# Detection of infectious disease outbreak by an optimal Bayesian alarm system

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# Outline of the talk

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- Objective
- Methods
  1. Construction of warning systems
  2. Event prediction and screening
- Application
- Discussion

# Background

# Introduction

- Let $\{Y_t\}$ be a time series (e.g. the number of dengue cases at time $t$ monthly, weekly or otherwise).
- The interest lies in predicting whether the process will upcross a fixed level $u$ at time $t+h$: $Y_{t+l-1} < u \leq Y_{t+l}$

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- A naive way to proceed is to foretell at time $t$ that $Y_{t+l}$ will upcross $u$ if a **point predictor**, $\widehat{Y}_{t+l,t}$, say

$$\widehat{Y}_{t+l,t} = E\left[Y_{t+l} | Y_s, -\infty < s \leq t, l > 0\right],$$

  upcrosses some level $\widehat{u}$.
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  upcrosses some level $\widehat{u}$.
- Since $V(\widehat{Y}_{t+l,t}) < V(Y_{t+l,t})$ it is reasonable to take $\widehat{u} < u$.
- However this alarm system (Lindgren, 1985), does not have a good performance on the ability to: detect the events, locate them accurately in time and give as few false alarms as possible.

# Warning systems - basic ideas

- Let $\{Y_t\}$, $t = 1, 2, ...$, be a discrete parameter stochastic process. Consider at time $t$ and for some $q > 0$,

  $\mathcal{D}_t = \{y_1, ..., y_{t-q}\}$ be the informative experiment (data)
  $\mathbf{Y}_{2,t} = \{Y_{t-q+1}, ..., Y_t\}$ be the present experiment
  $\mathbf{Y}_{3,t} = \{Y_{t+1}, ...\}$ be the future experiment

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The objective is to construct a region (**event predictor**) so that whenever the process enters the region a warning (alarm) is given for the event of interest.

- An event predictor $A_t$ (warning region) for $C_t$ is any event in the $\sigma$-field generated by $\mathbf{Y}_{2,t}$.

# Warning systems - basic ideas

The construction of that region is based on an optimality criterion; a warning (alarm) system is said to be optimal when for a set of available data it possesses the highest probability of correctly detecting the event giving as few false alarms as possible.

- The predictive probabilities $P(C_t|A_t, \mathcal{D}_t) = \gamma_t$ and $P(A_t|\mathcal{D}_t) = \alpha_t$ are the probability of correct detection and size of the warning region, respectively.

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- $A_t$ is optimal of size $\alpha_t$ if

$$A_t = \{\mathbf{y}_2 \in \mathbb{R}^q : \frac{P(C_t|\mathbf{y}_2, \mathcal{D}_t)}{P(C_t|\mathcal{D}_t)} \geq k_t\},$$

where $k_t$ is such that $P(A_t|\mathcal{D}_t) = \alpha_t$.

# Operating characteristics of the warning system

The following **predictive probabilities are the operating characteristics of the warning system**.

1. Warning size: $P(A_t|\mathcal{D}_t)$
2. probability of correct detection: $P(C_t|A_t, \mathcal{D}_t)$
3. probability of correct warning: $P(A_t|C_t, \mathcal{D}_t)$
4. probability of false warning $P(A_t|C_t^c, \mathcal{D}_t)$
5. probability of false detection $P(C_t|A_t^c, \mathcal{D}_t)$

It is an on-line warning system since the informative experiment constantly updates posterior probabilities of the events.

# Objective

The aim of this work is to develop a warning system for disease outbreak by:

the construction of a critical region (**event predictor** $A_t$) so that whenever a vector of variables related to the disease occurrence ($\{\mathbf{X}_t\}$ – e.g. weather conditions) enters the critical region, a warning (alarm) is given for the event of interest $C_t$ (e.g. the process $\{Y_t\}$ will upcross a fixed level $u$)

## Alternative warning system

- The warning system described does not answer the question of interest: relating the process $\{Y_t\}$ (dengue cases) with the processes $\{\mathbf{X}_t\} = (\{X_{1,t}\}, \{X_{2,t}\})$ (weather conditions: precipitation and temperature).
- A simple alternative is to construct a joint model using $[Y_t|\{\mathbf{X}_t\}][\{\mathbf{X}_t\}]$.
- But how?

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- But how?
- By using a screening procedure as in epidemiological studies.
- Most papers dealing with this issue (e.g. Lowe, et al 2010, Vasquez-Prokopec et al 2010) consider a Poisson regression model for $[Y_t|\{\mathbf{X}_t\} = \{\mathbf{x}_t\}]$, but no attempt is made to model $\{\mathbf{X}_t\}$.

# Proposed methodology

# Warning system based on screening

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- Similarly, the event predictor $A_t$ (warning region) for $C_t$ is any event in the in the $\sigma$-field generated by $\mathbf{X}_{2,t}$.
- The informative experiment (data) is $\mathcal{D}_t = \{(Y_1, \mathbf{X}_1), ...(Y_{t-q}, \mathbf{X}_{t-q})\}$, ie, all the data available till time $t-q$. This is used to obtain the posterior distribution for the parameters of the model.

# Warning system based on screening

- Now $A_t$ is optimal of size $\alpha_t$ if

$$A_t = \{\mathsf{x}_2 \in \mathbb{R}^{pq} : \frac{P(C_t|\mathsf{x}_2, \mathcal{D}_t)}{P(C_t|\mathcal{D}_t)} \geq k_t\},$$

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- If $p > 1$, in practice values of $q > 1$ can complicate the analysis unnecessarily.

# Model

- Adopting a Bayesian framework, the joint model for $[Y_{t+l}, \mathbf{X}_t]$ is described as follows:
    1. $[Y_{t+\ell}|\mathbf{X}_t = \mathbf{x}_t, z, \theta][\mathbf{X}_t|\psi]$, where $z$ contains any extra information;
    2. $[\theta, \psi] = [\theta][\psi]$.
- Construction of the region and calculation of operating characteristics (OC) can be obtained via Monte Carlo Methods if no analytical solution is available.
- We used $p = 2, q = 1$ and hence, at time $t$, the present experiment is just $\mathbf{X}_{2,t} = \{X_{1,t}, X_{2,t}\}$, (precipitation and temperature)

# Implementation of the procedure

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4 Let $u$ be the threshold. For each $\mathsf{x}_2 \in G$ compute the predictive probability
$P(Y_{t+\ell} > u|\mathbf{X}_t = \mathsf{x}_2, z, \mathcal{D}_t) \approx \frac{1}{M} \sum P(Y_{t+\ell} > u|\mathbf{X}_t = \mathsf{x}_2, z, \theta^{(i)})$

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5. For a fixed $k$ register the values of $\mathsf{x}_2$ for which the predictive probability is above $k$. These values belong to the region $A_t$
6. Find the boundaries of the region $A_t$ so that it is well defined.

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9. Similarly compute $P(Y_{t+\ell} > u, \mathbf{X}_2 \notin A_t)$.
10. $P(Y_{t+\ell} > u|\mathcal{D}_t) = P(Y_{t+\ell} > u, \mathbf{X}_2 \in A_t) + P(Y_{t+\ell} > u, \mathbf{X}_2 \notin A_t)$.

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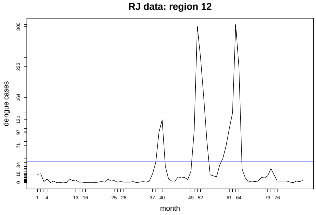
# Application

# Description of the data

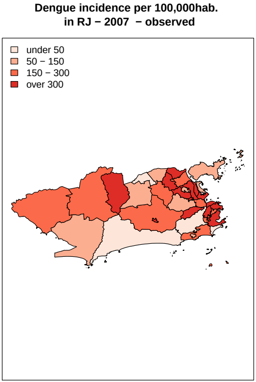
- RJ data: monthly notified cases of dengue ($Y_t$) for the 33 health administrative regions in the city of Rio de Janeiro (RJ), Brazil.
- RJ total population: 5,857,904
- The warning region is built based on $X_{1,t}$ – preciptation (known for all 33 regions) and $X_{2,t}$ – temperature (common to all regions).

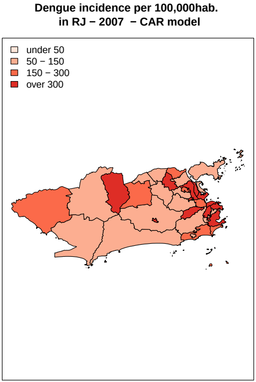


# Preliminary analysis

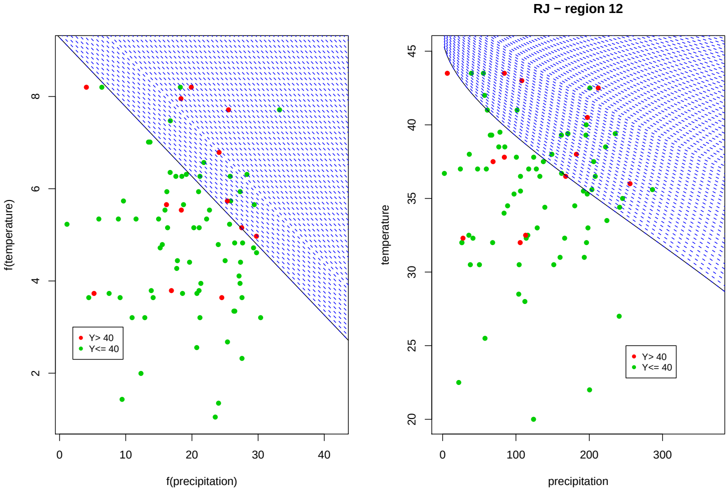
- A preliminary data analysis (cross correlations) suggested a lag $\ell = 2$ months
- Box-Cox transformation applied to maximum temperature $(\lambda = 2.65)$ and total amount of precipitation $(\lambda = 0.54)$
- $[Y_{t+\ell}|\mathbf{X}_t = \mathbf{x}_t, z, \theta]$ – Spatio-temporal Poisson regression model with transformed temperature and precipitation as covariates.
- $[\mathbf{X}_t|\psi]$ – Bivariate Gaussian model for the joint distribution of temperature and precipitation. Also a nonparametric Bayesian model was tested.

# Spatio-temporal Poisson regression model for the incidence of dengue (7 years of monthly data)



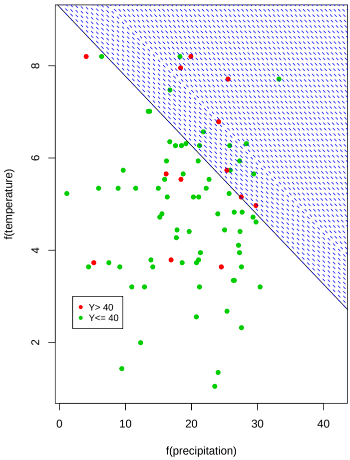



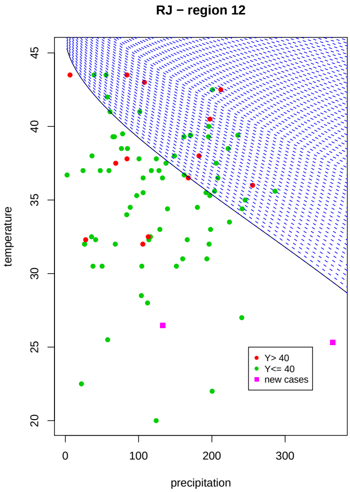
# Region 12 - warning region for $u = 40$, $k = 0.3$




Epidemic: 300 cases/100,000 inhab/year. Region 12: 161,178*(300/12)/100,000 $\approx$ 40 cases/month.

# Region 12 - warning region, new cases



# Region 12 - Operating characteristics

- Operating Characteristics (fixed - based on all available data), $u = 40, k = 0.3$, (yearly incidence rate - 298 in 100,000)
- Probability of the event: $P(Y > 40|\mathcal{D}) = 0.20$ (empirical estimate 0.16)

| | | |
|---|---|---|
| Warning region size | $P(A_t\|\mathcal{D}_t) =$ | 0.25 |
| Probability of correct detection | $P(C_t\|A_t, \mathcal{D}_t) =$ | 0.64 |
| Probability of correct warning | $P(A_t\|C_t, \mathcal{D}_t) =$ | 0.80 |
| Probability of false warning | $P(A_t\|C_t^c, \mathcal{D}_t) =$ | 0.11 |
| Probability of false detection | $P(C_t\|A_t^c, \mathcal{D}_t) =$ | 0.05 |

# Discussion

# Discussion and further work

- This is a work under progress; spatial data on temperature for Rio de Janeiro has just become available.
- The topography of RJ makes particularly difficult the spacial analysis of dengue.
- This warning system, as it was devised, is not time dependent. Warning region is fixed.
- However it is possible to improve on the model in order to construct a recursive system of warning regions. This is our next goal.
- Include in the model socio-economic and other environment characteristics which are relevant to explain dengue epidemics.
- Consider the construction of spatio-temporal warning systems.

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