Quantifying spatio-temporal risk factors of dengue to inform decision making

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Climate services for disease decision support systems

• To control the spread of dengue / impede dengue epidemics, decision support systems are required that take into account multiple dengue risk factors.
• Climate forecasts provide an opportunity to incorporate precursory climate information in a dengue decision support system to aid epidemic planning months in advance (e.g. targeted vector control activities, provision of medication).

RESEARCH QUESTIONS
• To what extent can spatio-temporal variations in dengue be account for by climatic variations?
• Which time lags are most relevant and what is the trade-off between forecast lead-time and predictive uncertainty?
• Which political, social economic and demographic factors play a role?

TOOLS: Model framework, visualisation technique

CASE STUDIES: Brazil, Ecuador & Thailand
Bayesian hierarchical mixed model framework for climate-sensitive diseases

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

**Solution** hierarchical model - add extra level uncertainty random effects

\[
\begin{align*}
Y_{st} | \phi_s, \nu_s, \omega_{t'}(t) & \sim \text{NegBin} \left( \mu_{st}, \kappa \right); \\
\log \mu_{st} & = \log e_{st} + \alpha + \delta_{1t'}(t) + \delta_{2s'}(s) + \delta_{3s'}(s)t'(t) \\
& \quad + \gamma_{1W1st} + \gamma_{2W2s} \\
& \quad + \beta_{1s'}(s)X_{1,s,t-2} + \beta_{2s'}(s)X_{2,s,t-2} + \beta_{3s'}(s)X_{3,s,t-6} \\
& \quad + \delta Z_{st} + \phi_s + \nu_s + \omega_{t'}(t)
\end{align*}
\]

Towards dengue EWS for Brazil
Lowe et al., 2011
*Computers and Geosciences*

Development of EWS for SE Brazil
Lowe et al., 2013
*Statistics in Medicine*

\[
\begin{align*}
\phi_s & \sim N(0, \sigma_{\phi}^2) \\
(\nu_s) & \sim \text{CAR} \left( \sigma_{\nu}^2 \right) \\
\omega_1 & = 0, \quad \omega_{t'(t)} \sim N(\omega_{t'(t)-1}, \sigma_{\omega}^2); \quad t'(t) = 2, \ldots, 12 \\
\sigma_{\lambda}^2 & \sim \text{Ga} \left( 0.5, 0.0005 \right), \quad \lambda = (\phi, \nu, \omega), \quad \kappa \sim \text{Ga} \left( 0.5, 0.0005 \right).
\end{align*}
\]
Tool for visualising probabilistic forecasts

Current practice with broad categories

NEAR NORMAL
\[ p = (0,1,0) \]

BELOW NORMAL
\[ p = (1,0,0) \]

ABOVE NORMAL
\[ p = (0,0,1) \]

Jupp, Lowe et al., 2012, Royal. Phil. Trans. A

More information gain using new tool
Visualising probabilistic forecasts

Visualisation technique (see Jupp et al., 2012) to convey the probability of disease risk falling within pre-defined risk categories.

Dengue risk forecast for South East Brazil during epidemic February-April 2008. Category boundaries: 100 and 300 cases per 100,000 inhabitants.

Lowe et al., 2013
Statistics in Medicine
Posterior prediction Feb-Apr 2008 epidemic
Rio de Janeiro

GLMM \((p(DIR) > 300 = 0.75)\)

CSM \((p(DIR) > 300 = 0.37)\)

- GLMM improvement to current practice
- Inclusion of climate information and observed and unobserved confounding factors improves model performance
Extending prediction lead-time with forecast climate

- EUROBRISA: EURO-BRazilian Initiative for improving South American seasonal climate forecasts http://eurobrisa.cptec.inpe.br/

- Correlation between forecast and observed precipitation anomaly using the integrated EUROBRISA forecasting system for the period 1981-2005. Forecasts issued in November, valid for DJF season.
Towards a climate-driven dengue early warning system for Ecuador

Advanced warning of a dengue epidemic obtained from climate information combined with knowledge of circulating virus serotypes, and mosquito abundance can help target interventions:

- Effective vector control
- Destruction potential mosquito breeding containers
- Education campaigns
Dengue and climate anomalies 1995-2010

- Graph showing dengue SMR and precipitation over time.
- Graph showing dengue SMR anomaly with temperature and precipitation anomalies.
- Graph showing temperature and precipitation over time.
- Graph showing SST anomaly over time.
Climate and non-climate drivers of dengue epidemics

Model 1995-2010: Climate and random effects

Month effects

Year effects

Oceanic Niño Index parameter

Model 2001-2010: Climate, non-climate, random effects

Stewart-Ibarra & Lowe 2013, AJHTM
Spatio-temporal dengue SMR variation
Thailand 1982-2012

Dengue peak: June

Epidemic years (total SMR>2):

<table>
<thead>
<tr>
<th>Risk</th>
<th>SMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>0-0.5</td>
</tr>
<tr>
<td>Low</td>
<td>0.5-1</td>
</tr>
<tr>
<td>Medium</td>
<td>1-1.5</td>
</tr>
<tr>
<td>High</td>
<td>1.5-2</td>
</tr>
<tr>
<td>Very High</td>
<td>&gt;2</td>
</tr>
</tbody>
</table>
Spatial risk layers

Rail

Road

Water bodies

Altitude

Land cover

Combined
El Niño-Southern Oscillation

Epidemic years (total SMR>2):

El Niño years
1982-3 1986-7 1991-2
1994-5 1997-8 2002-3
2009-10

La Niña years
1998-9 1990-00 2005
2007-8 2010-11
Quantifying risk factors

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior mean</th>
<th>95% credible interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation (lag 1)</td>
<td>0.0347</td>
<td>(0.0293, 0.0401)</td>
</tr>
<tr>
<td>Temperature (lag 2)</td>
<td>0.1014</td>
<td>(0.0903, 0.1124)</td>
</tr>
<tr>
<td>Oceanic Niño Index (lag 3)</td>
<td>0.1812</td>
<td>(0.1597, 0.2026)</td>
</tr>
</tbody>
</table>

Spatially structured and unstructured random effects

Monthly and annual autocorrelated random effects

Spatial relative risk:
- < 0.5
- 0.5 - 0.7
- 0.7 - 0.9
- 0.9 - 1.1
- 1.1 - 1.3
- 1.3 - 1.5
- >= 1.5
How can we effectively link modelling results to inform public health decision making?