













Spatio-temporal Modelling of Dengue Risk Towards an Early Warning System for Brazil

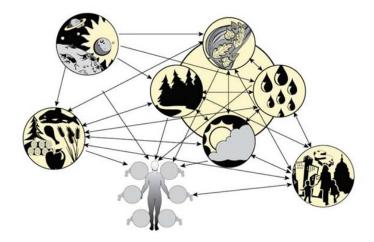
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Piracicaba, Brazil, July 2015

R Lowe, X Rodó (IC3), D Stephenson, T Jupp (UoE), R Graham (Met Office), C Coelho (CPTEC), M Sá Carvalho, C Barcellos, G Coelho (FIOCRUZ), A Monteiro (INPE)



A very complex set of interacting systems is involved

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(differentially aggregated or averaged over time/space)

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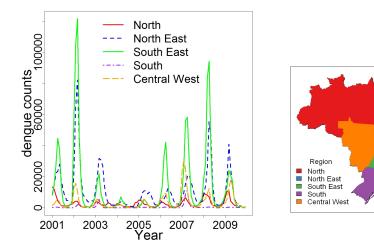
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- Relationships may exhibit threshold or extreme dependencies (rather than average behaviour)

Dengue in Brazil

- Dengue transmitted by Aedes aegypti mosquitoes
- Severe joint and muscle pain (rarely fatal)
- Epidemics depend on mosquito density and distribution, virus circulation and human susceptibility
- Brazil has more cases of dengue than anywhere else in the world
- More than 3 million cases in Brazil 2001-2009
- 2008 epidemic: 787,726 cases, 448 deaths
- Seasonal pattern: increases in Jan-May when climate warmer/humid
- Early warning systems that account for multiple dengue risk factors, are required to implement timely control measures
- Seasonal climate forecasts provide potential to anticipate dengue epidemics several months in advance.



Temporal variability in dengue in Brazil

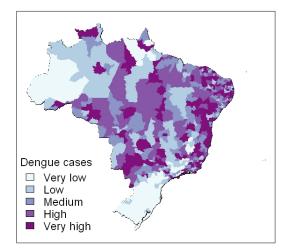


Monthly dengue counts for main regions of Brazil 2001-2009

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Spatial variability in dengue in Brazil



Total dengue cases in microregions (553) 2001-2009

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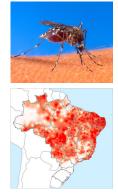
Dengue transmission

- Epidemiological drivers, e.g.
 - Susceptible population
 - Sero-type circulation
- Human drivers, e.g.
 - population growth/urbanisation/poverty (substandard housing)
 - abundance of water-storage (containers/bad drainage)
- Environmental drivers, e.g.
 - Precipitation (filling of containers)
 - Temperature/humidity (mosquito development)



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• Is it possible to develop a model to provide spatio-temporal probabilistic forecasts of dengue risk?



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- Is it possible to develop a model to provide spatio-temporal probabilistic forecasts of dengue risk?
 - To what extent can variations in dengue risk be accounted for by climate variations?





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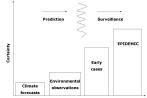
- Is it possible to develop a model to provide spatio-temporal probabilistic forecasts of dengue risk?
 - To what extent can variations in dengue risk be accounted for by climate variations?
 - Which observed and unobserved non-climatic confounding factors should be incorporated?





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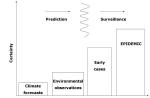
 Is climate information useful in a dengue Early Warning System (EWS) for Brazil?



Lead time



- Is climate information useful in a dengue Early Warning System (EWS) for Brazil?
 - How well can the developed model predict future and geographically specific dengue epidemics?

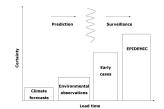


Lead time



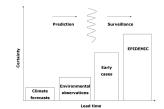
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 - How does this compare with current 'surveillance and response' approach in Brazil (observe early dengue cases Dec/Jan then estimate epidemic potential for late austral summer)
 - How can early warnings of dengue epidemics based on climate information be effectively communicated to public health decision makers?





Disease and Demographic Data

Disease data SINAN-DATASUS

- Monthly dengue cnts (originally Jan 2001 -Dec 2009, but now until 2013)
- Spatial unit: microregion

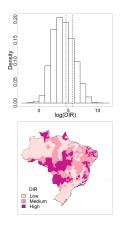
Census/cartographic data SIDRA-IBGE

- % urban population
- Altitude
- Administrative region
- Zone or Biome (e.g. Atlantic/Amazon Rainforest)

Original dataset: 108 months, 553 locations

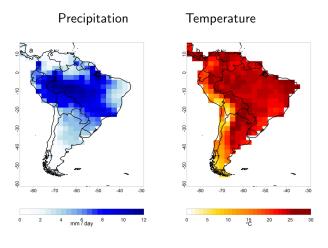
$$\begin{split} \mathsf{DIR}{=}\frac{y_{st}}{\rho_{st}} \times 12 \times 100,000\\ \mathsf{Low:} \ \mathsf{DIR} < 100\\ \mathsf{Med:} \ 100 < \mathsf{DIR} < 300 \end{split}$$

High: DIR > 300



Gridded climate data $(2.5^{\circ} \times 2.5^{\circ})$

- Average precipitation rate (GPCP)
- Reanalysis average temperature (NCEP/NCAR)



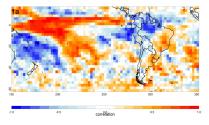
Dec-Feb climatology (2000-9)

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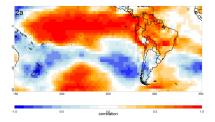
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Precipitation



Temperature



Correlation Oceanic Niño Index (ONI) vs Dec-Feb precipitation & temperature

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GLMM model framework

$$\begin{aligned} y_{st} | \phi_{s}, \nu_{s}, \omega_{t'(t)} &\sim \operatorname{NegBin}(\mu_{st}, \kappa); \quad s = 1, \dots, 553; t = 1, \dots, 108 \\ \log \mu_{st} &= \underbrace{\log e_{st}}_{\operatorname{offset}} + \alpha + \underbrace{\delta_{1t'(t)} + \delta_{2s'(s)} + \delta_{3s'(s)t'(t)}}_{\operatorname{month+zone factors}} \\ &+ \underbrace{\gamma_{1} w_{1st} + \gamma_{2} w_{2s}}_{\operatorname{non-climate vars: pop dens+altitude}} \\ &+ \underbrace{\beta_{1s'(s)} x_{1,s,t-2} + \beta_{2s'(s)} x_{2,s,t-2} + \beta_{3s'(s)} x_{3,t-6}}_{\operatorname{climate vars: precip+temp+ONI}} \\ &+ \underbrace{\phi_{s} + \nu_{s}}_{\operatorname{spatial random effects}} + \underbrace{\omega_{t'(t)}}_{\operatorname{monthly random effects}} \\ t'(t) = 1, \dots, 12 \\ s'(s) = 1, \dots, 8 \\ \phi_{s} \sim \operatorname{N}(0, \sigma_{\phi}^{2}); \quad s = 1, \dots, 553 \\ (\nu_{1}, \dots, \nu_{553}) \sim \operatorname{CAR}(\sigma_{\nu}^{2}) \\ \omega_{1} \sim \operatorname{N}(\omega_{12}, \sigma_{\omega}^{2}) \\ \omega_{t'(t)} \sim \operatorname{N}(\omega_{t'(t)-1}, \sigma_{\omega}^{2}); \quad t'(t) = 2, \dots, 12 \end{aligned}$$

GLMM model conclusions

• Climate signal is weak but highly significant

GLMM model conclusions

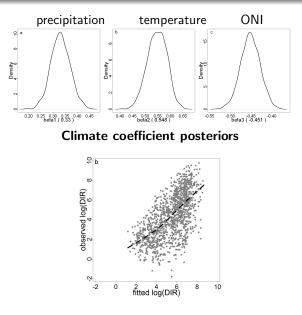
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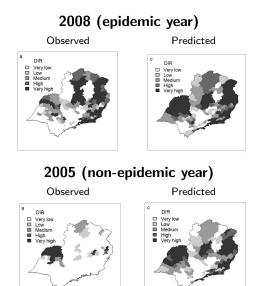
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- Precipitation and temperature averaged over preceding 3 month period, 2 month lag with dengue. (particularly seems to help in accounting for spatial variation)
- ONI lagged 6 months with dengue, 4 months with climate variables (particularly seems to help in temporal variation)
- Random effects are important
 - Unobserved confounding factors (population immunity to circulating serotype, health interventions/vector control measures)
 - Overdispersion
 - Temporal correlation and spatial clustering

Selected results - GLMM, SE Brazil



Observed log(DIR) vs model fit, FMA, 2001-2009

Selected results - GLMM, SE Brazil, FMA season

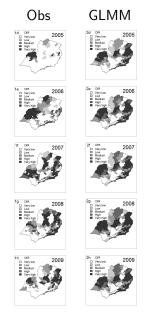


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GLMM and current surveillance practice, SE Brazil, FMA

Current surveillance practice effectively equates to the auto-regressive model (ARM):

$$\begin{array}{lll} y_{st} & \sim & \mathsf{NegBin}(\mu_{st},\kappa) \\ \log \mu_{st} & = & \log e_{st} + \alpha + \beta \log(\frac{y_{s,t-3}}{e_{s,t-3}}) \end{array}$$







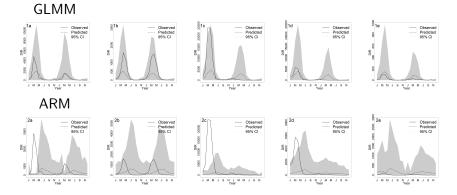








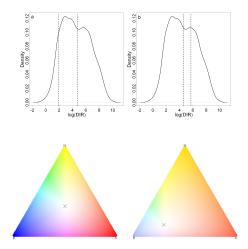
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(a) Três Marias, (b) Belo Horizonte, (c) Baía de Ilha Grande, (d) Rio de Janeiro, (e) São Jose dos Campos

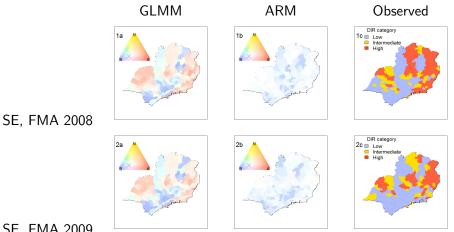
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Defining and visualising epidemic risk



Symmetric (tercile) and non-symmetric (100 and 300 cases per 100,000) category boundaries of the observed distribution of DIR, FMA 2001-2007, SE Brazil

Visualising GLMM probabilistic forecasts



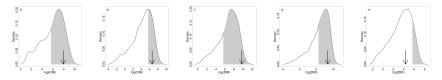
SE, FMA 2009

Epidemic prediction: FMA 2008, SE Brazil, GLMM

Posterior predictive results in 160 microregions in SE for DIR exceeding 300 cases per 100,000 at probability decision thresholds (50%&30%)

50%		Obs			30%		Obs	
		Yes	No				Yes	No
Pred	Yes	31	13	ĺ	Pred	Yes	51	31
	No	23	93			No	3	75
PC=78% HR=57% FAR=12%				PC=79% HR=94% FAR=29%				

Posterior predictive distributions and prob of > 300 per 100,000 in 5 selected regions (arrow indicates observed DIR)



(a) Três Marias, (b) Belo Horizonte, (c) Baía de Ilha Grande (d) Rio de Janeiro, (e) São Jose dos Campos

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Combined GLMM model framework

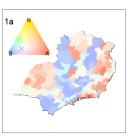
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Pred	Yes	34	10		Pred	Yes	47	24
	No	20	96			No	7	82
PC=81%, HR=63%, FAR=9%				,	PC=81%, HR=87%, FAR=23%			

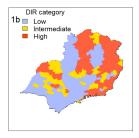
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Epidemic prediction combined model

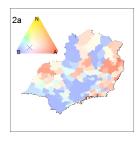


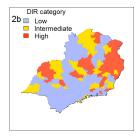
Combined GLMM

Observed



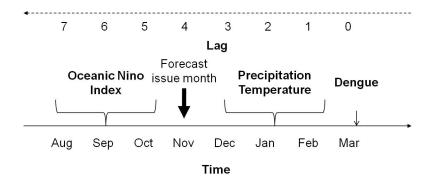
FMA 2008





FMA 2009

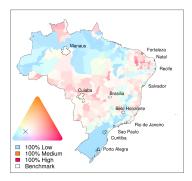
Extending prediction lead-time with forecast climate

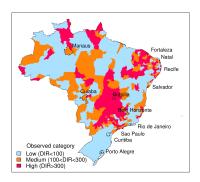


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Forecasting Dengue Risk Levels for the World Cup

Framework applied to predict dengue risk for June 2014 during the World Cup in Brazil, a mass gathering of more than 3 million local/international spectators.





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Evaluation of June 2014 Forecasts on National Basis

Observed Category								
		Low	Medium	High	Total			
Forecast	Low	193 (34.9%)	49 (8.9%)	40 (7.2%)	282			
Category	Medium	50 (9.0%)	20 (3.6%)	26 (4.7%)	96			
	High	38 (6.9%)	47 (8.5%)	90 (16.3%)	175			
	Total	281	116	156	n=553			

Hit: 54.8% Near hit: 31.1% Miss: 14.1%



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Did it make a difference?

•This timely warning complimented the national dengue control programme action plan, implemented ahead of the World Cup.

•Results disseminated to the **general public** and visitors travelling to Brazil (European Centre for Disease Control health risk assessment, UK National Health Service, >18 international press outlets, e.g. BBC) raising general **awareness** about dengue for **travellers** to endemic regions.

Case study in WHO/WMO and UNISDR publications.

White House "Predict the Next Pandemic" Initiative - dengue model intercomparison project.



Conclusions and Future Work



Lowe, R., Bailey T. et al. (2010), Spatio-temporal modelling of climate-sensitive disease risk: Towards an early warning system for dengue in Brazil, *Computers and Geosciences*



Lowe, R., Bailey T. et al. (2012) The development of an early warning system for climate-sensitive disease risk with a focus on dengue epidemics in Southeast Brazil, *Statistics in Medicine*



Lowe, R., Bailey T. et al. (2014) Dengue outlook for the World Cup in Brazil: an early warning model framework driven by real-time seasonal climate forecasts The Lancet: Infectious Diseases

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- Ongoing collaboration between public health and climate institutions and experts, including data managers, mathematical modellers and policy makers (vocabulary and local knowledge)
- Timely access to data (disease, human/vector/host structure, socio-economic, climate-observations, hindcasts, forecasts).
- Incorporation of serotype information, disease transmission process, health intervention/prevention information and movement of human hosts
- Iterative evaluation of model assumptions and predictive performance
- Communication to decision makers and the general public

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• Transformation of a case study into a sustainable service

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