

Spatio-temporal modeling of arboviruses

MSc in Statistics

Project Fair

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Viral genomic epidemiology
Epidemiology and viral epidemics
Outbreak preparedness

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Spatio-temporal statistics
Bayesian statistics
Computational methods for inference

Introduction

Four potential project ideas:

Project 1. Linking dengue transmission and social vulnerability

Project 2. Modelling the dynamic behavior and interaction of dengue virus lineages

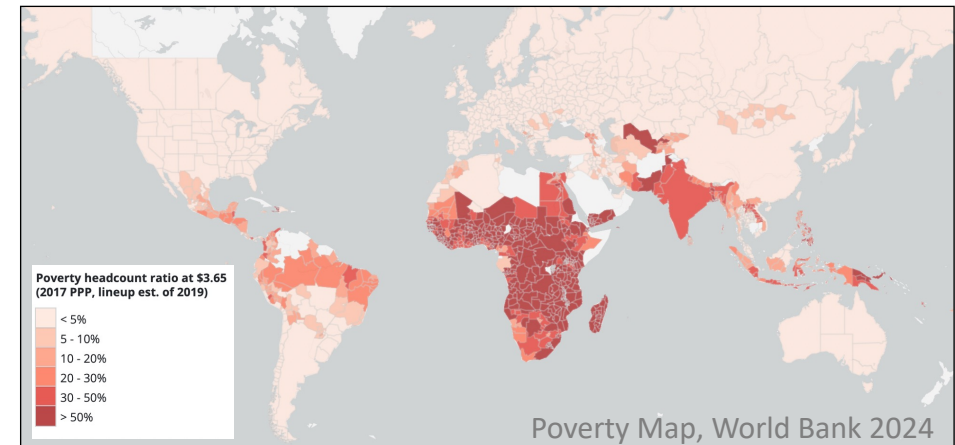
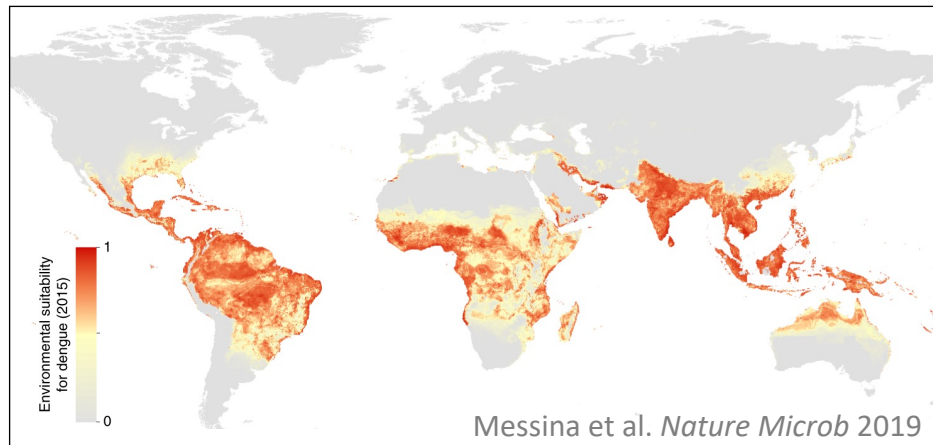
Project 3. Seasonal dengue forecasting

Project 4. Modeling yellow-fever incidence based on different types of transmission

Linking dengue transmission and social vulnerability

Overarching Aim: to investigate the correlations between socioeconomic factors and dengue incidence.

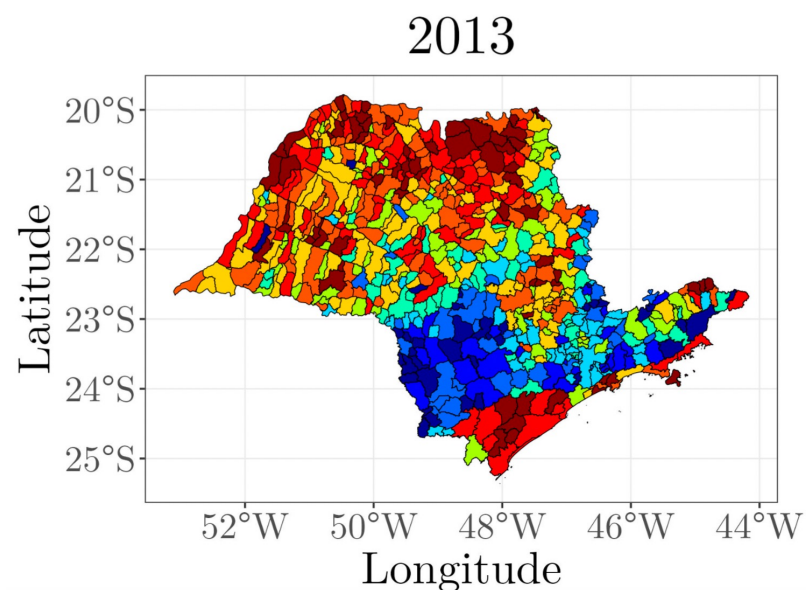
Climate factors, such as temperature and precipitation, contribute to the proliferation of *Aedes aegypti*. However, social aspects, including urbanization and poverty levels, also play significant roles both in dengue transmission and in dengue surveillance.



Dengue incidence in São Paulo, Brazil

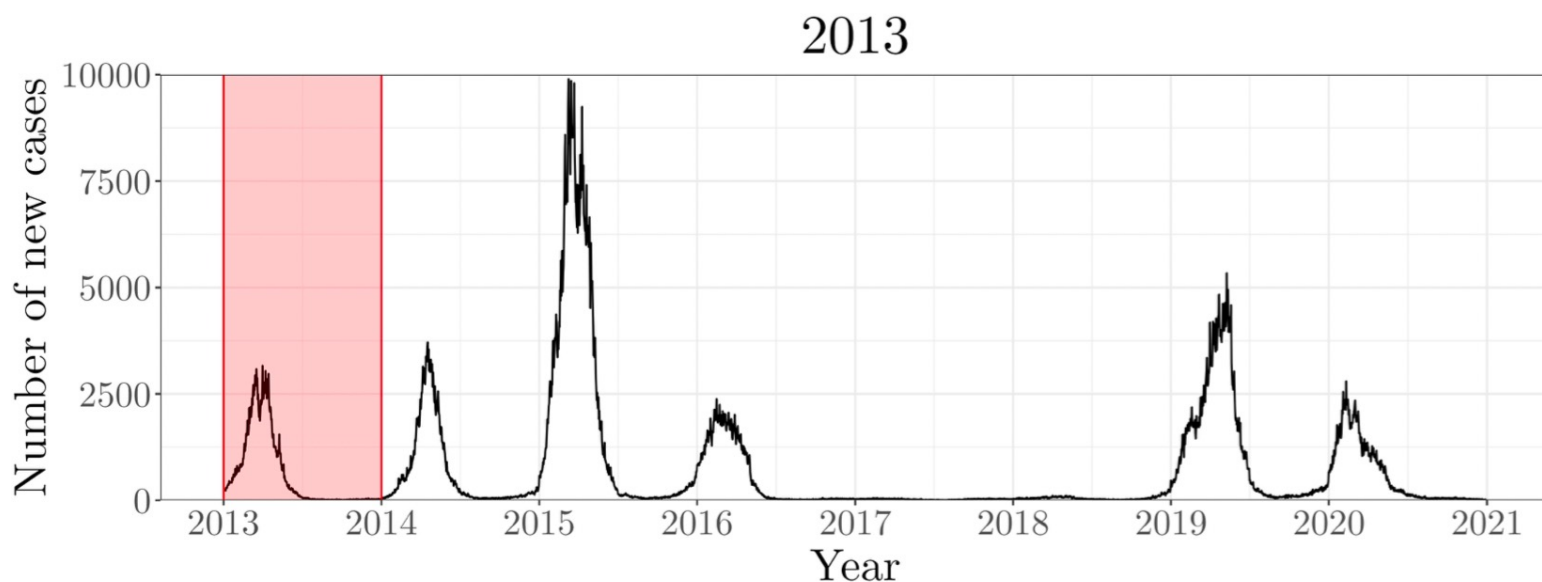
Data: 10-year municipality-level resolution dengue incidence data from São Paulo State, publicly available from SINAN, Brazil Ministry of Health. Municipality-level resolution poverty indicators available through collaboration with UK-Brazil CADDE Project.

Note: It is possible to evaluate link between dengue & socioeconomic vulnerability also at global scale.



Per 100,000 inhab.

0	10-20	50-100	200-500	1,000-2,000
1-10	20-50	100-200	500-1,000	2,000+



CADDE Project 2024

Modelling the dynamic behavior and interaction of dengue virus lineages

Overarching Aim: to investigate the dynamic behavior and interaction of dengue virus lineages in hyperendemic settings in Brazil (and/or e.g. Thailand).

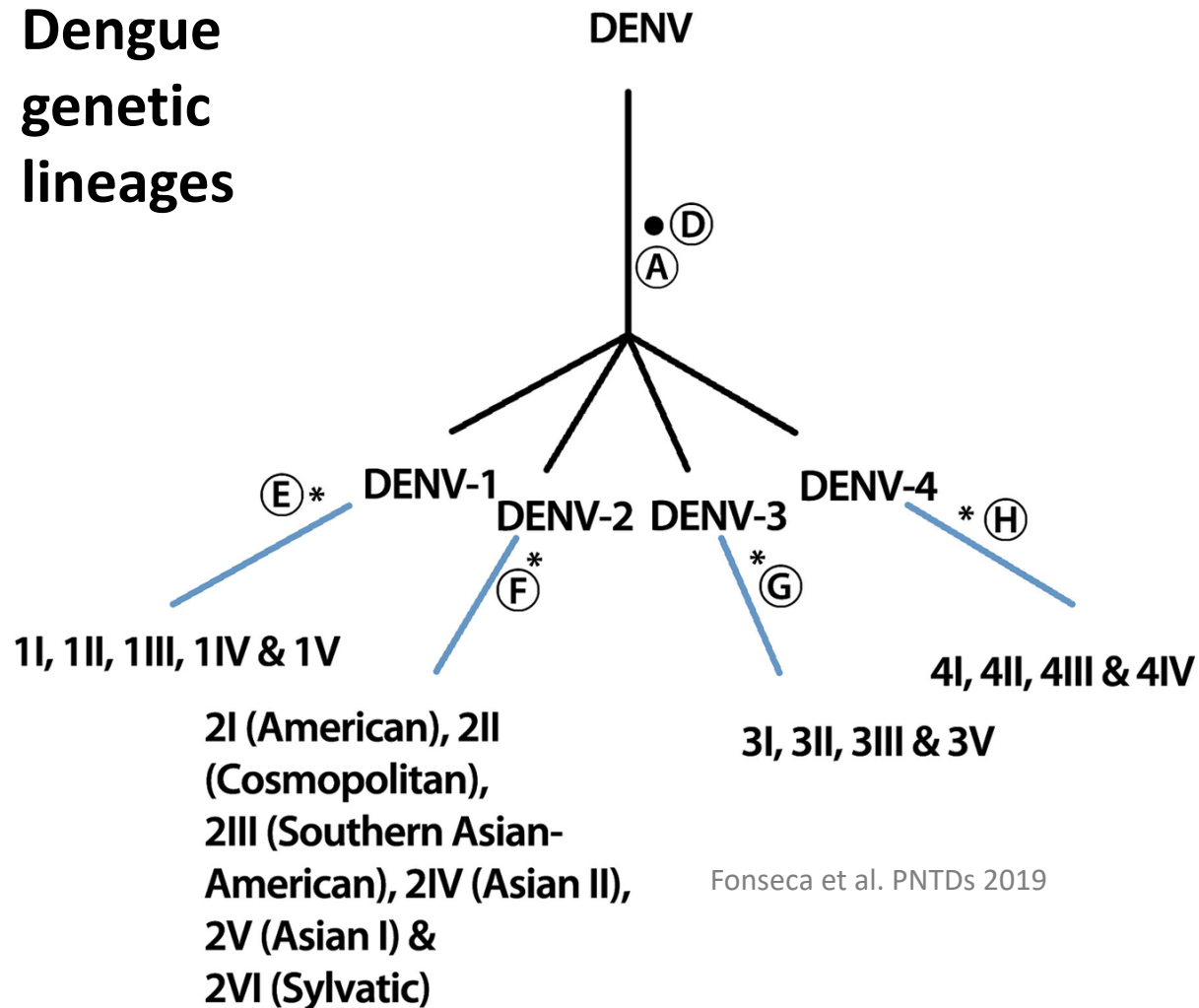
There are four dengue virus serotypes (DENV1-4), and >20 genotypes. Where detected, these lineages seem to go extinct and are replaced cyclically, with invasion of a new lineage typically associated with larger outbreaks.

While reinfection with the same serotype is rare in the short to mid-term, an individual who has previously experienced infection with a specific serotype does not develop immunity to others. These serotypes can circulate simultaneously (hyperendemicity).

The poor understanding of the dynamic behaviour and interaction between dengue serotypes makes it challenging to anticipate the occurrence of large outbreaks.

Dengue genetic and epidemiological data

Dengue genetic lineages



NCBI Virus Database

Nucleotide (45,733)		Protein (44,115)	RefSeq Genome (4)		Select Columns
Accession	Organism Name	Submitters	Organization	Release Date	
<input checked="" type="checkbox"/> NC_002640	dengue virus type 4	Durbin,A.P., et al.	National Center for Biotec...	2001-01-03	
<input checked="" type="checkbox"/> NC_001477	dengue virus type 1	Puri,B., et al.	National Center for Biotec...	1997-02-28	
<input checked="" type="checkbox"/> NC_001474	dengue virus type 2	Kinney,R.M., et al.	National Center for Biotec...	1993-08-02	

<https://www.ncbi.nlm.nih.gov/labs/virus/vssi/#/>

Open dengue database

 OPEN DENGUE

A global database of public dengue case data

<https://opendengue.org/project.html>

Seasonal dengue forecasting

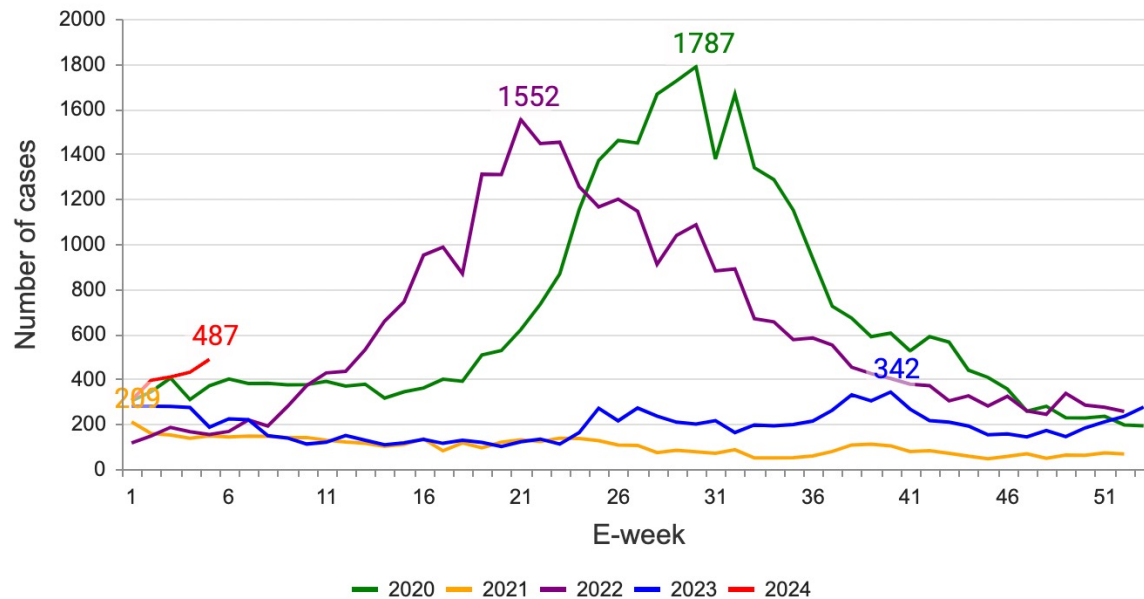
Overarching Aim: To develop an accurate forecasting model for dengue early warning system in Singapore and/or Brazil, using a wide range of weather factors as input variables.

Traditional machine learning models: Poisson regression models, hierarchical Bayesian models, autoregressive integrated moving average (ARIMA), least absolute shrinkage and selection operator (LASSO) regression, generalized additive models (GAMs).

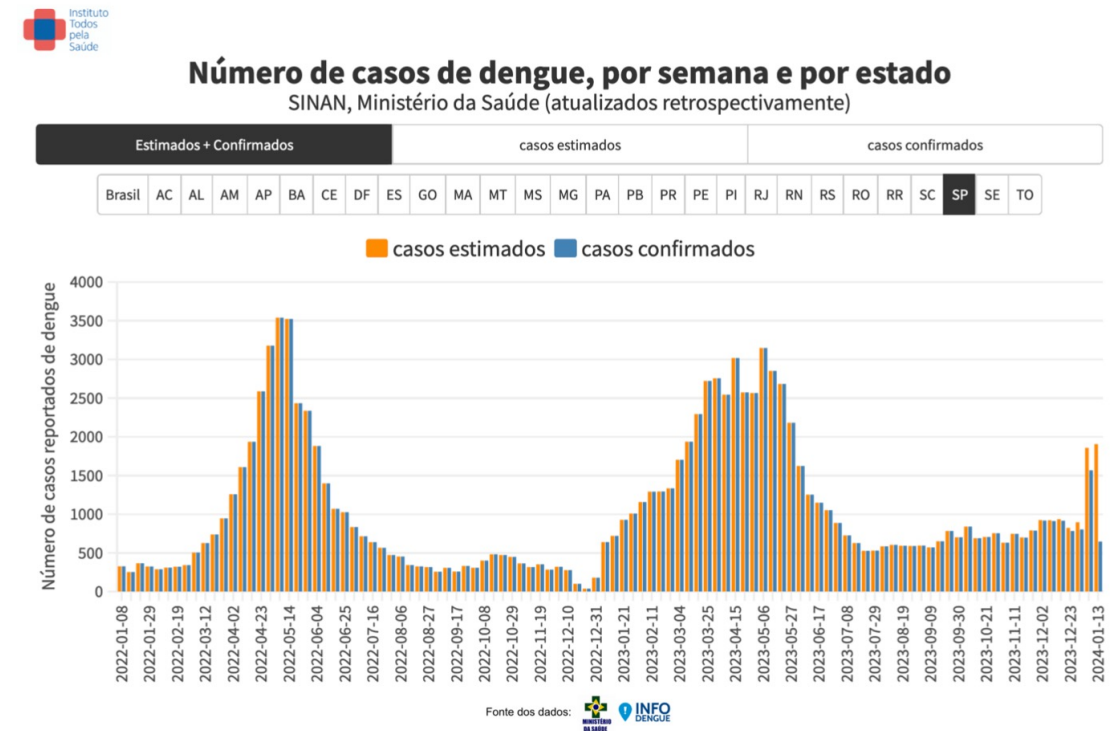
Deep learning models: Neural Networks (Artificial and Back-Propagation) and Long Short-Term Memory (LSTM) Models => more robust to missing data.

Seasonal dengue in Singapore and/or Brazil

Data: 5-year dengue cases per epidemiological week in Singapore and/or 10-year dengue cases per day São Paulo state, Brazil.



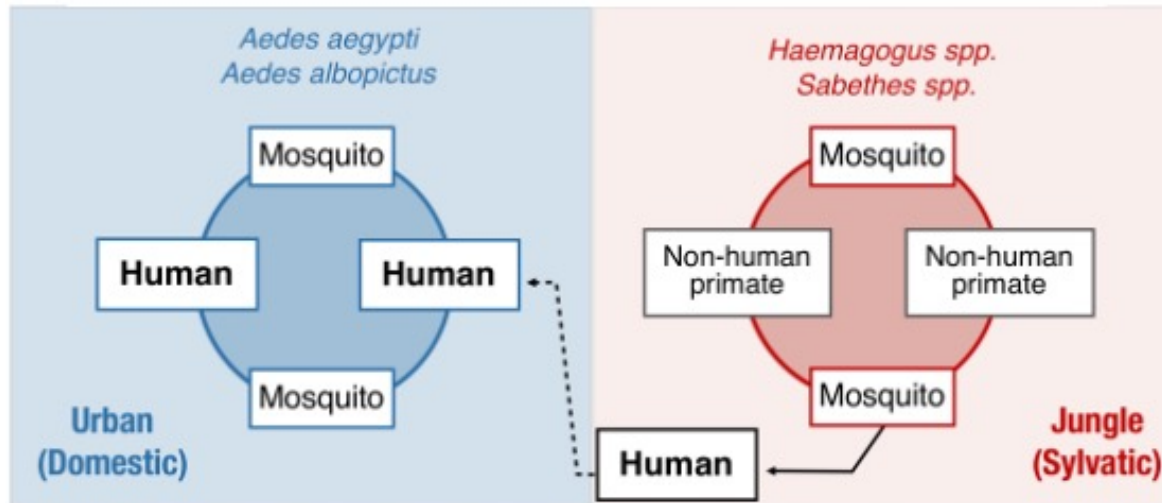
<https://www.nea.gov.sg/dengue-zika/dengue/dengue-cases>



<https://www.ltps.com.br>

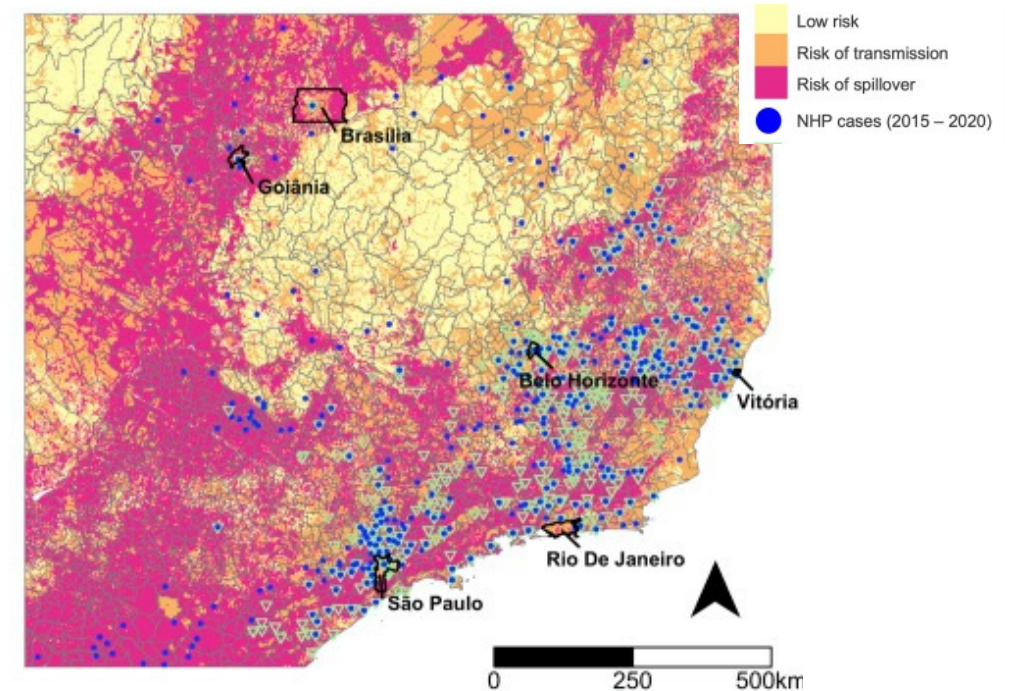
Modelling yellow fever transmission dynamics

Overarching Aim: to investigate the dynamic behavior of *Haemagogus leucocelanus*, the mosquito vector for sylvatic yellow fever in Brazil.



Faria et al. *Science* 2018

In South America, yellow-fever (YF) transmission occurs mainly via the non-urban cycle, in which non-human primates (NHP) are infected by mosquito vectors.

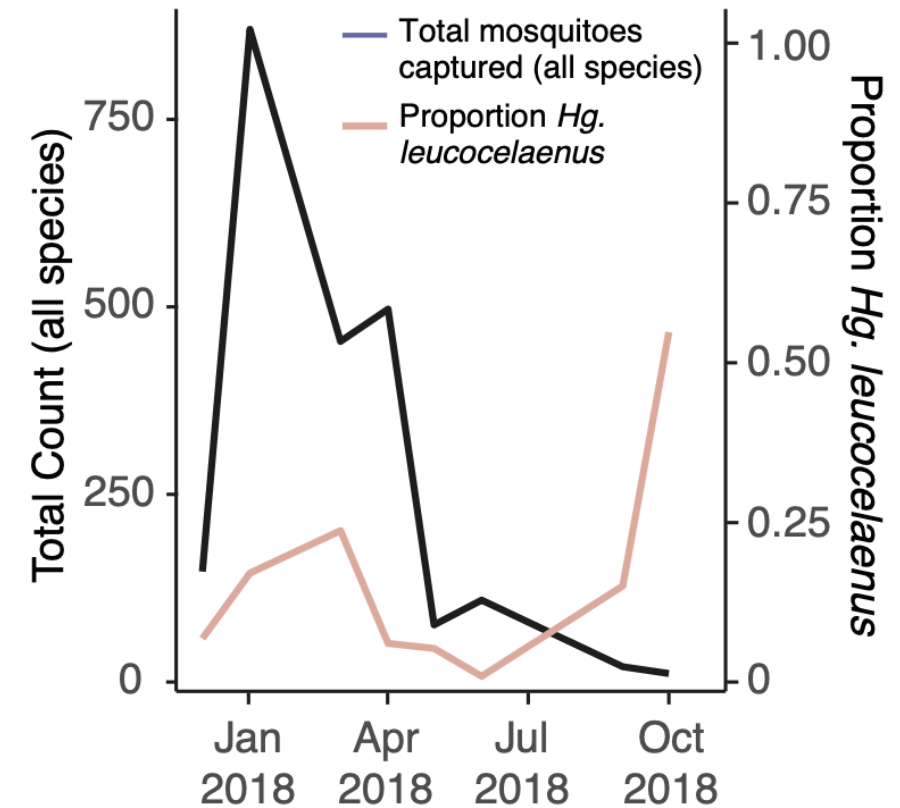


Li et al. *PNTDs* 2022

Modelling yellow fever transmission dynamics

Data. Environmental covariates (temperature, humidity, rain), and mosquito occurrence data (*Haemagogus leucocelanus*, the main vector for YF in southeast Brazil) captured by local public health teams in São Paulo State, Brazil.

Note: non-human primate cases, human cases, and vaccination data are also available for more detailed analysis.



de Deus *in prep* 2024

A final note on Statistics

$$y = (y_1, \dots, y_n)$$

Observed data

$$y \sim p(y|g^{-1}(\eta), \theta)$$

Observational model

$$\eta = X\beta + f_{\text{GP}}$$

Linear predictor

$$f_{\text{GP}} \sim \text{GP}(\mu, \Sigma(\theta))$$

Random effects (GPs)

This modeling scheme can be used for, e.g., “point patterns,” “areal data,” or “geostatistical data.”

Our goal is to estimate $g(\mathbb{E}(y|f_{\text{GP}})) = X\beta + f_{\text{GP}}$; however, it scales with $\mathcal{O}(n^3)$.

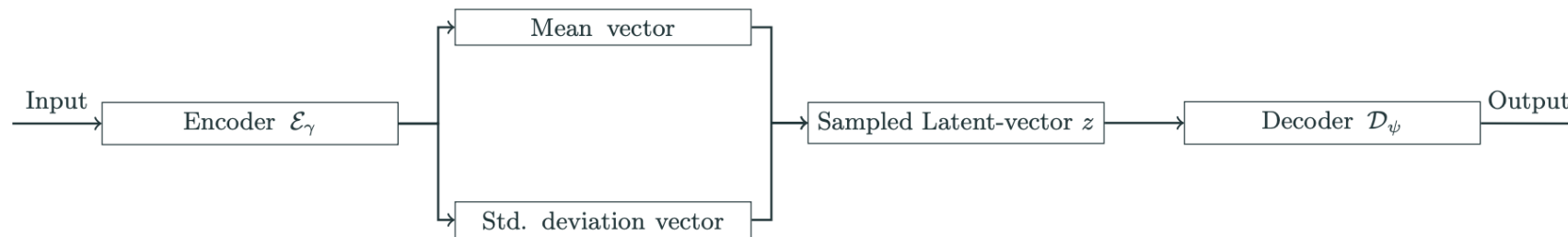
A final note on Statistics

$y = (y_1, \dots, y_n)$	Observed data
$y \sim p(y g^{-1}(\eta), \theta)$	Observational model
$\eta = X\beta + f_{\text{GP}}$	Linear predictor
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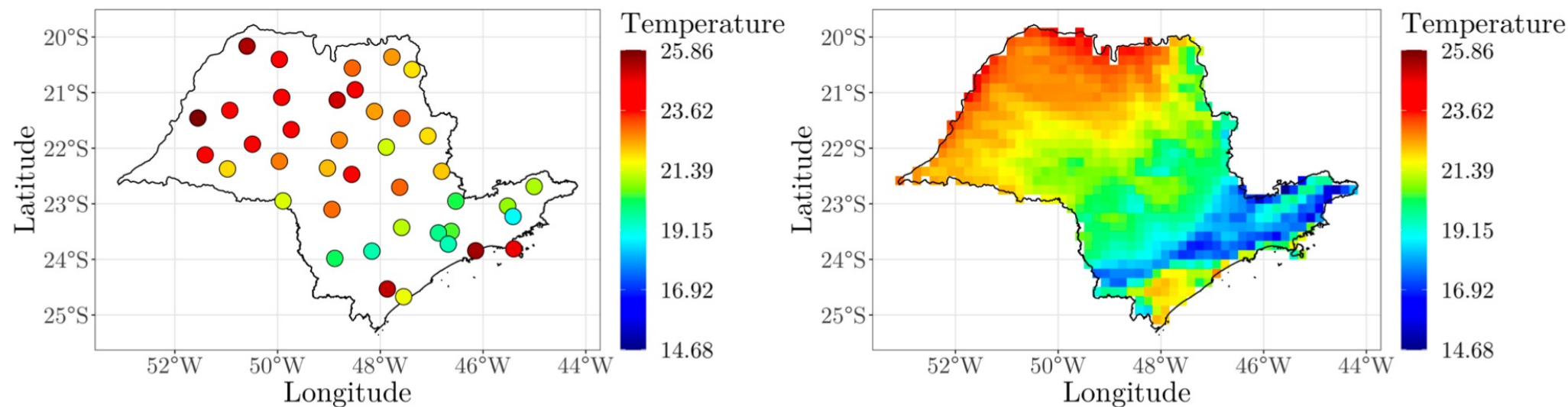
Our goal is to estimate $g(\mathbb{E}(y|f_{\text{GP}})) = X\beta + f_{\text{GP}}$; however, it scales with $\mathcal{O}(n^3)$.

To overcome this issue, we substitute f_{GP} by f_{VAE} .



A final note on Statistics

For many of these problems, we may want to integrate various data sources and at different resolutions. Within the previously introduced framework,



$$y(x_i)|f, \mu, \sigma^2 \sim \mathcal{N}(\mu(x_i) + f(x_i), \sigma^2) \quad \text{and} \quad y(B_j)|f, \mu, \sigma^2 \sim \mathcal{N}\left(\frac{1}{|B_j|} \int_{B_j} [\mu(x) + f(x)] dx, \sigma^2\right)$$