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3 Sep 2021

Impact of climate and local environment on Dengue and Zika dynamics in Brazil: A joint Bayesian spatio-temporal model

BaYSM 2021: Application

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Introduction

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Objective

Joint modelling of Dengue and Zika virus cases using environmental and climatic variables during 2015-2019, while adjusting for socio-economic local conditions.

Literature

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- Normalized Difference Vegetation Index (NDVI) owing to transmissions errors [3]
- Optimal temperature range for mosquitoes
- One/two-month lagging effects of climate variables, eg. excessive rainfall can cause breeding sites to overflow

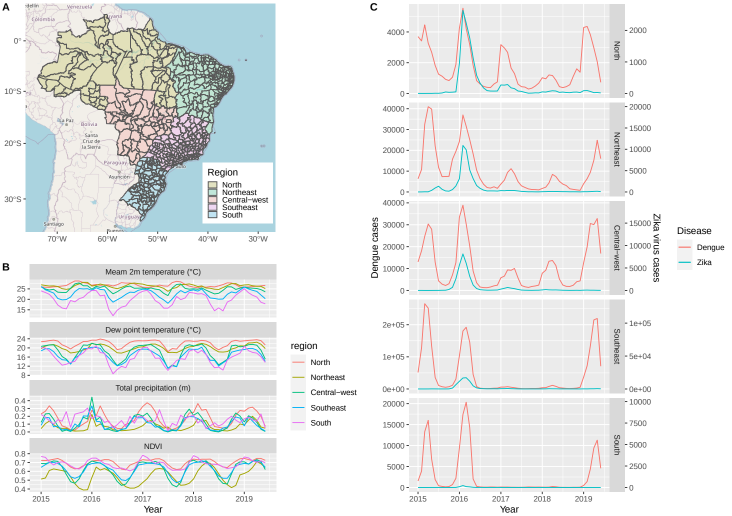

Figure 1: **Climate, Dengue and Zika virus in Brazil. A** The five geographic regions in Brazil with micro-region border. **B** The climate variables and the Normalized Difference Vegetation Index (NDVI) monthly time series between 2015 and mid-2019 in the Brazilian regions. **C** Dengue and Zika virus cases monthly time series in the Brazilian regions between 2015 and mid-2019.

Methodology

High-dimensional space-time joint model

For i-th municipality ($i = 1, \ldots, I$) within the k_i-th micro-region, t-th month ($t = 1, \ldots, T$), and j-th disease ($j = 1, 2$)

$$Y_{itj} \sim nBin(\mu_{itj}, \phi_{itj})$$

where ϕ_{itj} is the (local) dispersion parameter and the mean μ_{itj} is linked to the linear predictor by $\mu_{itj} = E_{it} \exp(\eta_{itj})$, where $\log(E_{it})$ (offset term) is assigned with E_{it} equal to the WorldPop mid-year population estimates by 10^{-3} due to numerical stability issue, hence, the response Y_{itj} refers to an incidence rate per 10,000 people [5].

High-dimensional space-time joint model (cont')

Then the link predictor:

$$\eta_{itj} = \alpha_j + f_1(X_{it1}) + f_2(X_{it2}) + \Sigma_q \beta_q X_{itq} + \theta_{k_i j} + \gamma_{tj} + \delta_{k_i tj}$$

where α_j is the disease specific intercept;

f_1 and f_2 are nonlinear (temporally) smoothed functions for NDVI and temperature with RW2 prior;

$\Sigma_q \beta_q X_{itq}$ refer to the (fixed) effect of the q-th standardised covariate, i.e. biome, socio-economic factors, precipitations, dew point temperature;

$\theta_{k_i j}$ and γ_{tj} are the random effects capturing spatial pattern and temporal trends of Dengue and Zika;

$\delta_{k_i tj}$ is the spatio-temporal interaction effect.

M-model from Vicente's paper [6]

We first denote for spatial random effect,

$$\Theta = \{\theta_{k_i j} : i = 1, ..., I; j = 1, 2\}$$

for temporal random effect,

$$\Gamma = \{\gamma_{tj} : t = 1, ..., T; j = 1, 2\}$$

and for spatio-temporal interaction,

$$\Delta_j = \{\delta_{k_i tj} : i = 1, ..., I; t = 1, ..., T; j = 1, 2\}$$

M-model (cont')

Hence, we have for spatial random effect,

$$\Theta = \Phi_\theta M_\theta$$

for temporal random effect,

$$\Gamma = \Phi_\gamma M_\gamma$$

and for spatio-temporal interaction,

$$vec(\Delta_j) \sim N(0, \sigma^2_{\delta_j} Q^-_\delta)$$

where M_θ and M_γ matrices' columns are the random effects accounting for spatial and temporal dependencies respectively [6]; Δ_j captures the spatio-temporal interaction within diseases; and Q^-_δ is defined depending on the type of space-time interaction [1].

M-model(con't)

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- The covariance matrix of the separable spatial or temporal structure can be estimated via $M'_\theta M_\theta$ with a Wishart prior, i.e. $M'_\theta M_\theta \sim Wishart(J, \sigma^2_\theta I_J)$ and $M'_\gamma M_\gamma \sim Wishart(J, \sigma^2_\gamma I_J)$.

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- The fixed effects M model (FE) assumes $N(0, \sigma^2)$ prior with a large σ for the elements in M; while a random effects M model (RE) draws inference on σ [6].
- The models (RE M models with Type I interaction) are fitted by using the integrated nested Laplace approximation (INLA) [4].

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Preliminary results

	North		Central-west	
Fixed effect covariate	mean	95%CI	mean	95%CI
Dew point temperature	2.46	[0.80, 4.11]	4.57	[3.30, 5.85]
Total precipitation (m)	-5.83	[-8.09, -3.56]	-0.63	[-2.65, 1.39]
Percentage of the population living in households with running water	6.53	[5.17, 7.89]	4.92	[3.42, 6.42]
Percentage of people in households with inadequate water supply and sanitation	0.26	[-1.70, 2.22]	7.13	[5.91, 8.36]
Municipal Human Development Index (MHDI)	3.74	[2.03, 5.46]	2.80	[0.97, 4.63]
Biome - Amazon Forest	1.72	[0.40, 3.06]	-0.56	[-2.61, 1.49]
Biome - Atlantic Forest	N/A	N/A	2.43	[0.92, 3.94]
Biome - Tropical Wetland	N/A	N/A	-19.57	[-24.61, -14.51]

Table 1: Posterior mean and the 95% Credible Intervals of parameters associated to the covariates related to climatological, environmental and socioeconomic factors transformed back in original scale. Biome - Tropical savanna is the reference level and N/A indicates that these biomes do not exist in the North region.

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Non-linear Effect of Temperature across Regions

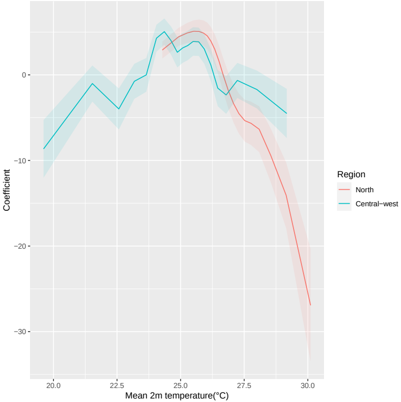


Figure 2: Smooth term on grouped mean 2m temperature using second-order Random walk prior

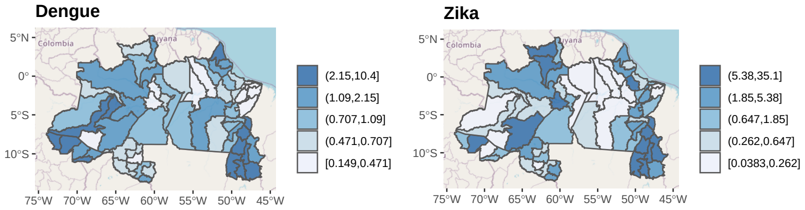


Figure 3: Posterior mean of the micro-region-specific spatial pattern in North region, $\exp(\theta_{k_i j})$ for Dengue (left) and Zika virus (right)

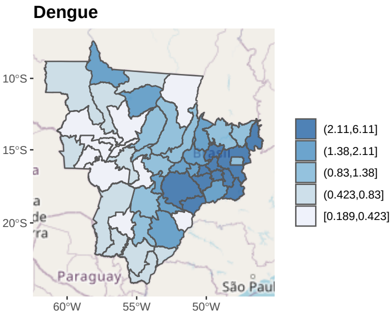
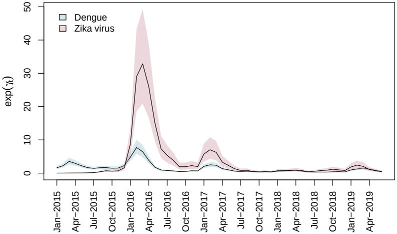
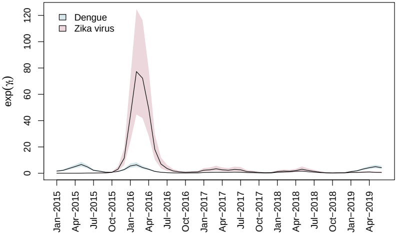


Figure 4: Posterior mean of the micro-region-specific spatial pattern in Central-West region, $\exp(\theta_{k_i j})$ for Dengue (left) and Zika virus (right)



(a) North



(b) Central-West

Figure 5: The temporal pattern captured by the temporal random effects (posterior means of $exp(\gamma_{tj})$).

Conclusion and on-going work

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- Sensitivity analysis on prior specification.

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- Extension of the model to the other Brazilian regions.
- Sensitivity analysis on prior specification.
- Evaluation of predictive capability of the model.

Acknowledgement

- This work was supported by the Wellcome Trust (UNS88765).
- Special thanks to
  - My collaborators in the Univeristy of Sao Paulo, Prof. Francisco Chiaravalloti Neto and Dr. Camila Lorenz;
  - My supervisors, Prof. Marta Blangiardo and Dr. Monica Pirani at Imperial College London;
  - Dr. Ilaria Dorigatti and Dr. Lorenzo Cattarino at Imperial College London; and,
  - Prof. Patrick Brown from University of Toronto.

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