2453-15

School on Modelling Tools and Capacity Building in Climate and Public Health

15 - 26 April 2013

Challenges for modelling climate-sensitive diseases

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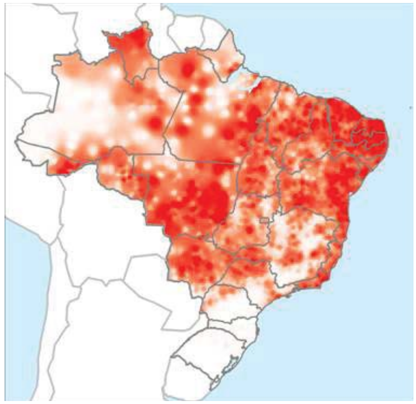

Challenges for modelling climate-sensitive diseases

Rachel Lowe

Spring School on modelling tools and capacity building in climate and public health, 15-26 April 2013, ICTP, Trieste, Italy.

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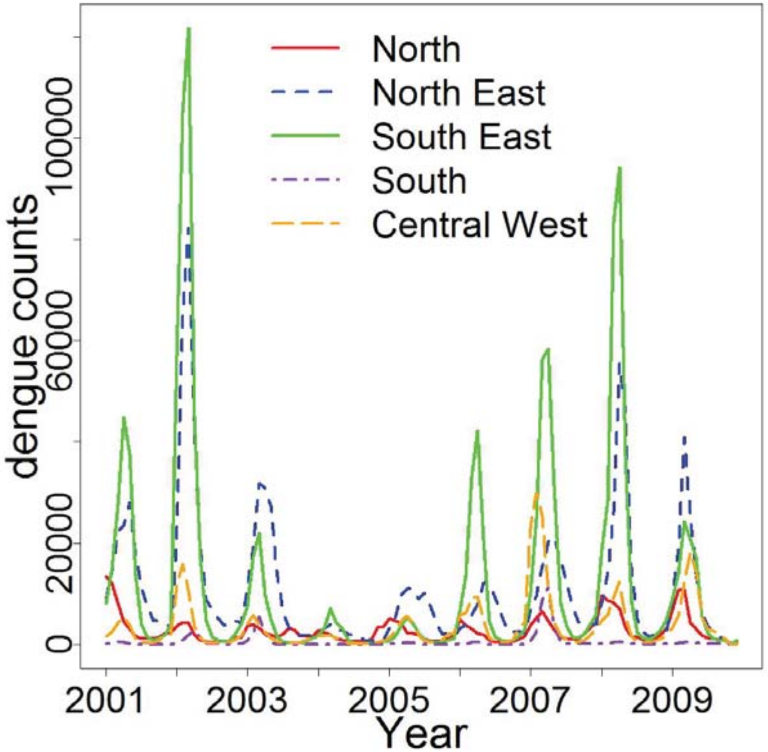
Objective

- Demonstrate how to collate, analyse and model data on climate, population, environment and health.

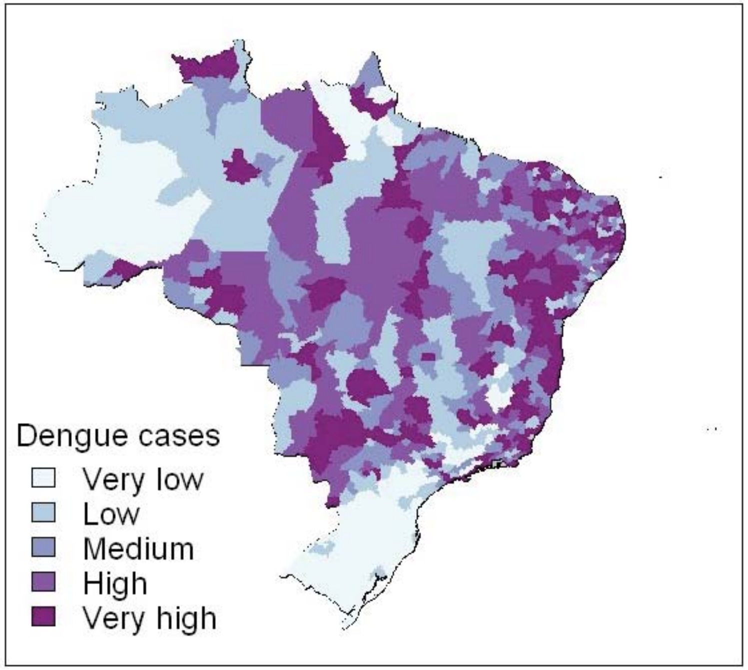
- Present a spatio-temporal modelling framework, including data requirements, results interpretation and model validation.

- Case studies: dengue in Brazil and Ecuador, malaria in Malawi.

Dengue in Brazil: spatial/temporal variation



Monthly dengue cases in main regions of Brazil 2001-2009



Total dengue cases in microregions of Brazil 2001-2009

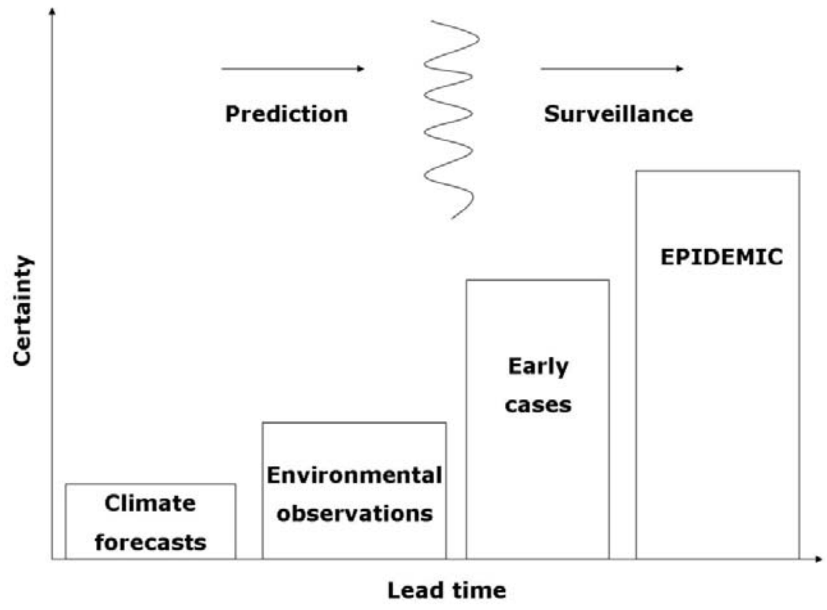
Dengue transmission

- **Human drivers**, e.g.
  - Population growth / urbanisation / poverty (substandard housing)
  - abundance of water-storage containers/bad drainage
- **Environmental drivers**, e.g.
  - Rainfall (filling of containers)
  - Temperature/humidity (mosquito development)

Research questions

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

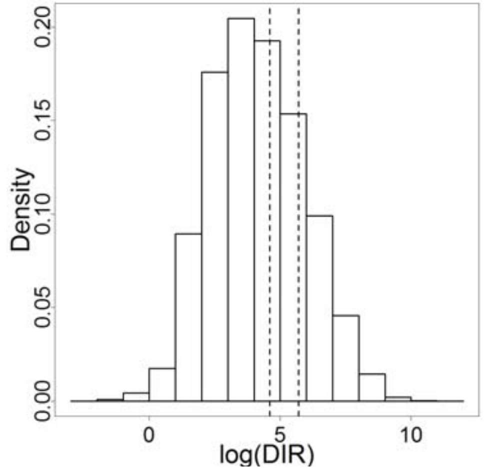
- To what extent can spatio-temporal variations in dengue risk be accounted for by climate variations?
- Which observed and unobserved non-climatic confounding factors should be incorporated?



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

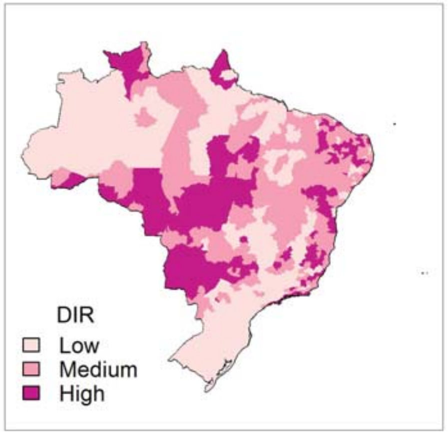
- How well can the developed model predict future and geographically specific dengue epidemics?
- How does this compare with current `surveillance and response' approach in Brazil?
- How can early warnings of dengue epidemics based on climate information be effectively communicated to public health decision makers?

Dengue and demographic data



Disease data SINAN-DATASUS

- Monthly dengue cases Jan 2001 - Dec 2009
- Spatial unit: microregion



Census/cartographic data SIDRA-IBGE

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

Overall dataset 108 months, 558 locations

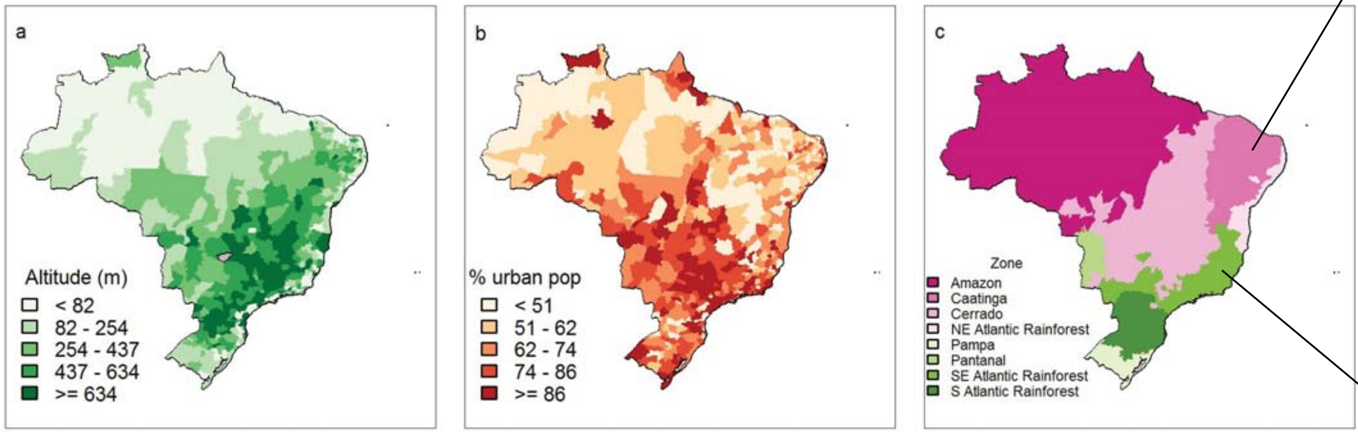
$$\text{DIR} = \frac{y_{st}}{p_{st}} \times 100,000$$

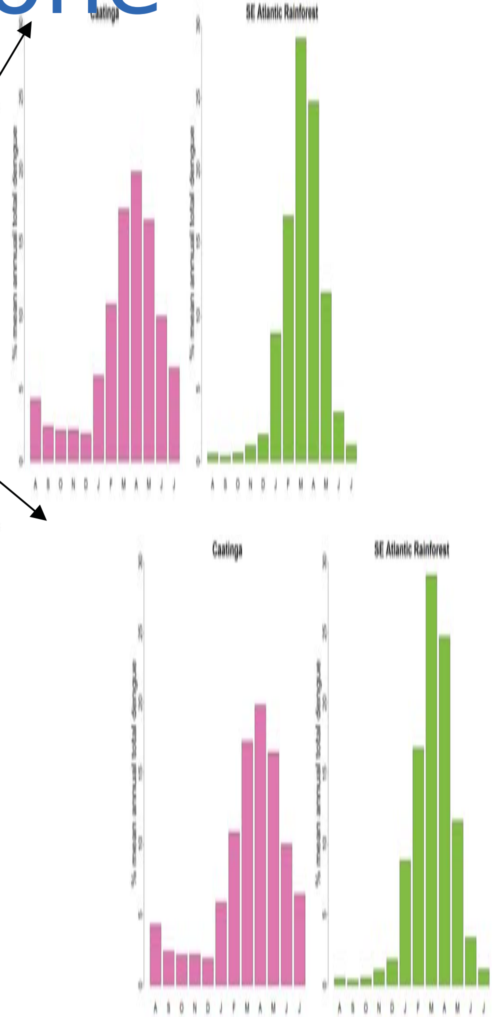
Low: $\text{DIR} < 100$

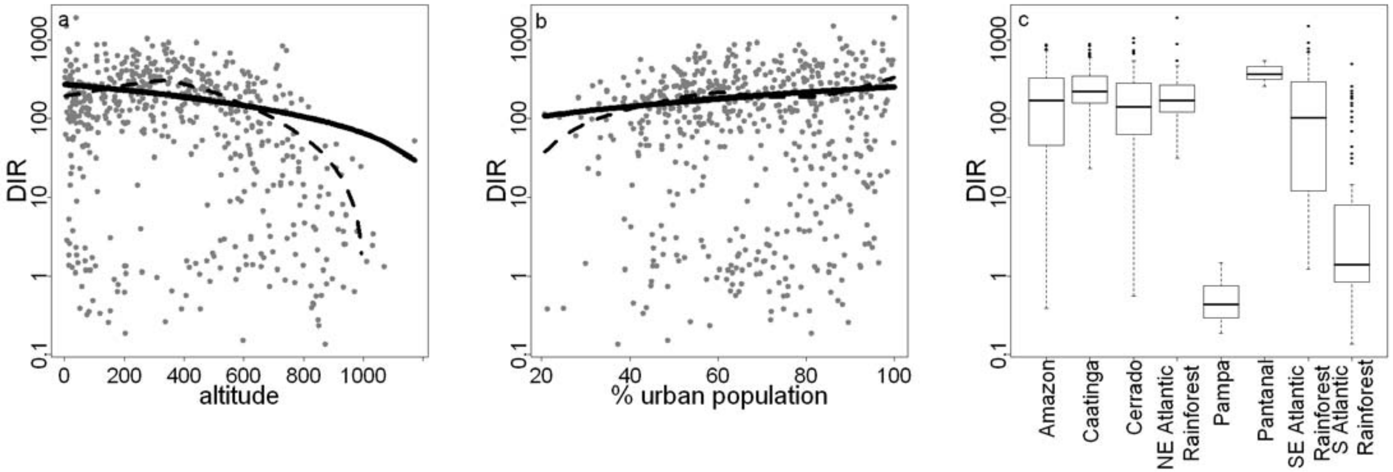
Med: $100 < \text{DIR} < 300$

High: $\text{DIR} > 300$

Dengue related to altitude, urban population and geographic zone





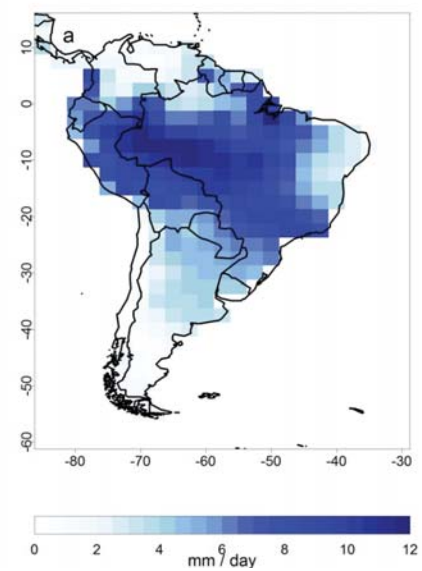


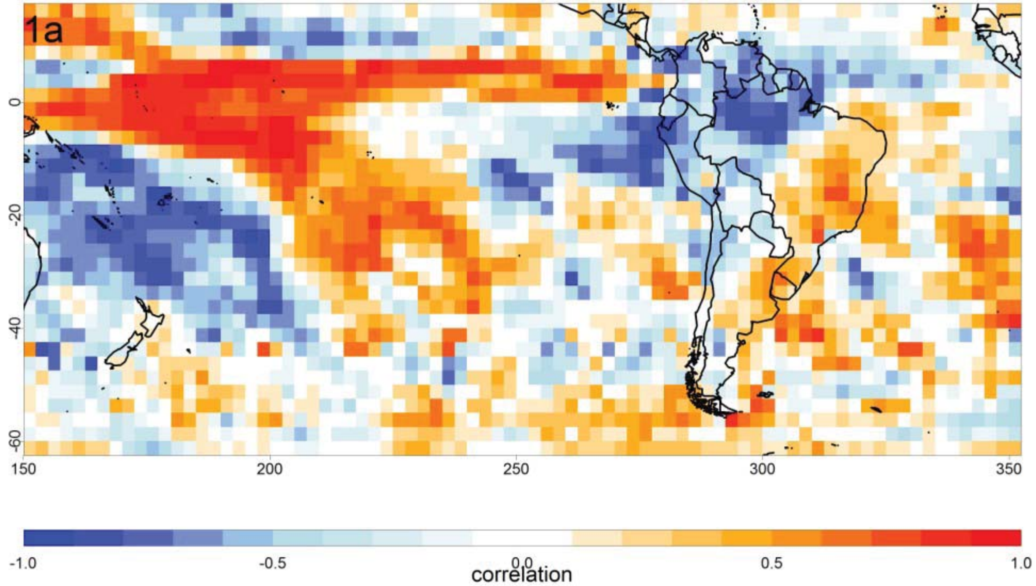
Lowe *et al.*, 2011, Computers & Geosciences

Climate information

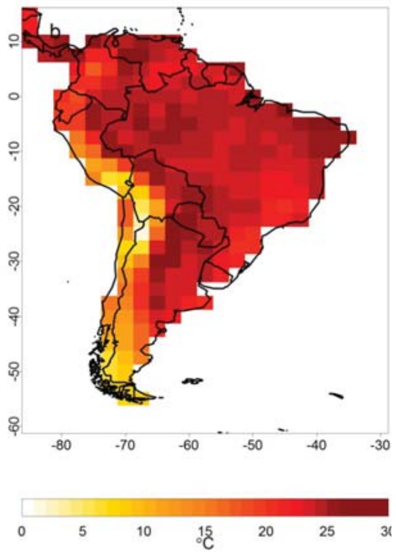
Correlation of DJF precipitation and temperature with ASO Oceanic Nino Index (ONI)

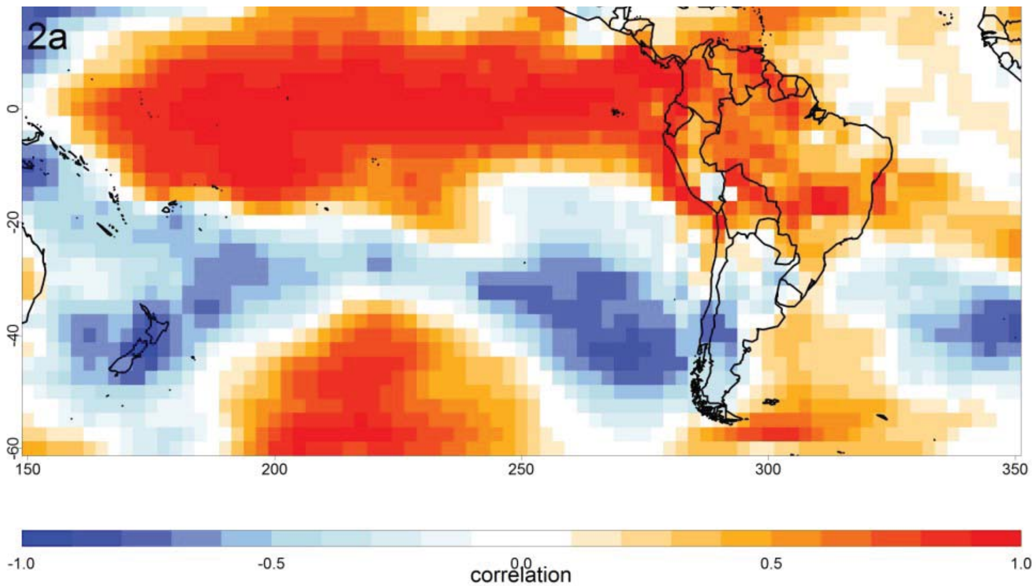
GPCP average precipitation rate Dec-Feb climatology 2000-2009





NCEP/NCAR reanalysis average temperature Dec-Feb climatology 2000-2009





Selected statistical mixed model framework

Problem lack of data to model disease system
Solution hierarchical model - add extra level uncertainty random effects

$$
\begin{aligned}
y_{st} | \phi_s, \nu_s, \omega_{t'(t)} &\sim \text{NegBin}(\mu_{st}, \kappa); \quad s = 1, \ldots, 558; \; t = 1, \ldots, 108 \\
\log \mu_{st} &= \underbrace{\log e_{st}}_{\text{offset}} + \alpha + \underbrace{\delta_{1t'(t)} + \delta_{2s'(s)} + \delta_{3s'(s)t'(t)}}_{\text{month+zone factors}} \\
&+ \underbrace{\gamma_1 w_{1st} + \gamma_2 w_{2s}}_{\text{non-climate vars: pop dens+altitude}} \\
&+ \underbrace{\beta_{1s'(s)} x_{1,s,t-2} + \beta_{2s'(s)} x_{2,s,t-2} + \beta_{3s'(s)} x_{3,t-6}}_{\text{climate vars: precip+temp+ONI}} \\
&+ \underbrace{\delta z_{st}}_{\text{early cases}} + \underbrace{\phi_s + \nu_s}_{\text{spatial random effects}} + \underbrace{\omega_{t'(t)}}_{\text{monthly random effects}}
\end{aligned}
$$

$$
\begin{aligned}
&\phi_s \sim \text{N}(0, \sigma^2_\phi) \\
&(\nu_s) \sim \text{CAR}(\sigma^2_\nu) \\
&\omega_1 = 0, \quad \omega_{t'(t)} \sim \text{N}(\omega_{t'(t)-1}, \sigma^2_\omega); \quad t'(t) = 2, \ldots, 12 \\
&\sigma^2_\lambda \sim \text{Ga}(0.5, 0.0005), \lambda = (\phi, \nu, \omega), \kappa \sim \text{Ga}(0.5, 0.0005).
\end{aligned}
$$

Model results

Climate signal is weak but statistically significant

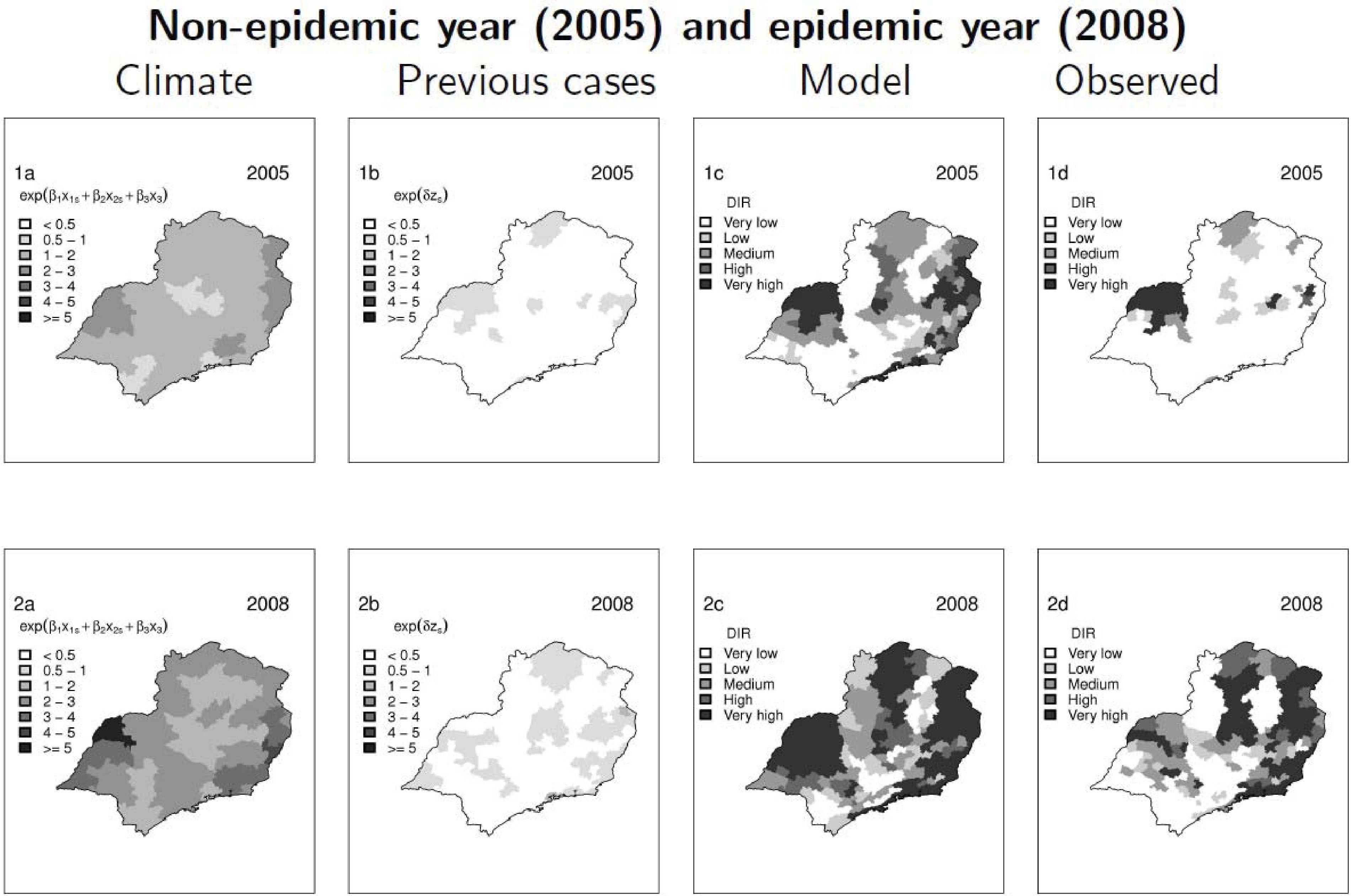
- Precipitation and temperature averaged over preceding 3 month period, 2 month lag with dengue (helps account for spatial variation)
- ONI lagged 6 months with dengue, 4 months with climate variables (helps with temporal variation)

Accounting for unknown confounding factors

- Early cases as surrogate for changes in mosquito populations/ circulation new serotype?
- Random effects important to account for unobserved latent structures (e.g. population immunity to circulating serotype, health interventions/ vector control measures)
- Overdispersion
- Temporal correlation and spatial clustering

South East Brazil peak dengue season February-April (FMA)

Multiplicative decomposition of risk

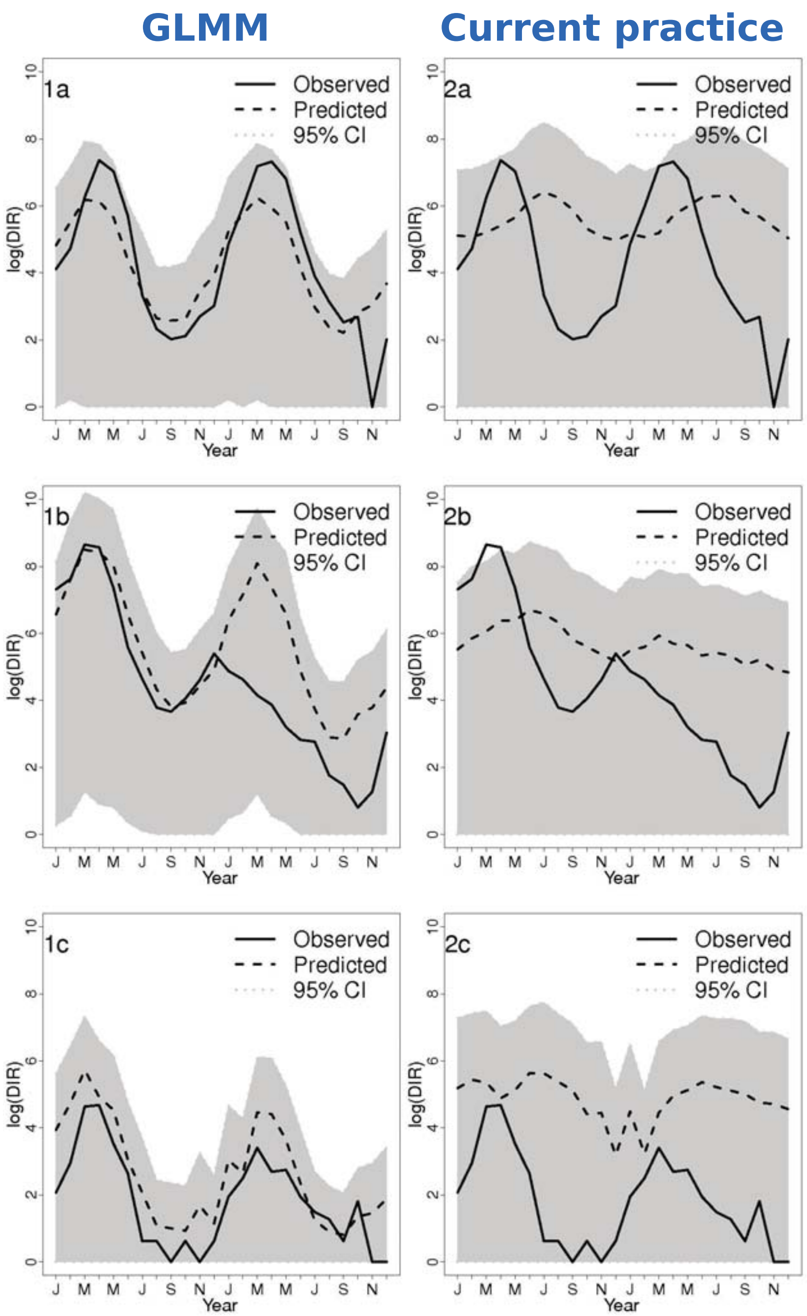


Posterior prediction microregions 2008-09

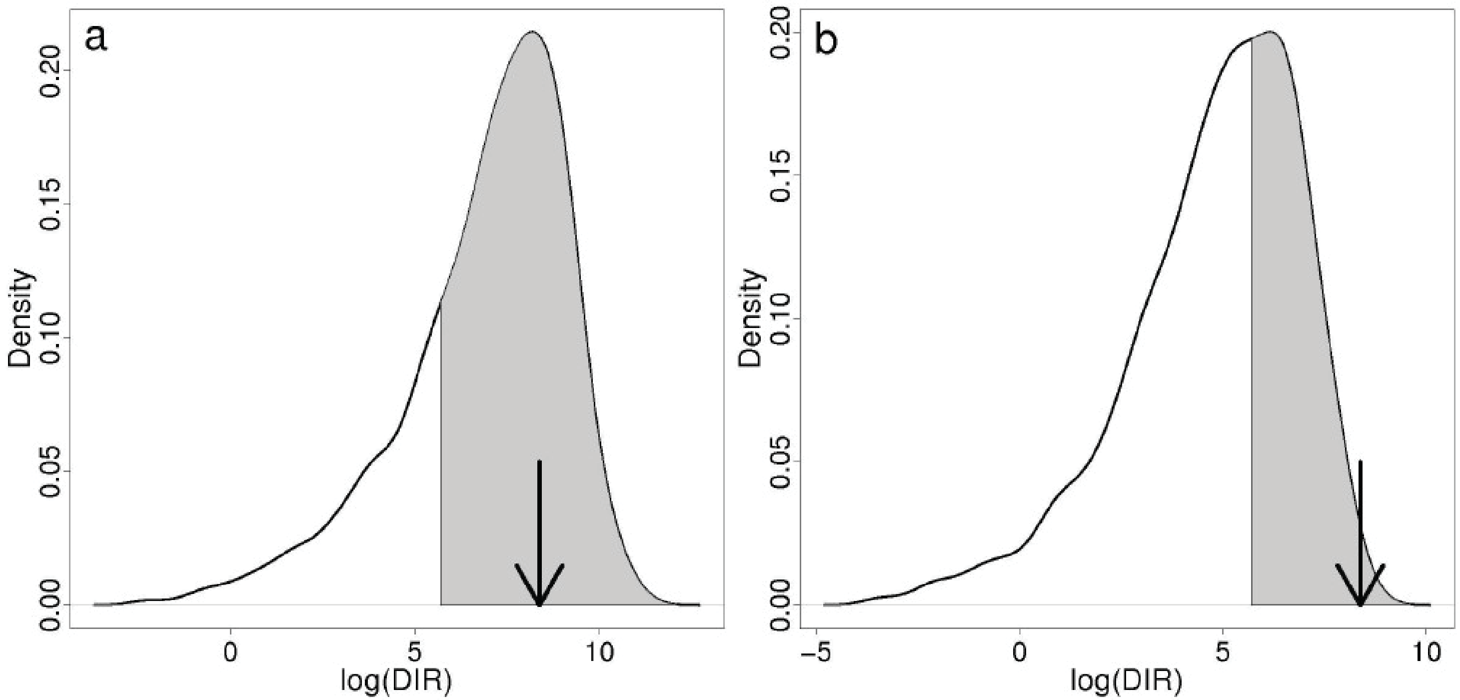
Belo Horizonte

Rio de Janeiro

São José dos Campos



Posterior prediction FMA 2008 epidemic Rio de Janeiro

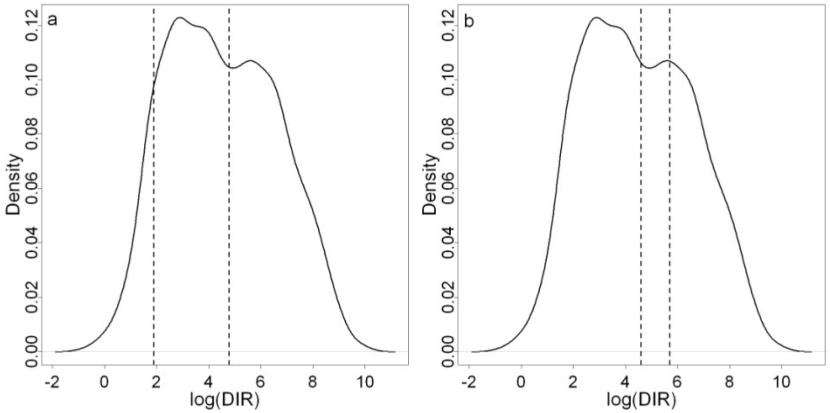


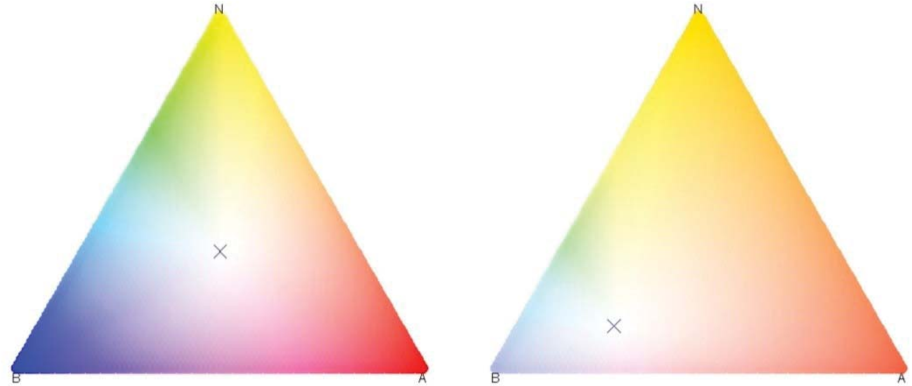
GLMM $(p(\text{DIR}) > 300 = 0.75)$ CSM $(p(\text{DIR}) > 300 = 0.37)$

- GLMM improvement to current practice
- Inclusion of climate information and observed and unobserved confounding factors improves model performance

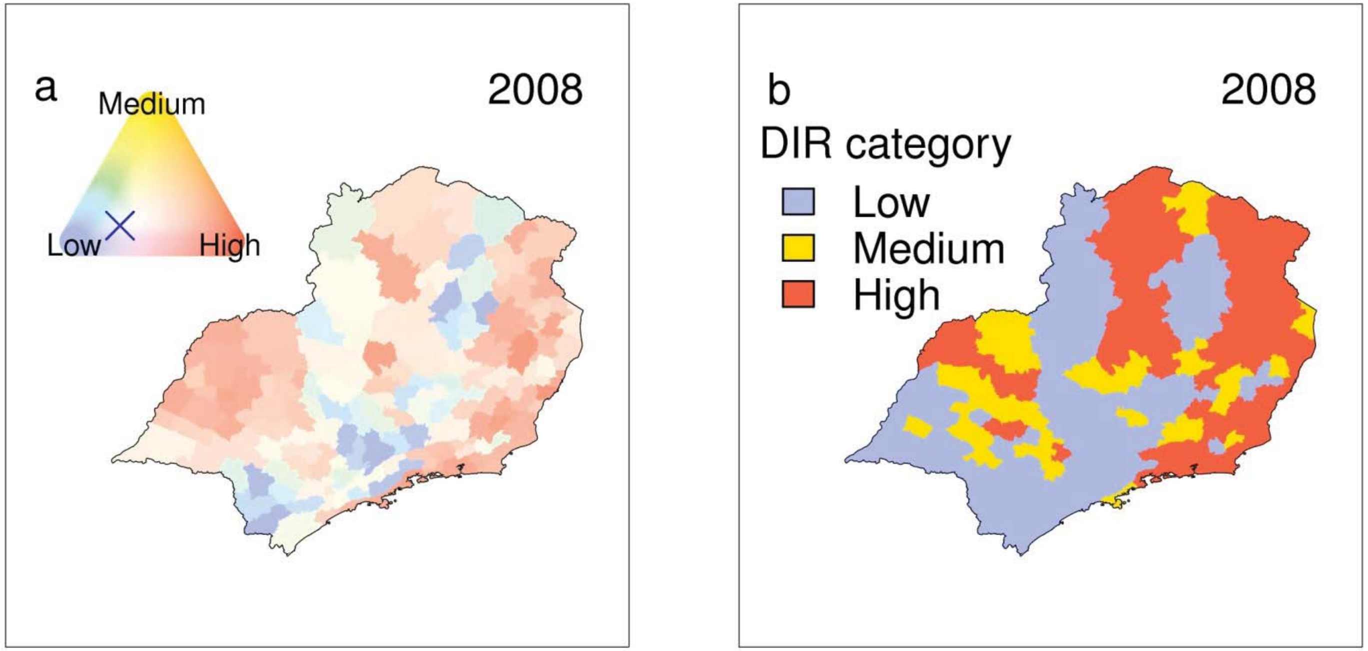
Visualising probabilistic forecasts

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





Dengue risk forecast South East Brazil FMA 2008

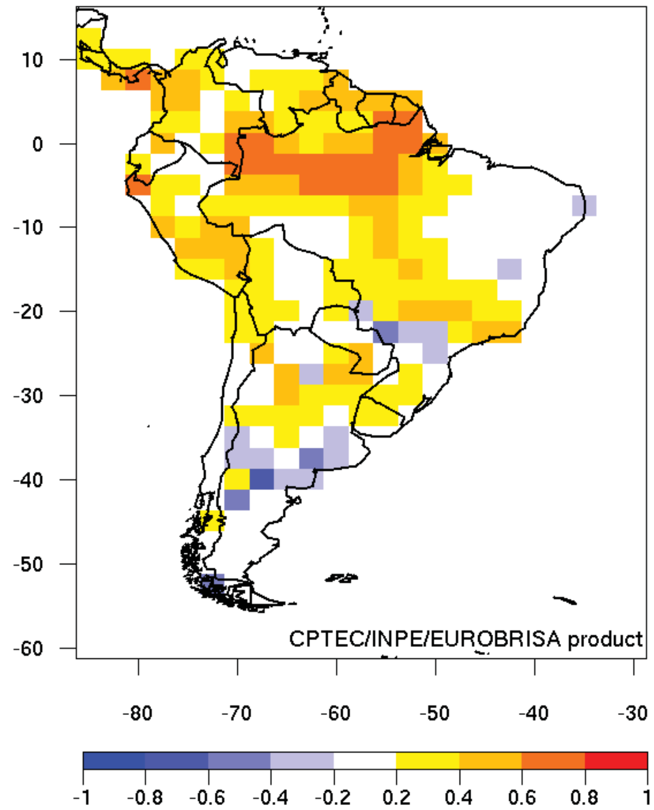


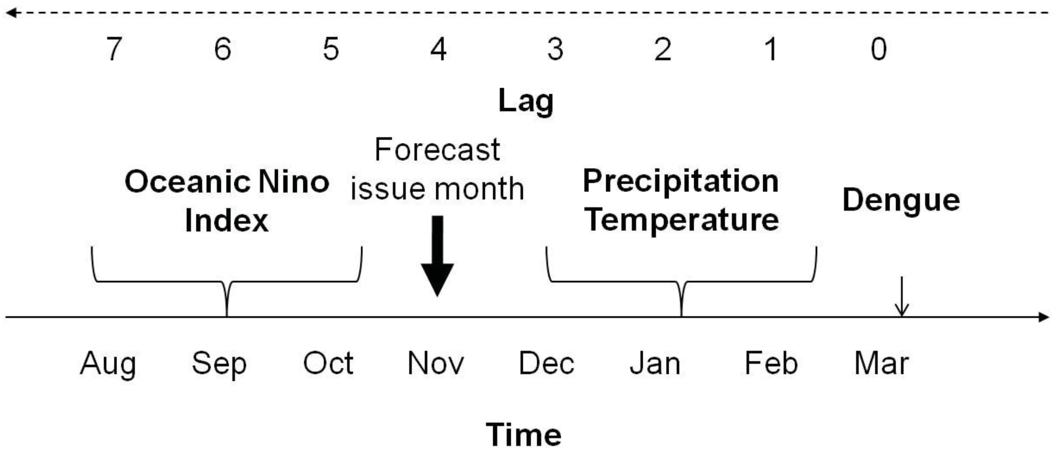
Lowe *et al.*, 2012
Statistics in Medicine

Extending prediction lead-time with forecast climate

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

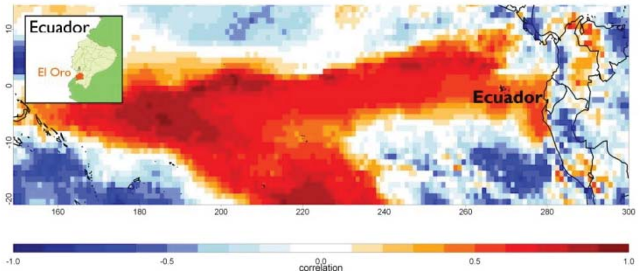
- Correlation between forecast and observed precipitation anomaly using the integrated EUROBRISA forecasting system for the period 1981-2005. Forecasts issued in November, valid for DJF season





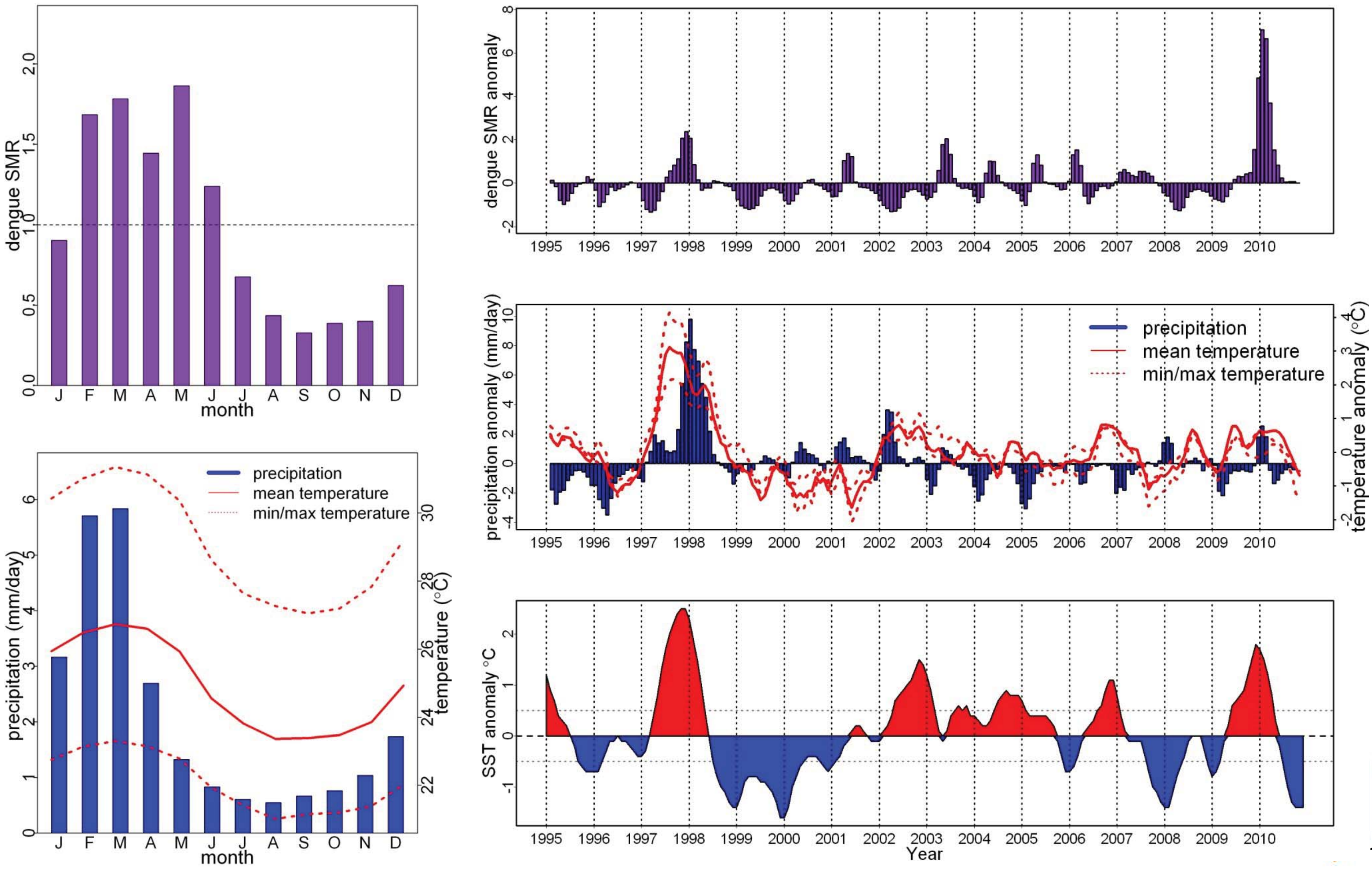
Towards a climate-driven dengue early warning system for Ecuador

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

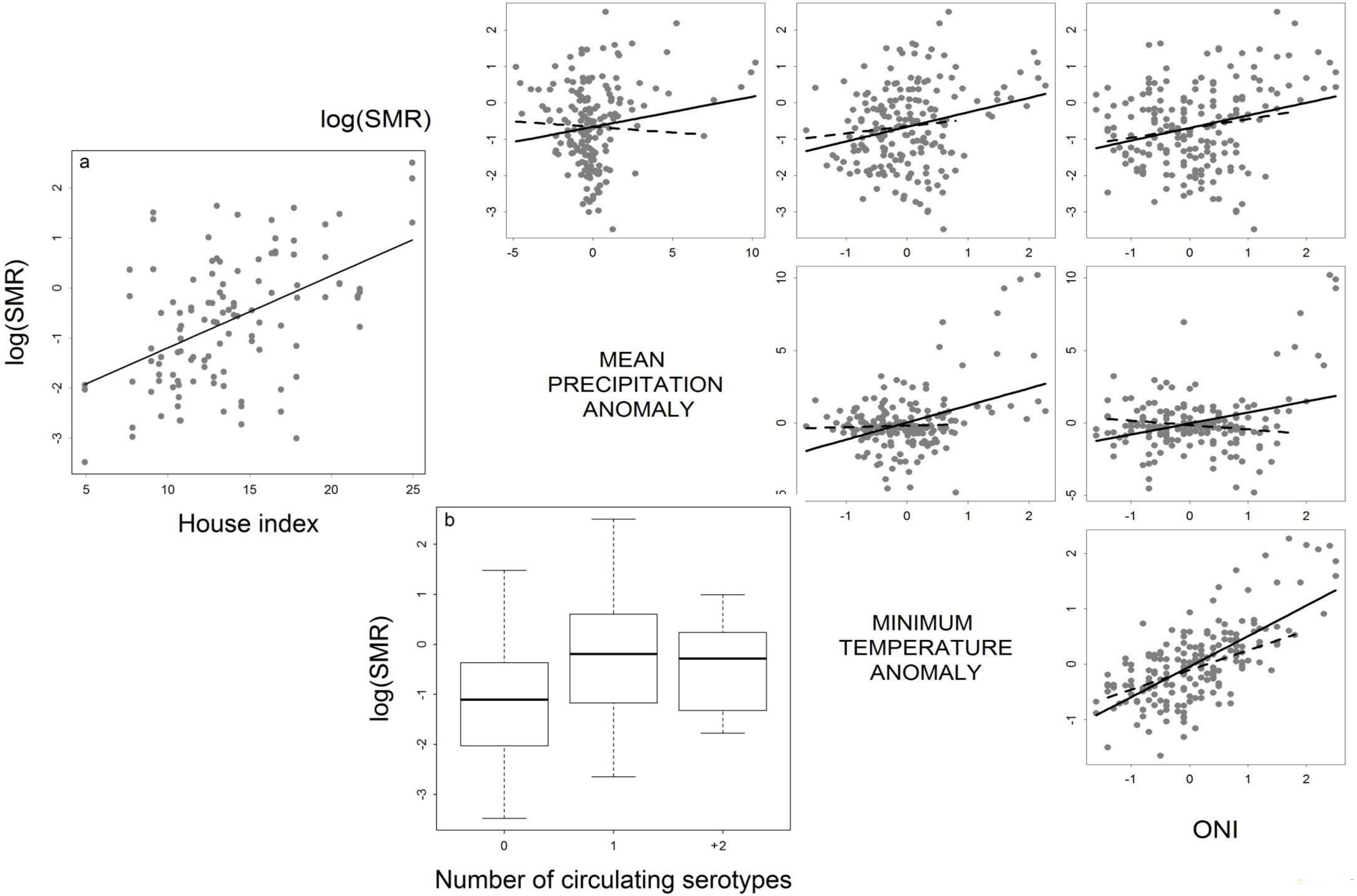


- Effective vector control
- Destruction potential mosquito breeding containers
- Education campaigns

Dengue and climate anomalies 1995-2010

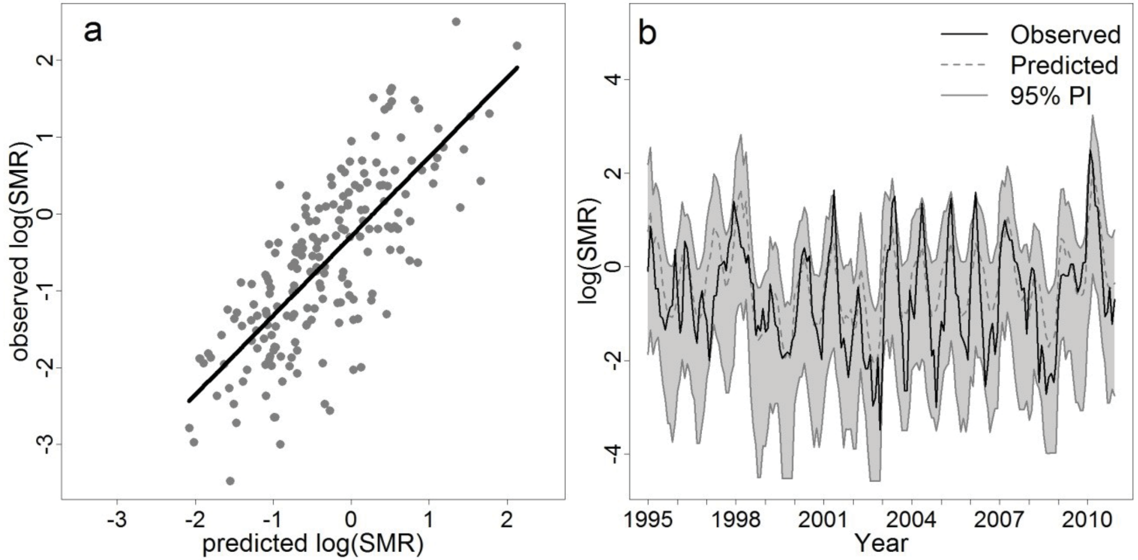


Relation dengue and potential drivers

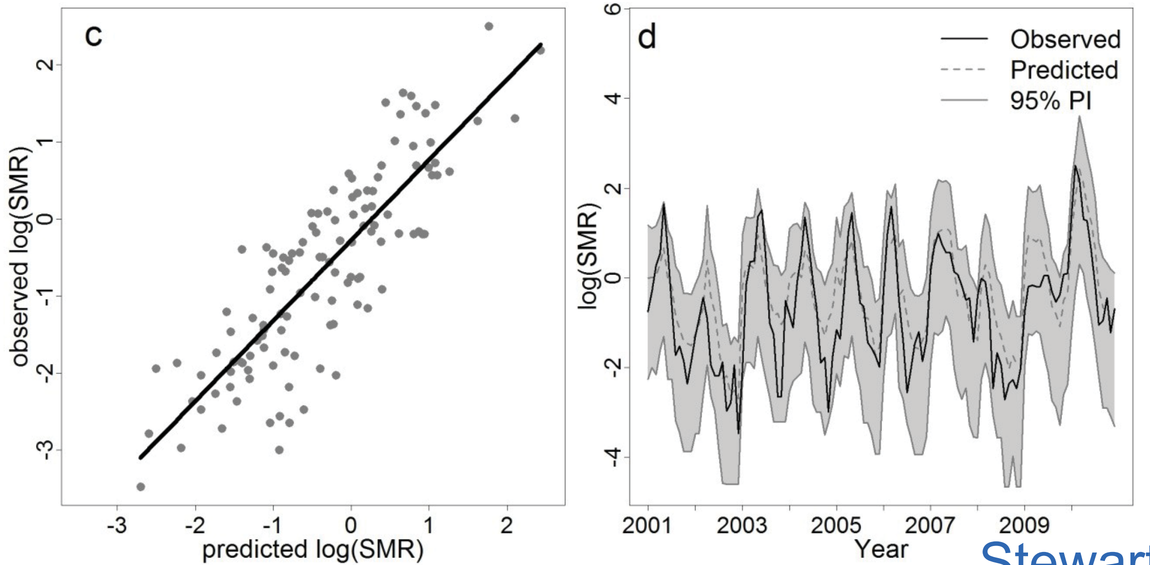


Model results

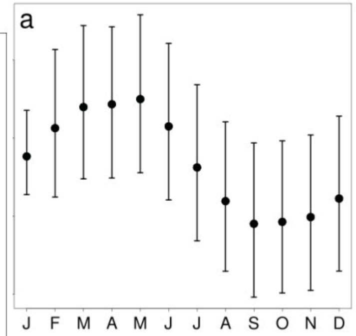
Model 1995-2010



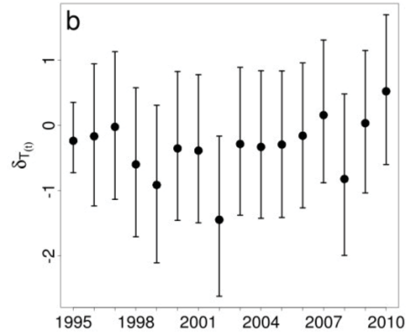
Model 2001-2010



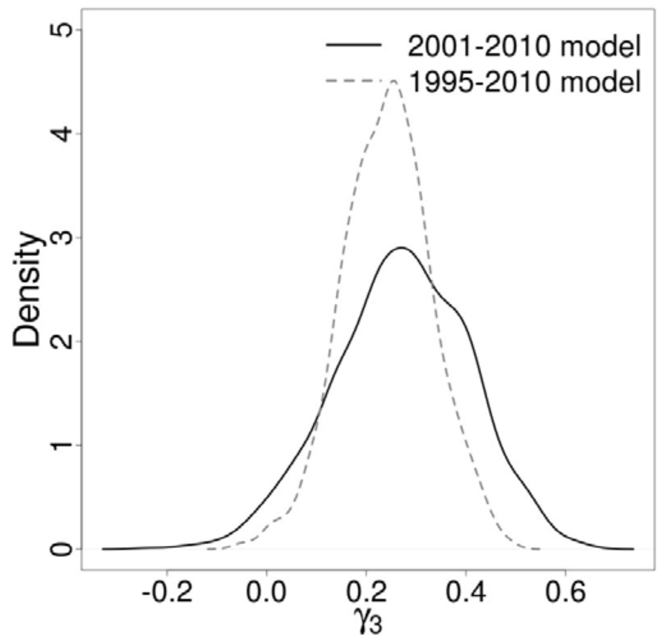
Month effects



Year effects



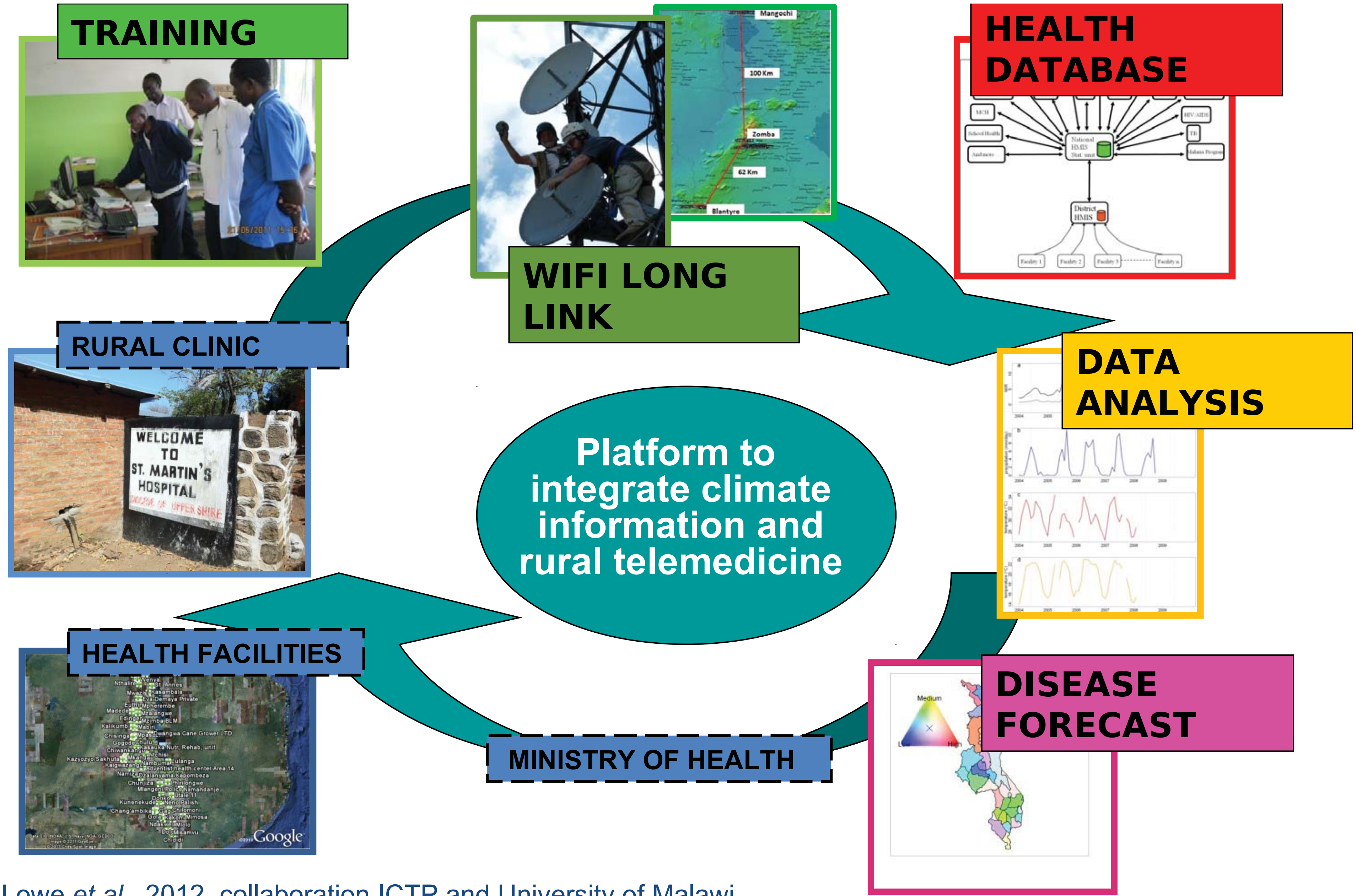
Oceanic Niño Index parameter



Stewart-Ibarra & Lowe 2013, AJHTM

Malawi pilot project

- Malaria leading cause of morbidity/mortality (>6 million episodes per year), >85% *Plasmodium falciparum*.
- Direct costs: treatment. Indirect costs: workdays lost agriculture/industry, absenteeism school.
- RBM Objective: under 5 and pregnant women access to personal and community protective measures.
- National Malaria Control Programme established in 2002 to coordinate control measures.
  - Insecticide-treated mosquito nets (ITNS)
  - Effective case management (diagnosis and treatment of illness within 24 hours)
  - Acesss to intermittent preventive treatment (IPT) for pregnant women.



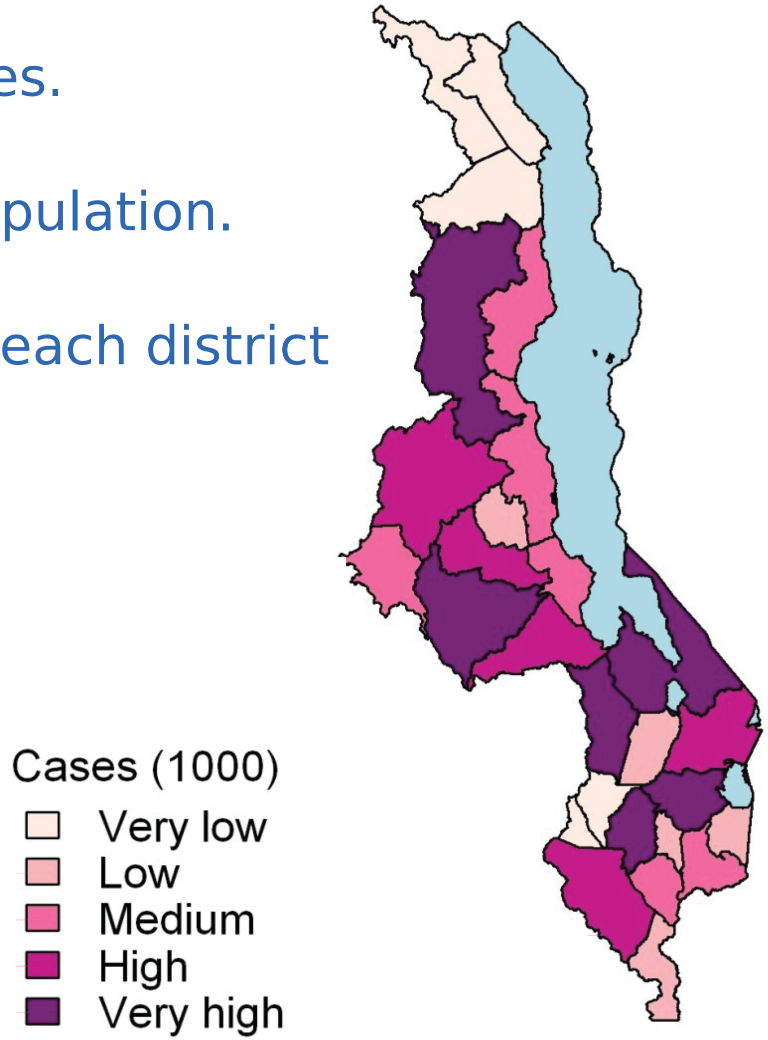
Lowe *et al.*, 2012, collaboration ICTP and University of Malawi.

EMPLOY NEW TECHNOLOGY
VOIP & WEATHER SENSORS

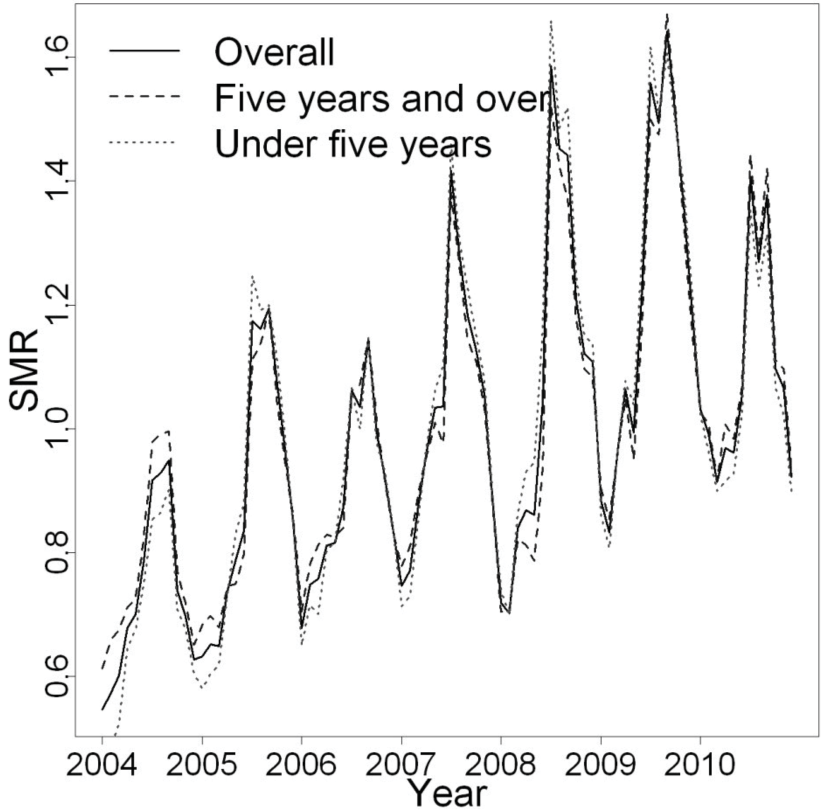
OVERCOME CHALLENGES
RELIABILITY LINK, FUEL SHORTAGES, SPEED OF DATA TRANSFER

Malaria, demographic and socio-economic data

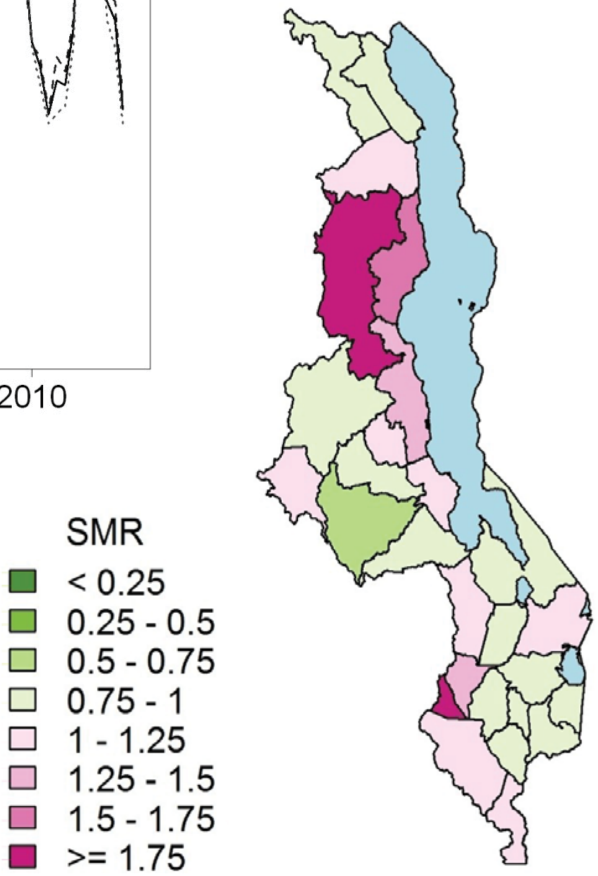
- Counts of malaria cases for under 5 and 5 years and over July 2004 – June 2011 (84 months).
- Annual population and density estimates.
- Number of health facilities per 1000 population.
- Yearly estimates of ITN distribution for each district by different agencies: UNICEF, PMI
- Proportion of population in district
  - Urban areas
  - One room for sleeping
  - No toilet
  - Living in traditional housing
  - Literate
  - Do not attend school



Standardised Morbidity Ratio (SMR)



- SMR ratio of observed to expected cases
- Excess risk when SMR>1

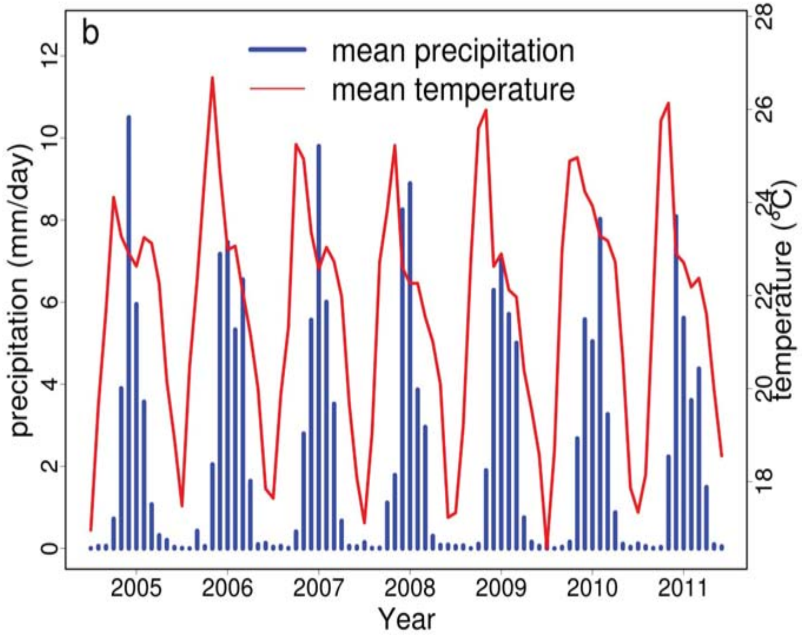


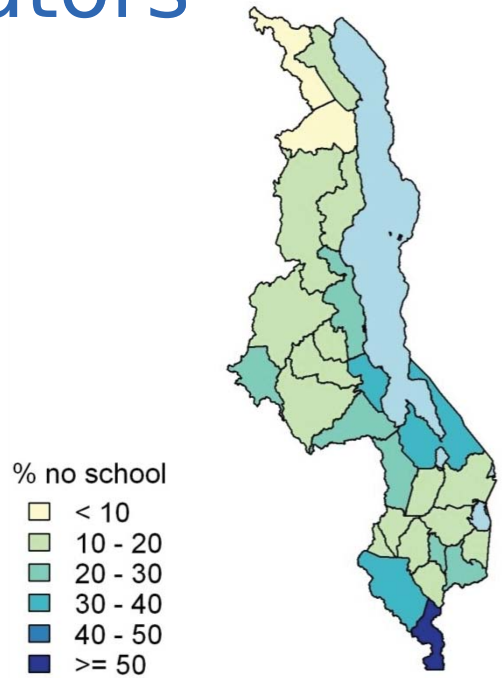
$$SMR_{st} = \frac{y_{st}}{e_{st}},$$

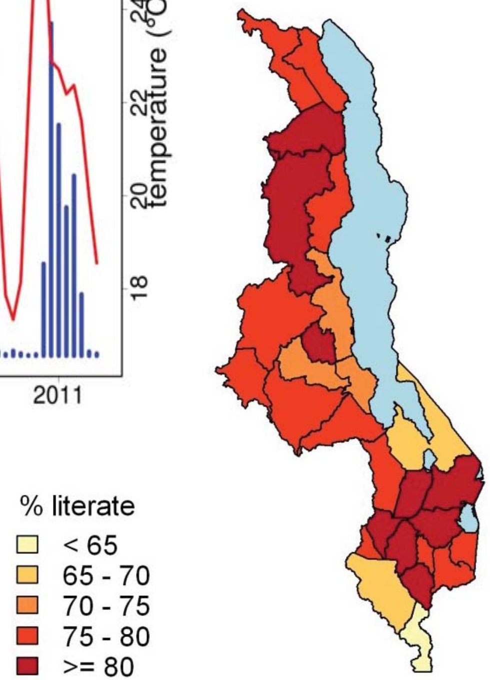
$$e_{st} = p_{st}\pi,$$

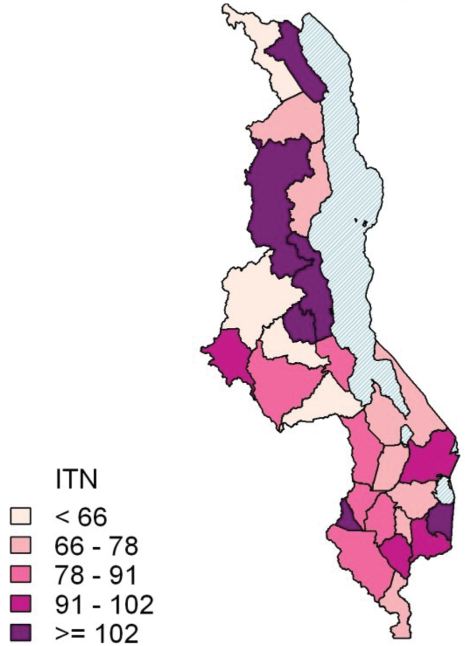
$$\pi = \frac{\sum y_{st}}{\sum p_{st}}.$$

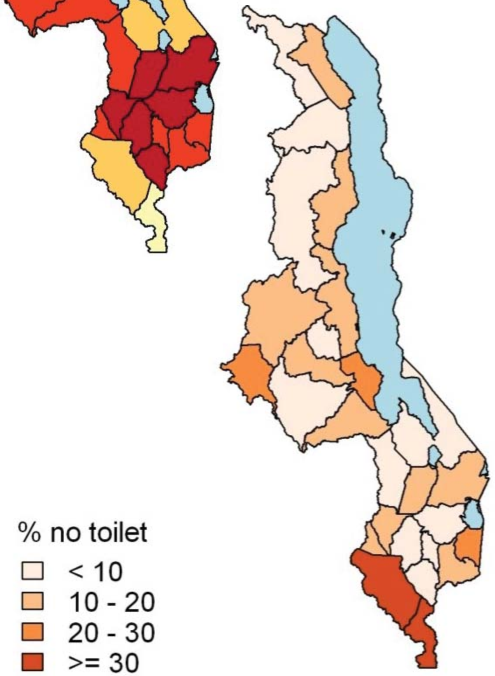
Climate and Poverty indicators

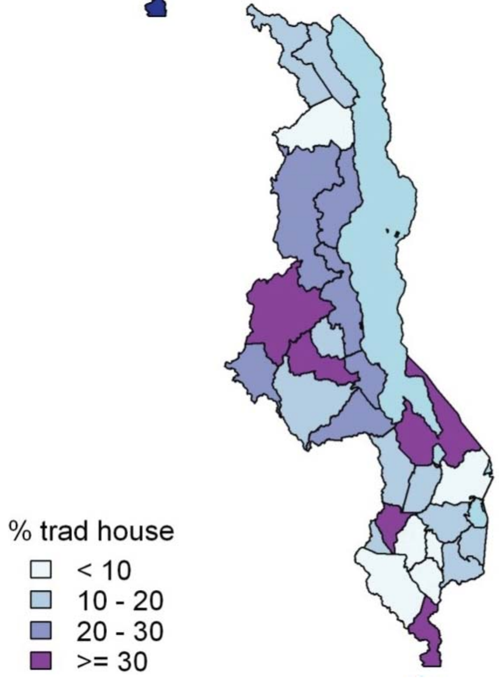




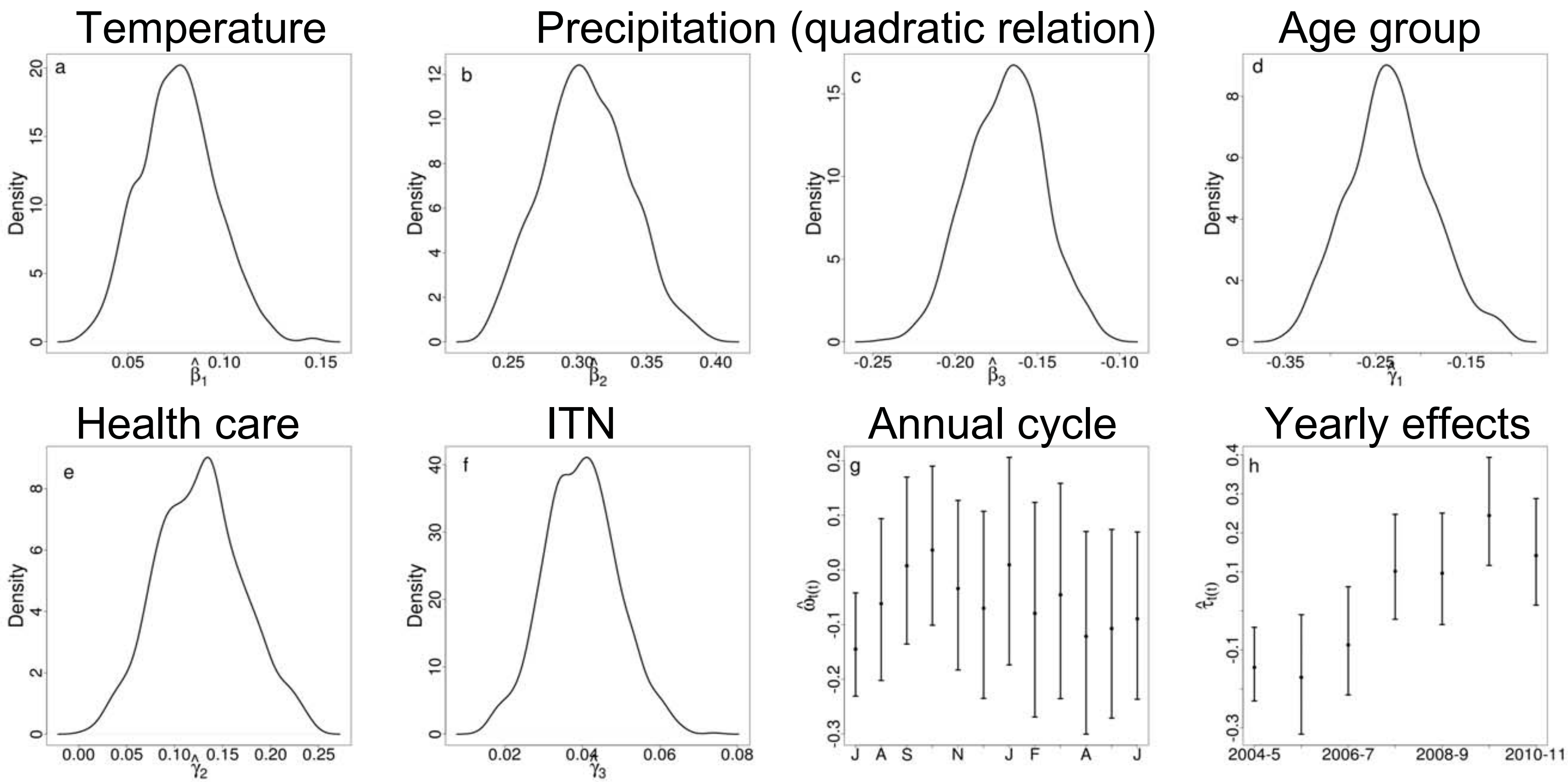


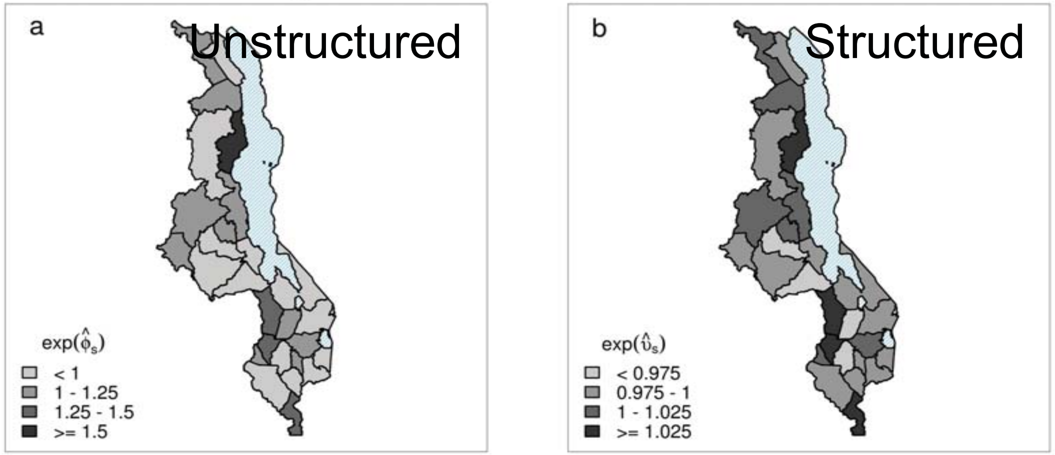






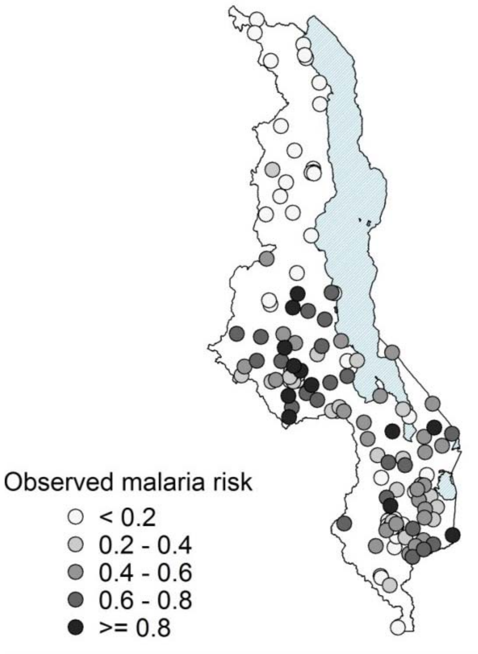
Accounting for temporal and spatial structure

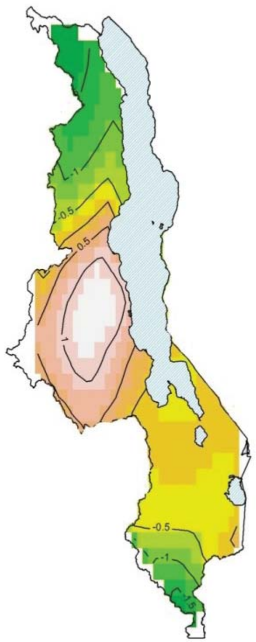




Geostatistical analysis of household malaria risk in Malawi

- MSc thesis James Chirombo, Ministry of Health.
- 2010 Malaria indicator survey data, malaria status of child determined by RDTs.
- Statistical analysis Bayesian structured additive logistic regression model. Response: Probability of testing +ve.





- Important to account for non-linear effects and spatial autocorrelation.

- Risk map aid targeted interventions.

Thank you!

Questions?