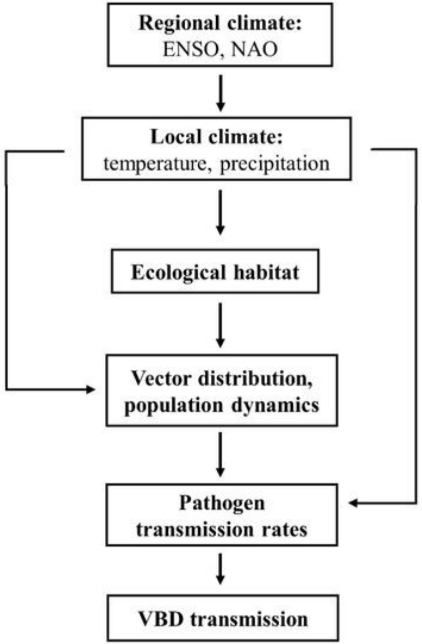
Anthropogenic impacts on twentieth-century ENSO variability changes

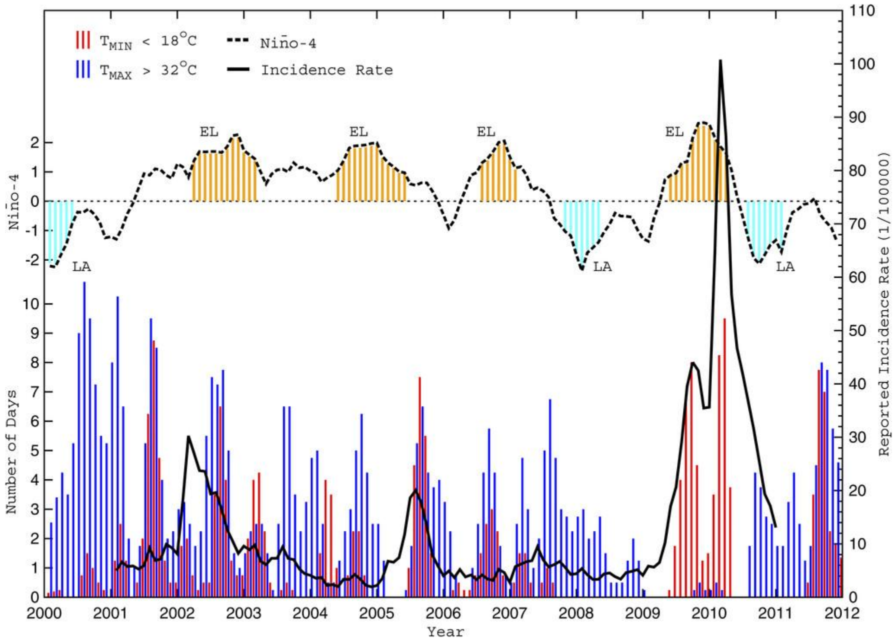
Wenju Cai, Benjamin Ng, Tao Geng, Fan Jia, Lixin Wu, Guojian Wang, Yu Liu, Bolan Gan, Kai Yang, Agus Santoso, Xiaopei Lin, Ziguang Li, Yi Liu, Yun Yang, Fei-Fei Jin, Mat Collins & Michael J. McPhaden

Nature Reviews Earth & Environment **4**, 407–418 (2023) | Cite this article

Oceanic indices

ENSO (El Nino Southern Oscillation) and **IOD** (Indian Ocean Dipole) are potential drivers of interannual variation in climate-sensitive infectious disease patterns.





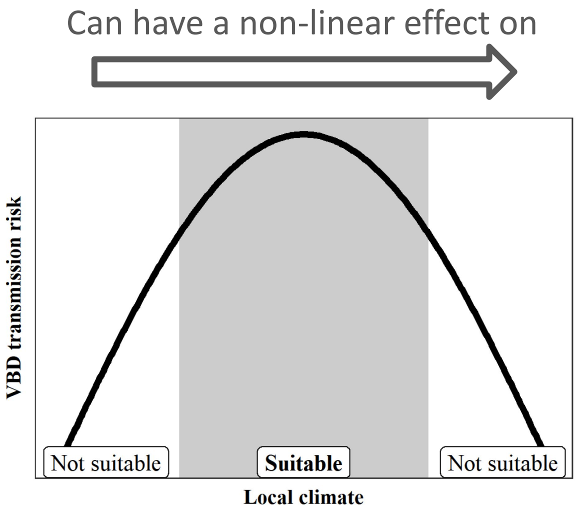
In this study in Cali, Colombia, dengue incidence often peaked 4–6 months after an El Niño event associated with above-average local temperatures and below-average local rainfall and humidity.

Ma *et al., Biology* 2022

Eastin *et al., Am. J. Trop. Med. Hyg.,2014*

Non-linear, lagged and interacting effects

Non-linear effects



Ma *et al.*, *Biology* 2022

Pathogen traits (e.g. viruses, bacteria and parasites):

- Replication and development rates
- Survival and mortality

Ectothermic vector traits (e.g. mosquitoes, ticks, sandflies, midges, blackflies, and snails):

- Reproduction and development rates
- Survival and mortality
- Biting rate
- Vector competence (the probability of becoming infectious after biting an infectious host)

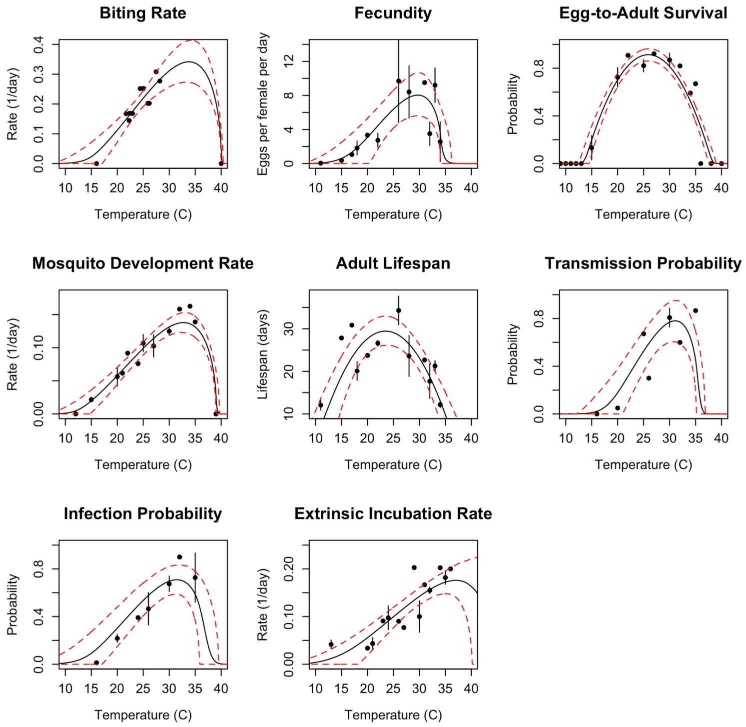
Alcayna *et al.*, *Lancet Planet Health* 2025

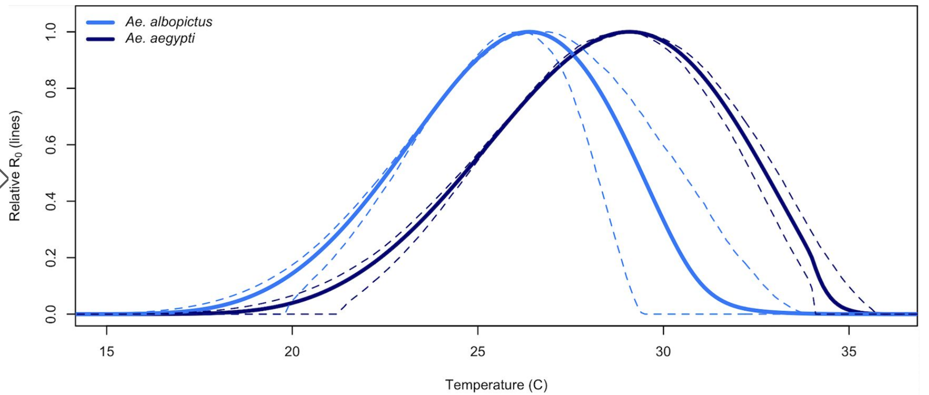
Non-linear, lagged and interacting effects

Non-linear effects

The effect of temperature on dengue virus transmission is non-linear.

Thermal responses of *Ae. aegypti* and DENV traits that drive transmission





Ae. aegypti transmission peaks at 29.1°C.

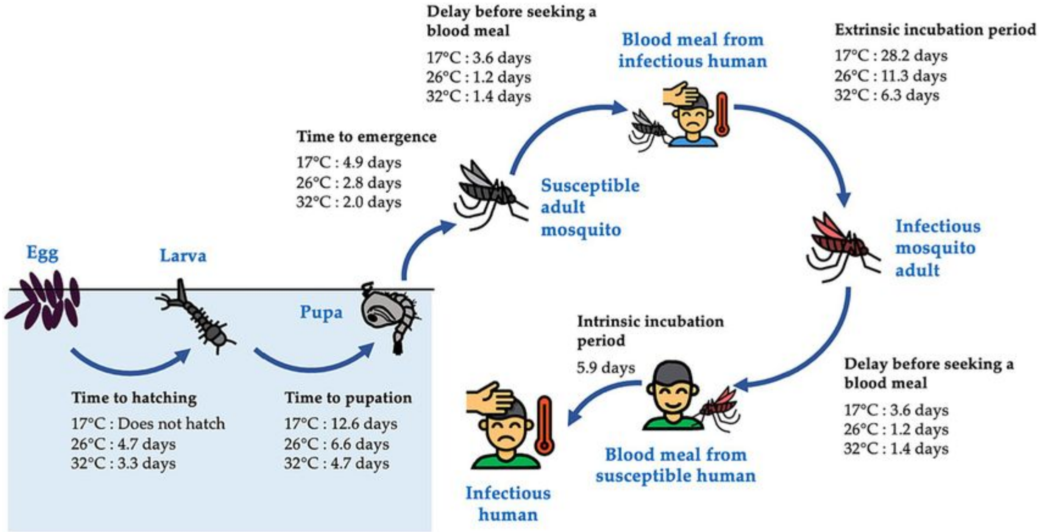
Mordecai *et al. PLOS NTD* 2017

Lagged effects

Climate-sensitive infectious diseases often have a delayed response to climate drivers. Delays might be due to:

- vector or non-human host lifecycles
- the extrinsic and intrinsic incubation period of the pathogen
- the time between symptom onset and health-seeking behaviour.

Life stages of *Aedes* mosquitoes and transmission of dengue virus

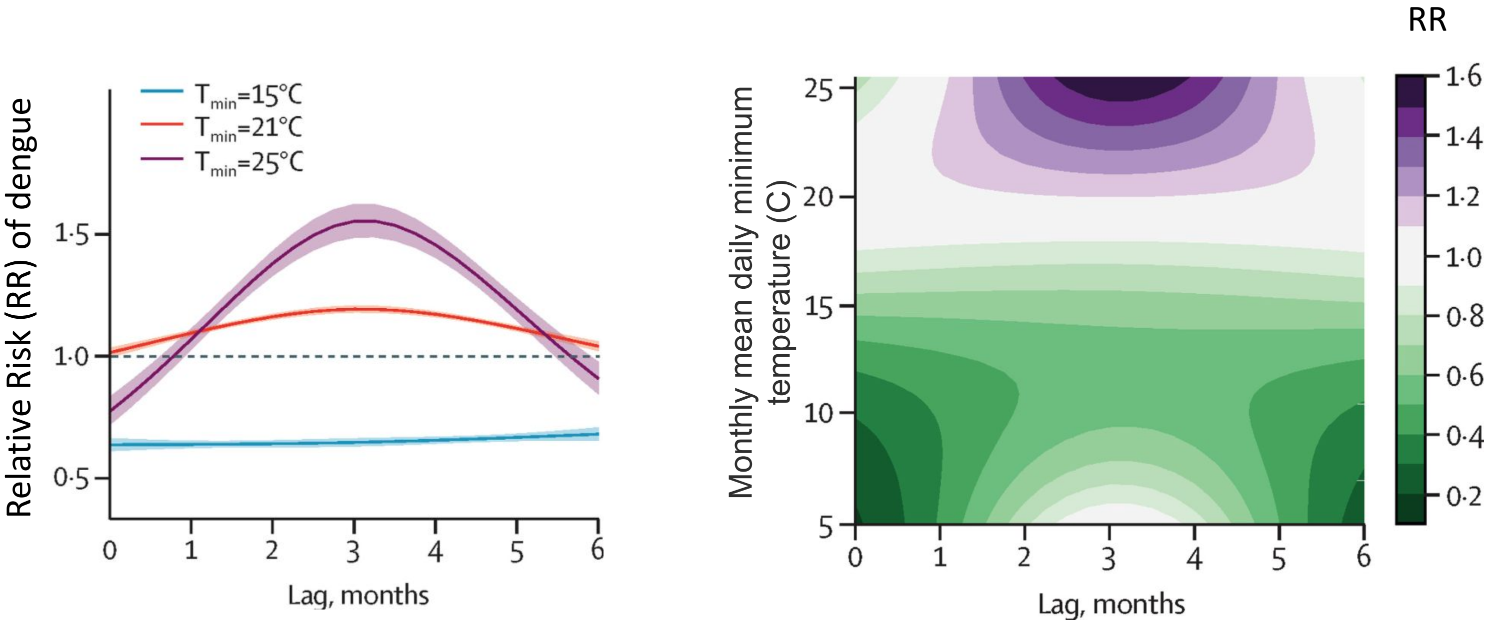


Cheng *et al.*, *Front. in Public Health* 2023

Non-linear, lagged and interacting effects

Lagged effects

The effect of temperature on dengue virus transmission is non-linear and lagged.
In this study in Brazil the greatest relative risk (RR) of dengue was found at Tmin of 25.5°C at a lag of 2–4 months.



Lowe *et al. Lancet Planetary Health* 2021

Non-linear, lagged and interacting effects

Interacting effects

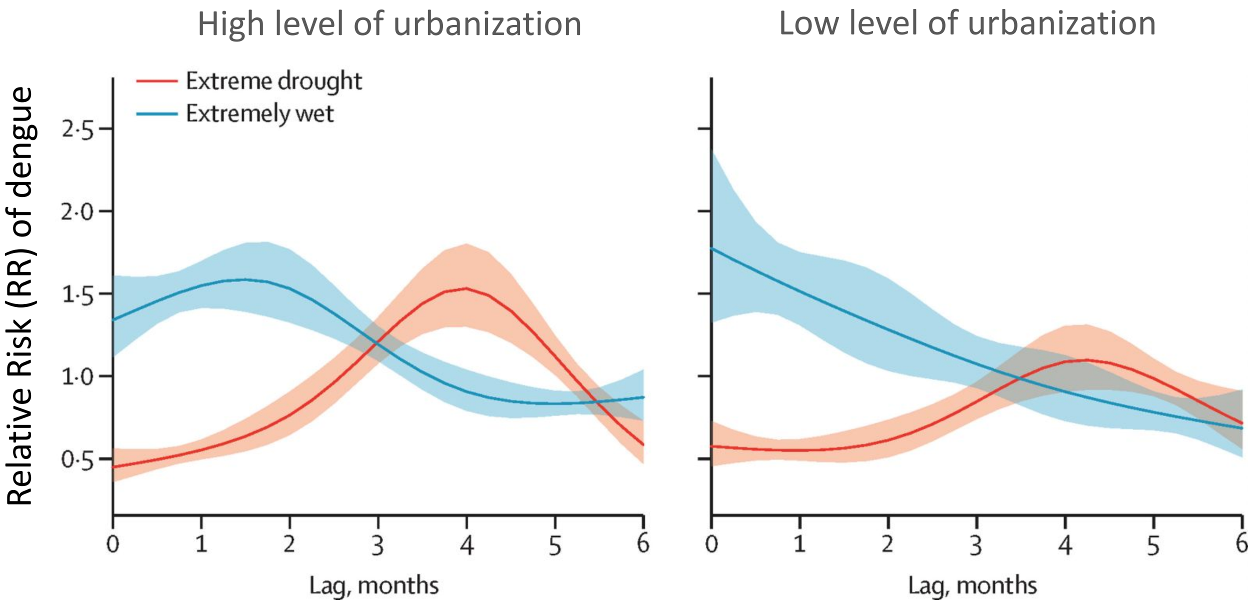
Non-climatic factors can modulate disease transmission:

- Habitat degradation and land-use change:
  - influence the density and contact among reservoirs, vectors, and humans
  - modify local climatic and environmental conditions.
- Urbanisation and human infrastructure (e.g. sanitation and water systems)
- Population demographics and socio-economic factors: can influence susceptibility and vulnerability to disease.
- Behavioural factors (such as clothing, use of insect repellent, time spent outdoors)

Non-linear, lagged and interacting effects

Interacting effects

In this study in Brazil there was an interacting effect between urbanization level and extreme values of PDSI: the greater the level of urbanisation, the higher the risk of dengue after extreme drought, while at lower levels of urbanisation the relative risk of dengue after extremely wet conditions was greater and more immediate.

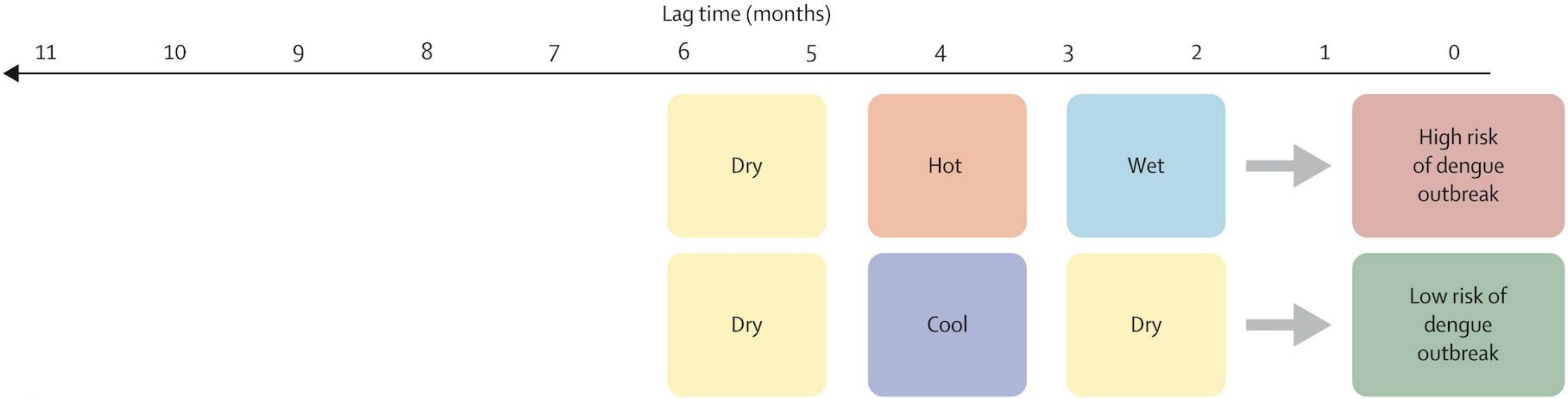


Lowe *et al. Lancet Planetary Health* 2021

Non-linear, lagged and interacting effects

Climatic factors can interact with each other at short and long lags leading to a compound effect on disease risk. Excessive rainfall following a period of abnormally low rainfall or drought is important for outbreaks of cholera, diarrheal diseases, and dengue.

In this study in Barbados, long-lag dry (lagged by 5 months), mid-lag hot (lagged by 3 months), and short-lag wet (lagged by 1 month) conditions led to the greatest dengue risk



Fletcher *et al. Lancet Planetary Health* 2025

Climate variables associated with infectious diseases

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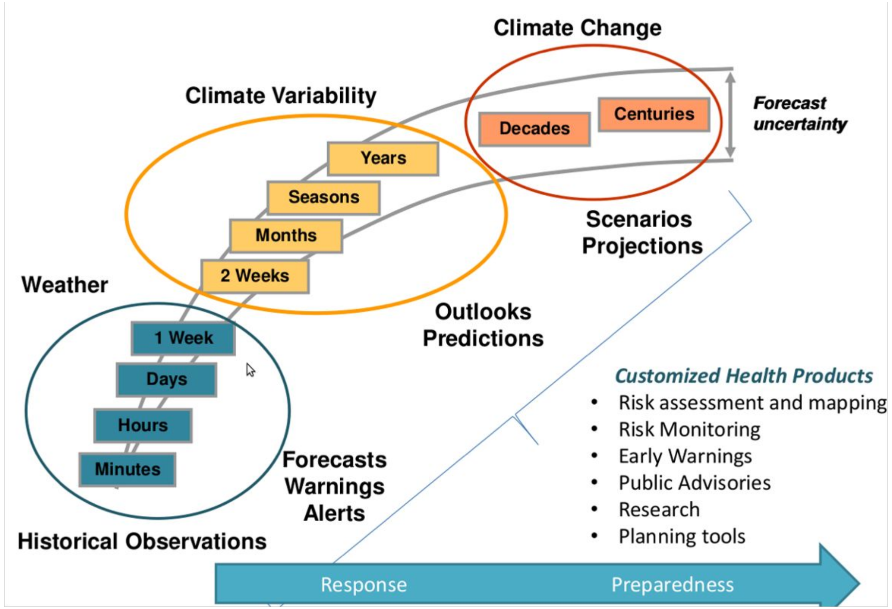
CSID	Climate/weather trigger	Confidence	References
Cholera	Abrupt and heavy/extreme rainfall, extensive flooding	High agreement, medium evidence	De Magny et al. 2012; Passeto et al. 2018; Sinyange et al 2018; Cann et al 2013
	Higher temperatures/heatwave (one study reported drier conditions being a risk modifier, whilst the other reported rainfall was a significant risk modifier)	Medium agreement, low evidence	Charnley et al. 2021; Wu et al. 2018
Diarrheal diseases	Heavy and extended rainfall (torrential) and flooding	High agreement, high evidence	Ding et al 2013; Chen et al 2012; Thompson et al. 2014; Kim et al. 2013; Deng et al 2015; Jones et al 2016; CDC 1983; Wade et al. 2003; Saulnier et al. 2017
	High temperatures	High agreement, Medium evidence	Kraay et al. 2020; Levy et al. 2016; Mertens et al. 2019; Thompson et al. 2014; Xu et al. 2014
	Heavier and longer duration of flood, than a flash flood	Low evidence	Ding et al 2013
	Excessive rainfall especially when following a dry period or period of low rainfall	High agreement, Medium evidence	Despande et al 2020; Levy et al 2016; Carlton et al. 2014; Mertens et al 2019
Malaria	Amount and duration of heavy rainfall, leading to extensive flooding	High agreement, high evidence	Boyce et al. 2018; Maes et al. 2014; Ding et al. 2014; Okaka et al. 2018; Himeidan et al. 2007
Dengue	Extreme heavy rain	High agreement, medium evidence	Chen et al. 2012; Lowe et al. 2018; Lowe et al. 2021; Cheng et al. 2021
	Above normal temperatures or drought followed by extremely high rainfall, 1-3 months lag time	High agreement, medium evidence	Lowe et al. 2018; Lowe et al. 2021; Cheng et al. 2021
	Drought conditions, especially with increased temperatures	High agreement, medium evidence	Stanke et al 2013; Ayambe et al. 2014; Lowe et al. 2018; Lowe et al. 2021
	Heatwaves delay timing and increase magnitude of dengue outbreaks, up to a point as longer duration of heatwaves (number of heatwave days) may reduce dengue outbreak risk	Medium agreement, medium evidence	Cheng et al 2020; Cheng et al. 2021; Seah et al. 2021

Alcayna *et al*. One Earth, 2022

Climate-informed early warning systems

Climate-informed early warning systems: lead times

Climate-informed early warning systems integrate climate data to predict the risk of an infectious disease outbreak.



Courtesy: J. Shumake-Guillemot, WMO

For vector-borne diseases, a typical lead time ranges from 1 to 6 months

Early warning systems: engagement

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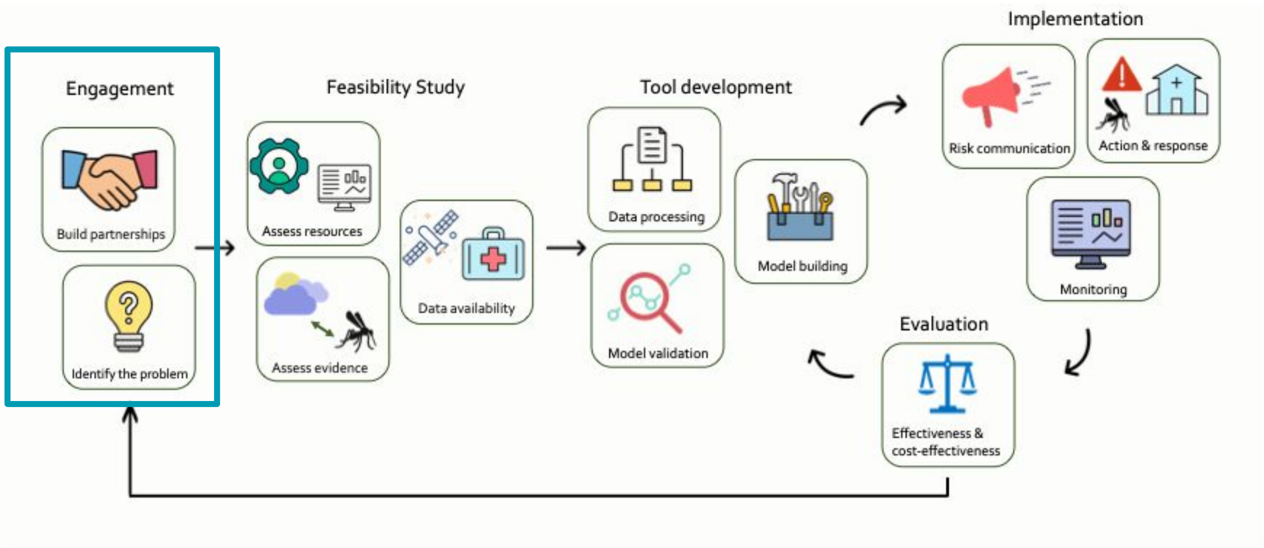
Stages involved in the co-creation of an early warning system for vector-borne disease



1. Engagement
2. Feasibility study
3. Development
4. Implementation
5. Evaluation

CHAPTER 12

Early warning systems for vector-borne diseases: engagement, methods and implementation

Emilie Finch[1,2], Martín Lotto Batista[3,4], Tilly Alcayna[1,2,5], Sophie A. Lee[1,2], Isabel K. Fletcher[6] and Rachel Lowe[1,2,4,7*]*

Early warning systems: feasibility

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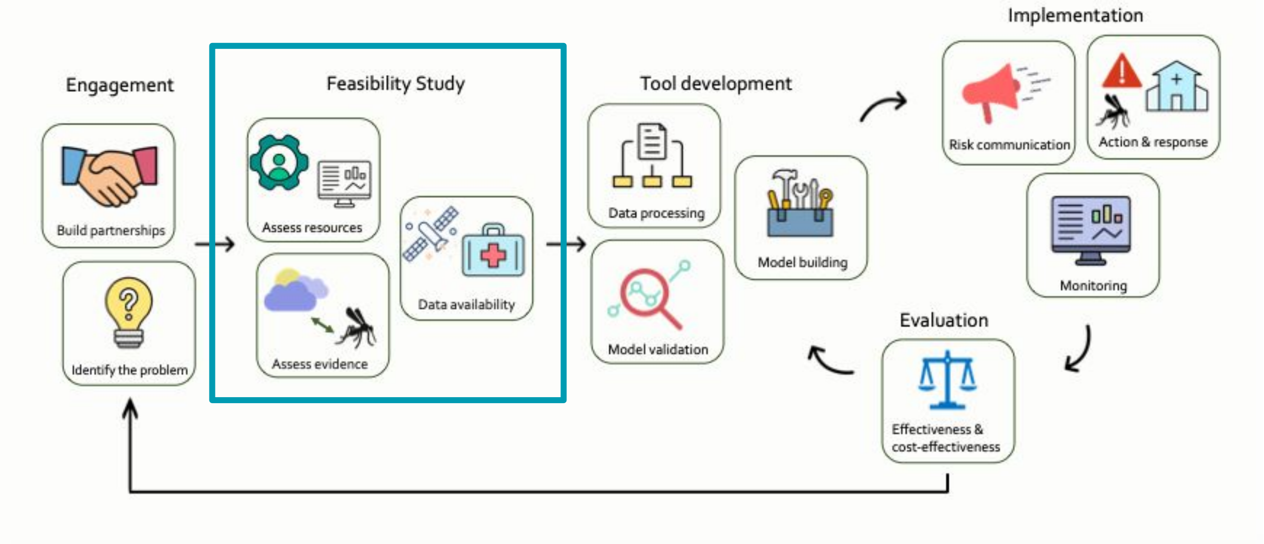
Stages involved in the co-creation of an early warning system for vector-borne diseases



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Early warning systems: development

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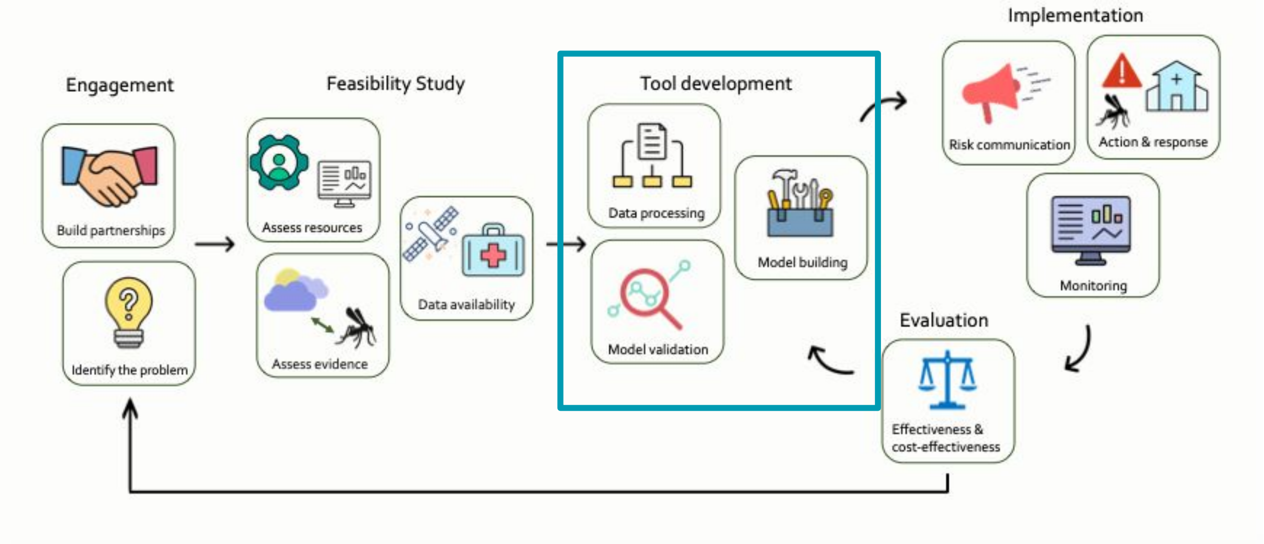

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Early warning systems: development

Statistical

- Characterise the relationship between outcome and exposure under a set of assumptions.
- Require long time series.
- Can produce reliable uncertainty estimates.
- Examples: hierarchical models, ARIMA models.

Machine learning

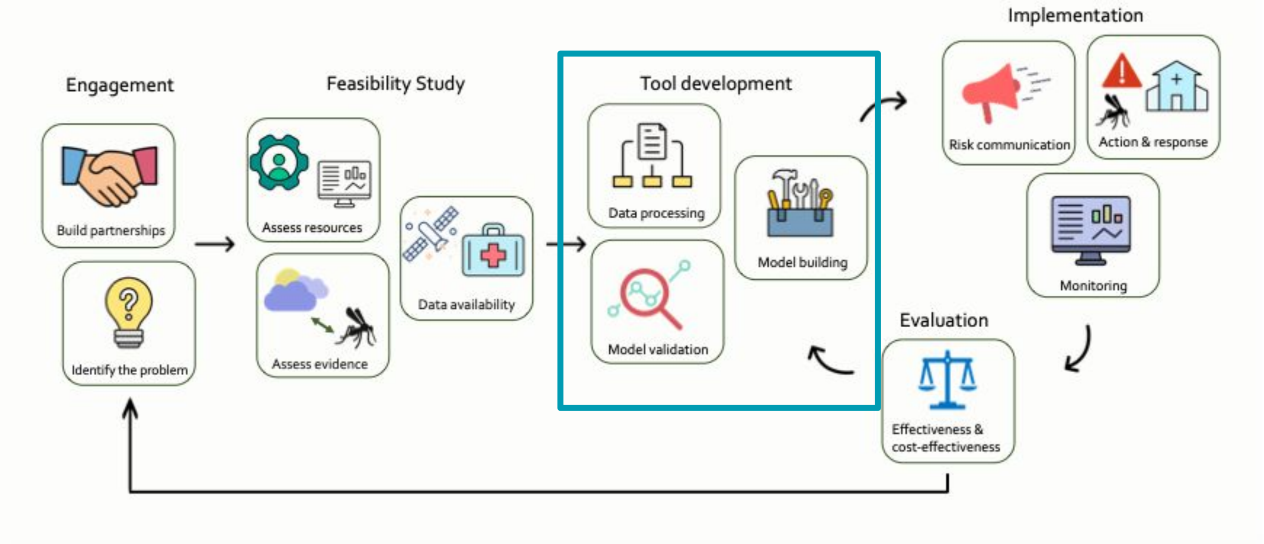
- More flexible than statistical models, can achieve better results but require more data.
- More difficult interpretation and uncertainty quantification.
- Examples: neural networks, random forest.

Mechanistic

- Capture the underlying biological processes, population immunity, contact patterns, population mobility and control measures.
- Require deep understanding and many assumptions, not always feasible/realistic.
- Examples: compartmental model, agent-based models

Early warning systems: development

Stages involved in the co-creation of an early warning system for vector-borne disease



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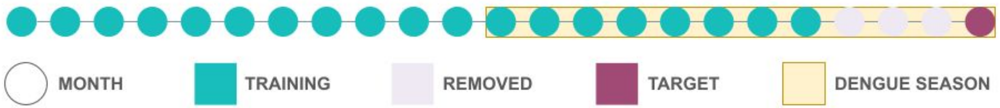
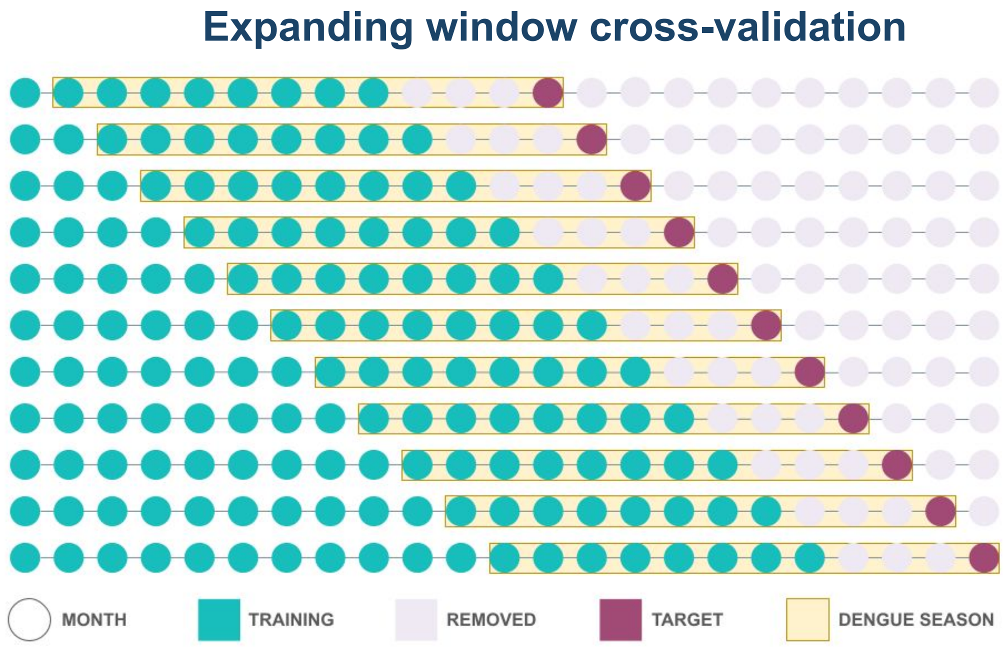
Early warning systems: development

Expanding window



Fletcher 2025

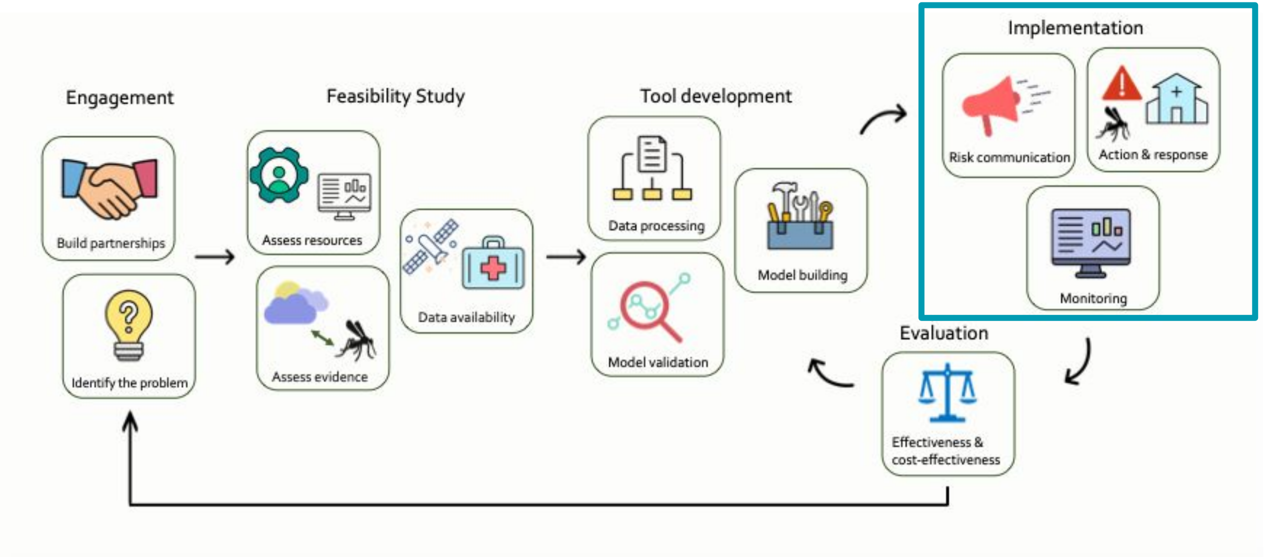
Early warning systems: development



Fletcher 2025

Early warning systems: implementation

Stages involved in the co-creation of an early warning system for vector-borne disease



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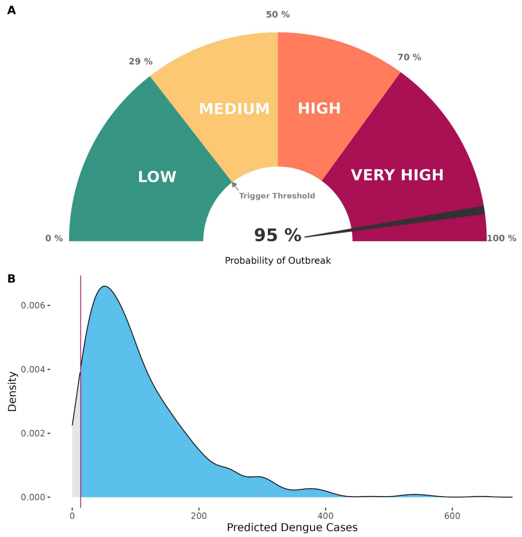
Early warning systems: implementation

Barbados - Dengue forecast



TAKE ACTION

BE PREPARED

BE AWARE

ROUTINE ACTION

Associated levels of intervention

- Predicting cases vs. outbreaks.
- Translate complex results into clear insights.
- Conveying uncertainty.

Fletcher *et al. Lancet Planetary Health* 2025

Early warning systems: implementation

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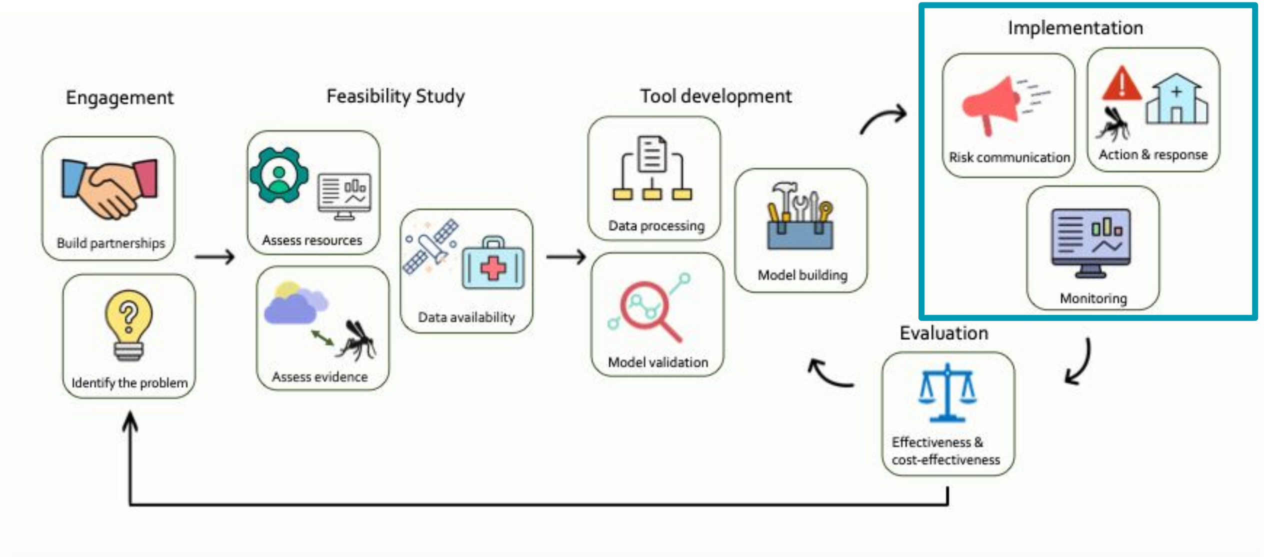
Stages involved in the co-creation of an early warning system for vector-borne disease



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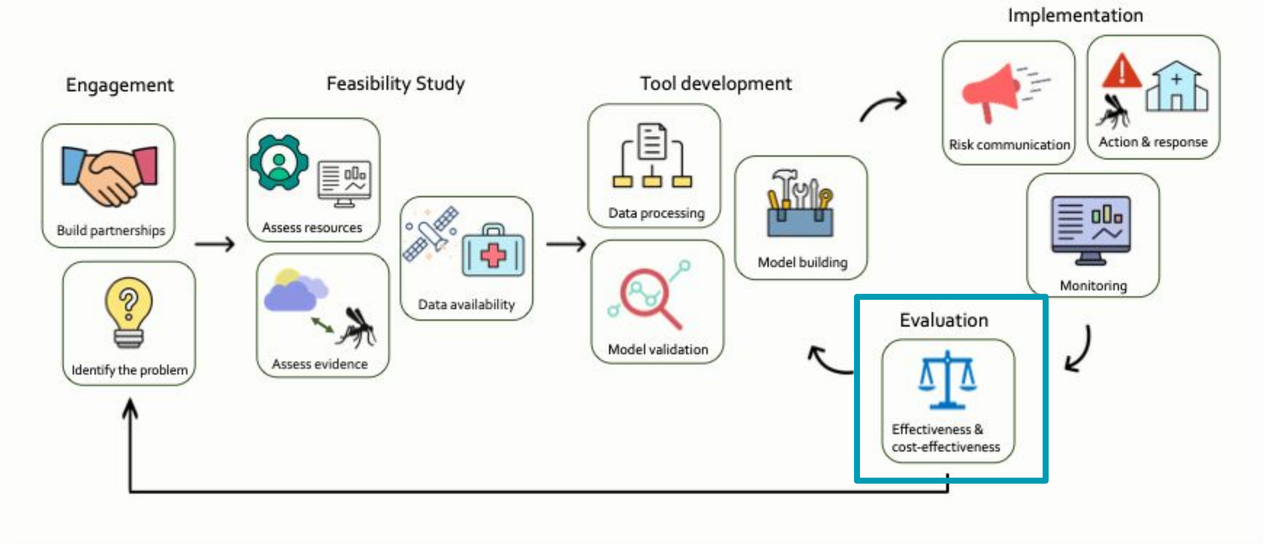
Early warning systems: evaluation

Stages involved in the co-creation of an early warning system for vector-borne disease



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Data structure, pre-processing and exploration

Types of data

HARMONIZE

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Weather & Climate Data

Met station

Reanalysis

Seasonal forecasts

Weather and hydrological sensors

Type depends on EWS

Temperature, precipitation, oceanic indices

Land use and land cover data

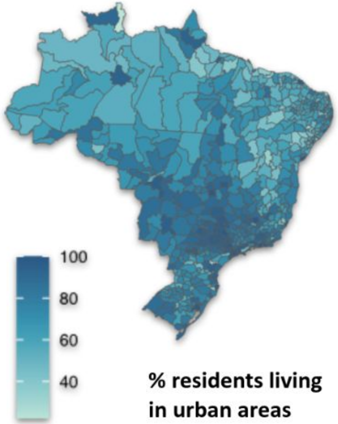
Satellite Images

Drone Images

Vegetation indices

Water indices

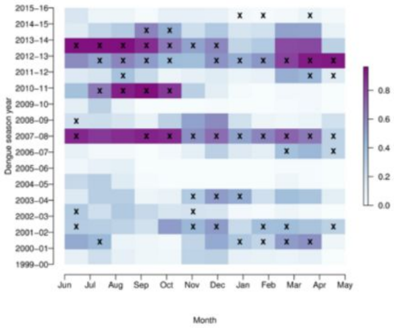
Demographic and socio-economic indicators



Vulnerability and inequality

Population at risk

Disease surveillance data



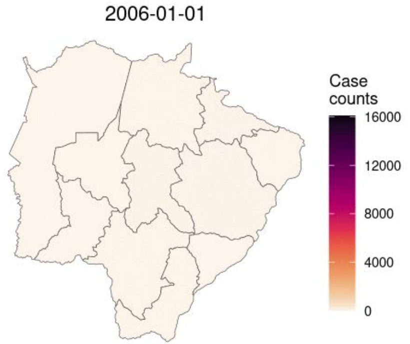
Variable of interest

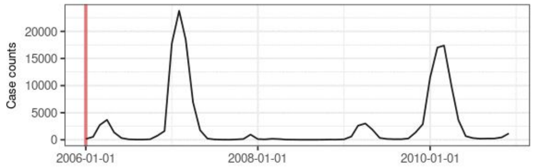
Location-dependent

Data structure

Regular time series of one or several areas containing:

- Temporal ID (date)
- Spatial ID (area)
- Diseases counts for a specific time/area
- Population at risk for a specific time/area
- Predictors:
  - Spatio-temporal: climate
  - Temporal: ENSO indicator
  - Spatial: climate area (Köppen)





	date	geocode	cases	tas	prlr	nino
1	2010-01-01	24001	3	26.40411	66.1383667	1.52
2	2010-02-01	24001	2	27.24414	52.0459404	1.27
3	2010-03-01	24001	2	27.49093	49.4391060	0.95
4	2010-04-01	24001	5	26.88115	116.6783752	0.49
5	2010-05-01	24001	23	26.77081	44.9898071	-0.10
6	2010-06-01	24001	29	25.48106	70.8722610	-0.55
7	2010-07-01	24001	15	24.37067	91.5613556	-0.96
8	2010-08-01	24001	12	24.27328	28.0503407	-1.36

Pre-processing: temperature and precipitation rolling statistics

Cumulative climate data can capture factors that a single-point variable doesn't reflect:

- Temperature (average):
  - Duration of warm/cold conditions -> vector cycle
- Precipitation (sum):
  - Persistent low precipitation -> drought
  - Persistent high precipitation -> high soil moisture and humidity

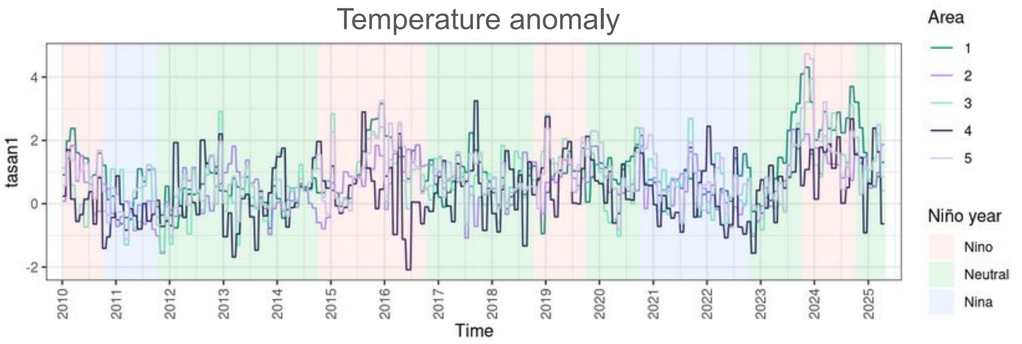
Date	Temperature	Temperature - 3 months
2015-01-01	12	
2015-02-01	13	
2015-03-01	15	13.3
2015-04-01	17	15
2015-05-01	20	17.3
2015-06-01	23	20

Averaging times depend on the health outcome.

Vector-borne: 3-12 months.

Pre-processing: temperature and precipitation anomalies

We can create **anomaly indices** to compare the precipitation for a given location and time to their respective climatologies (30+ years of historical data)



1. We compute historical monthly means and standard deviations for each location in our dataset.

2. We standardise the values (z-scores) in our dataset using these values.

Precipitation values require an extra standardization step due to their skewed distribution

https://doi.org/10.1175/2009JCLI2909.1

Pre-processing: lagging climate data

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We want of include **lags of the exposures** because:

- Delayed effects.
- Be able to use observations in forecasts.
  - If we use a 3-month lag, we will be able to predict in 3 months using the observed weather today.

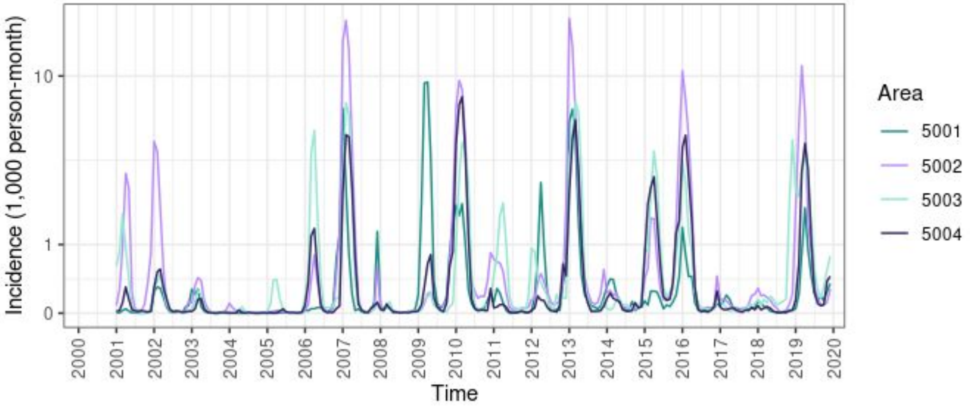
Date	Temperature	Temperature - lag 3
2015-01-01	12	
2015-02-01	13	
2015-03-01	15	
2015-04-01	17	12
2015-05-01	20	13
2015-06-01	23	15

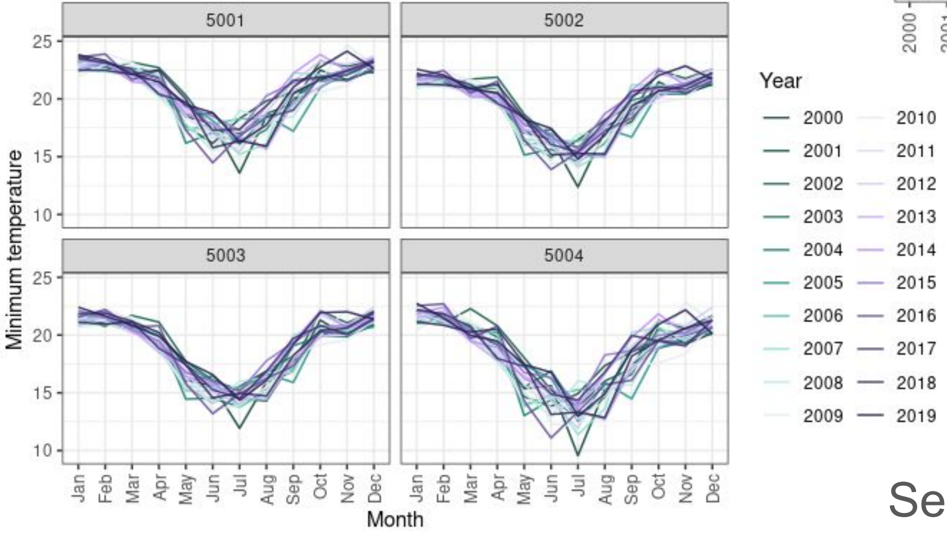
The lag value will depend on the health outcome.

Vector-borne: 1-6 months.

Exploring: temporal component

Time series





Seasonality plots

Exploring: spatial and spatio-temporal component

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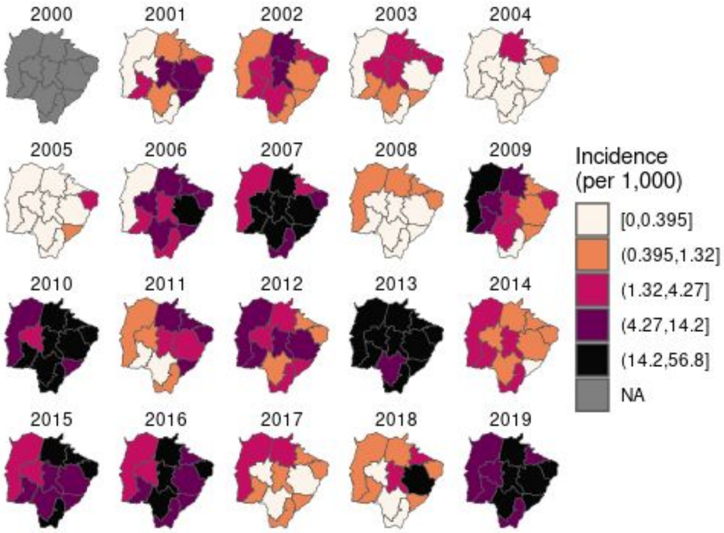
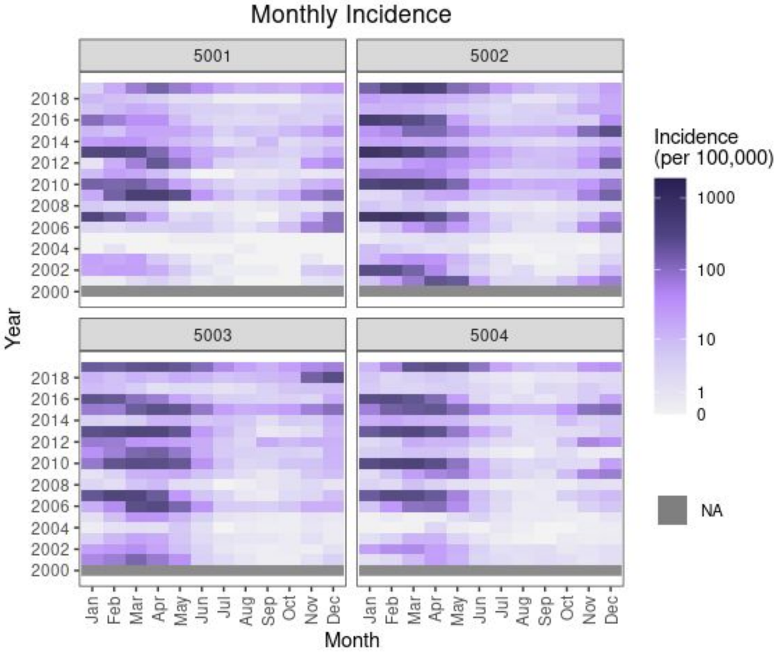
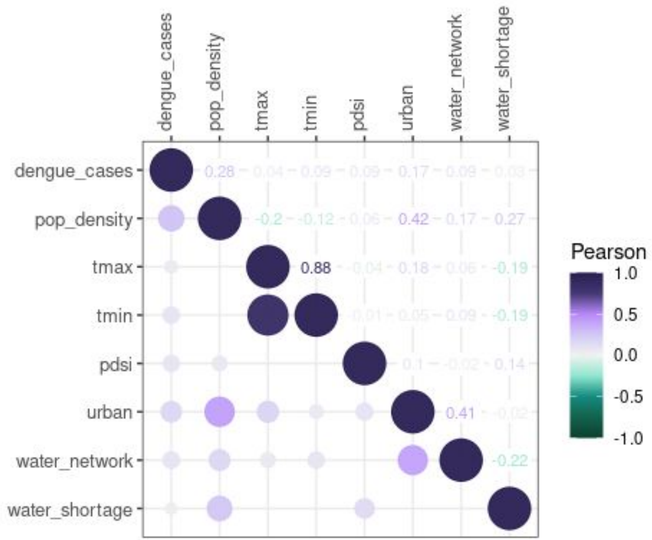
Choropleth maps



Heatmaps

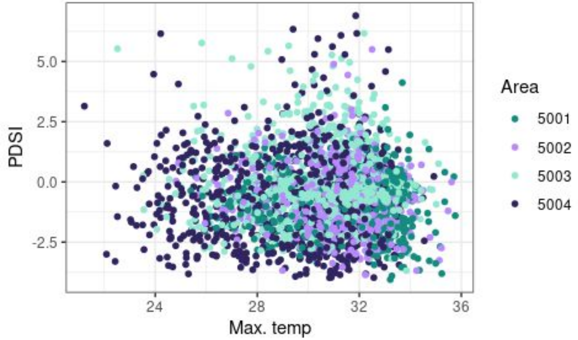


Exploring: correlation

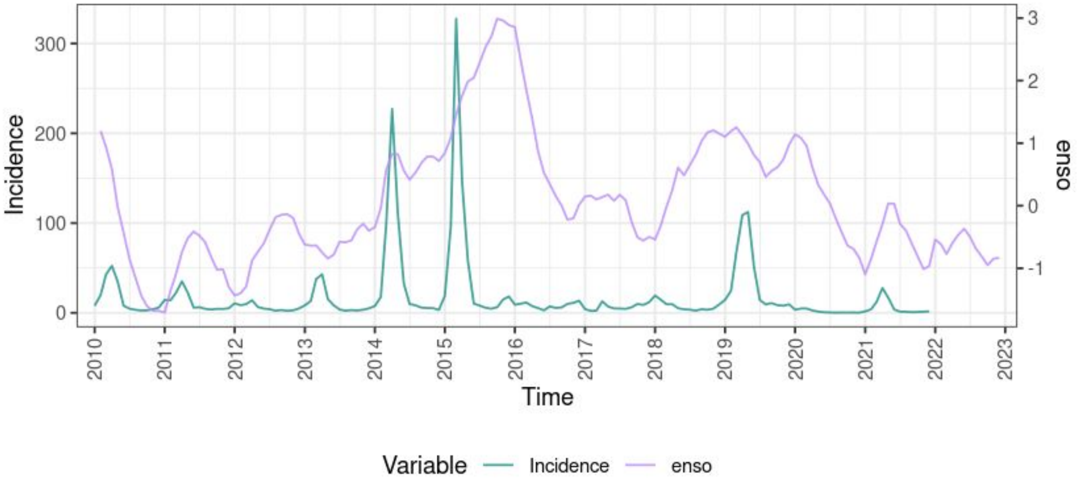


Correlation matrices

Scatterplots



Dual-axis time series



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Reading guide

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- Di Napoli, C., McGushin, A., Romanello, M. *et al.* Tracking the impacts of climate change on human health via indicators: lessons from the *Lancet* Countdown. *BMC Public Health* 22, 663 (2022). https://doi.org/10.1186/s12889-022-13055-6
- Patz, J., Campbell-Lendrum, D., Holloway, T. *et al.* Impact of regional climate change on human health. *Nature* 438, 310–317 (2005). https://doi.org/10.1038/nature04188
- Luber, B., CDC: Building Resilience in the Public Health Sector: The Development of an Evidence–Based Framework for Climate change Adaptation Planning
- Alcayna, T., Rao, V. B., & Lowe, R. (2025). Identifying the climate sensitivity of infectious diseases: A conceptual framework. *The Lancet Planetary Health*, *9*(8), 101291. https://doi.org/10.1016/j.lanplh.2025.101291
- Shocket, M. S., Anderson, C. B., Caldwell, J. M., Childs, M. L., Couper, L. I., Han, S., Harris, M. J., Howard, M. E., Kai, M. P., MacDonald, A. J., Nova, N., & Mordecai, E. A. (2020). Environmental Drivers of Vector-Borne Diseases. In J. M. Drake, M. Bonsall, & M. Strand (Eds.), *Population Biology of Vector-Borne Diseases* (1st ed., pp. 85–118). Oxford University PressOxford. https://doi.org/10.1093/oso/9780198853244.003.0006
- Jones, N., Bouzid, M., Few, R., Hunter, P., & Lake, I. (2020). Water, sanitation and hygiene risk factors for the transmission of cholera in a changing climate: Using a systematic review to develop a causal process diagram. *Journal of Water and Health*, *18*(2), 145–158. https://doi.org/10.2166/wh.2020.088
- *IPCC AR6 Working Group 1: Technical Summary | Climate Change 2021: The Physical Science Basis*. (n.d.). https://www.ipcc.ch/report/ar6/wg1/chapter/technical-summary/
- Mordecai, E. A., Caldwell, J. M., Grossman, M. K., Lippi, C. A., Johnson, L. R., Neira, M., Rohr, J. R., Ryan, S. J., Savage, V., Shocket, M. S., Sippy, R., Stewart Ibarra, A. M., Thomas, M. B., & Villena, O. (2019). Thermal biology of mosquito-borne disease. *Ecology Letters*, *22*(10), 1690–1708. https://doi.org/10.1111/ele.13335
- Mordecai, E. A., Caldwell, J. M., Grossman, M. K., Lippi, C. A., Johnson, L. R., Neira, M., Rohr, J. R., Ryan, S. J., Savage, V., Shocket, M. S., Sippy, R., Stewart Ibarra, A. M., Thomas, M. B., & Villena, O. (2020). Climate change could shift disease burden from malaria to arboviruses in Africa. *The Lancet Planetary Health*, 4(9), e416–e423. https://doi.org/10.1016/S2542-5196(20)30178-9
- Barcellos, C., Matos, V., Lana, R. M., & Lowe, R. (2024). Climate change, thermal anomalies, and the recent progression of dengue in Brazil. *Scientific Reports*, *14*(1), 5948. https://doi.org/10.1038/s41598-024-56044-y
- Romanello, M., Walawender, M., Hsu, S.-C., Moskeland, A., Palmeiro-Silva, Y., Scamman, D., Ali, Z., Ameli, N., Angelova, D., Ayeb-Karlsson, S., Basart, S., Beagley, J., Beggs, P. J., Blanco-Villafuerte, L., Cai, W., Callaghan, M., Campbell-Lendrum, D., Chambers, J. D., Chicmana-Zapata, V., … Costello, A. (2024). The 2024 report of the Lancet Countdown on health and climate change: Facing record-breaking threats from delayed action. *Lancet (London, England)*, *404*(10465), 1847–1896. https://doi.org/10.1016/S0140-6736(24)01822-1
- 2024 Report Visual Summary. (n.d.). *Lancet Countdown*. https://lancetcountdown.org/2024-visual-summary/
- Cai, W., Ng, B., Geng, T., Jia, F., Wu, L., Wang, G., Liu, Y., Gan, B., Yang, K., Santoso, A., Lin, X., Li, Z., Liu, Y., Yang, Y., Jin, F.-F., Collins, M., & McPhaden, M. J. (2023). Anthropogenic impacts on twentieth-century ENSO variability changes. *Nature Reviews Earth & Environment*, *4*(6), 407–418. https://doi.org/10.1038/s43017-023-00427-8
- Cai, W., Santoso, A., Collins, M., Dewitte, B., Karamperidou, C., Kug, J.-S., Lengaigne, M., McPhaden, M. J., Stuecker, M. F., Taschetto, A. S., Timmermann, A., Wu, L., Yeh, S.-W., Wang, G., Ng, B., Jia, F., Yang, Y., Ying, J., Zheng, X.-T., … Zhong, W. (2021). Changing El Niño–Southern Oscillation in a warming climate. *Nature Reviews Earth & Environment*, *2*(9), 628–644. https://doi.org/10.1038/s43017-021-00199-z

Reading guide

- *ENSO and Climate Change: What does the new IPCC report say? | NOAA Climate.gov*. (2021, September 27). https://www.climate.gov/news-features/blogs/enso/enso-and-climate-change-what-does-new-ipcc-report-say
- *Has climate change already affected ENSO? | NOAA Climate.gov*. (2023, July 27). https://www.climate.gov/news-features/blogs/enso/has-climate-change-already-affected-enso
- Ma, J., Guo, Y., Gao, J., Tang, H., Xu, K., Liu, Q., & Xu, L. (2022). Climate Change Drives the Transmission and Spread of Vector-Borne Diseases: An Ecological Perspective. *Biology*, *11*(11), 1628. https://doi.org/10.3390/biology11111628
- Eastin, M. D., Delmelle, E., Casas, I., Wexler, J., & Self, C. (2014). Intra- and Interseasonal Autoregressive Prediction of Dengue Outbreaks Using Local Weather and Regional Climate for a Tropical Environment in Colombia. *The American Journal of Tropical Medicine and Hygiene*, *91*(3), 598–610. https://doi.org/10.4269/ajtmh.13-0303
- Mordecai, E. A., Cohen, J. M., Evans, M. V., Gudapati, P., Johnson, L. R., Lippi, C. A., Miazgowicz, K., Murdock, C. C., Rohr, J. R., Ryan, S. J., Savage, V., Shocket, M. S., Stewart Ibarra, A., Thomas, M. B., & Weikel, D. P. (2017). Detecting the impact of temperature on transmission of Zika, dengue, and chikungunya using mechanistic models. *PLOS Neglected Tropical Diseases*, *11*(4), e0005568. https://doi.org/10.1371/journal.pntd.0005568
- Cheng, Q., Jing, Q., Collender, P. A., Head, J. R., Li, Q., Yu, H., Li, Z., Ju, Y., Chen, T., Wang, P., Cleary, E., & Lai, S. (2023). Prior water availability modifies the effect of heavy rainfall on dengue transmission: A time series analysis of passive surveillance data from southern China. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1287678
- Alcayna, T., Fletcher, I., Gibb, R., Tremblay, L., Funk, S., Rao, B., & Lowe, R. (2022). Climate-sensitive disease outbreaks in the aftermath of extreme climatic events: A scoping review. *One Earth*, *5*(4), 336–350. https://doi.org/10.1016/j.oneear.2022.03.011
- Fletcher, C., Moirano, G., Alcayna, T., Rollock, L., Van Meerbeeck, C. J., Mahon, R., Trotman, A., Boodram, L.-L., Browne, T., Best, S., Lührsen, D., Diaz, A. R., Dunbar, W., Lippi, C. A., Ryan, S. J., Colón-González, F. J., Stewart-Ibarra, A. M., & Lowe, R. (2025). Compound and cascading effects of climatic extremes on dengue outbreak risk in the Caribbean: An impact-based modelling framework with long-lag and short-lag interactions. *The Lancet Planetary Health*, *9*(8), 101279. https://doi.org/10.1016/j.lanplh.2025.06.003
- Lowe, R., Lee, S. A., O'Reilly, K. M., Brady, O. J., Bastos, L., Carrasco-Escobar, G., De Castro Catão, R., Colón-González, F. J., Barcellos, C., Carvalho, M. S., Blangiardo, M., Rue, H., & Gasparrini, A. (2021). Combined effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: A spatiotemporal modelling study. *The Lancet Planetary Health*, *5*(4), e209–e219. https://doi.org/10.1016/S2542-5196(20)30292-8
- Finch, E., Batista, M. L., Alcayna, T., Lee, S. A., Fletcher, I. K., & Lowe, R. (2023). Early warning systems for vector-borne diseases: Engagement, methods and implementation. In *Planetary health approaches to understand and control vector-borne diseases* (pp. 347–386). Wageningen Academic. https://doi.org/10.3920/9789004688650_014
- *HARMONIZE*. https://www.harmonize-tools.org
- Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, *23*(7), 1696–1718. https://doi.org/10.1175/2009JCLI2909.1
- Milà, C., Moirano, G., Kawiecki, A. B., Lowe, R. (2025). *GHRexplore: Exploratory Analysis of Temporal and Spatio-Temporal Health Data* (Version 0.2.1) [Computer software]. https://cran.r-project.org/web/packages/GHRexplore/index.html