Risk Analysis to Extreme Rainfall: A retrospective approach

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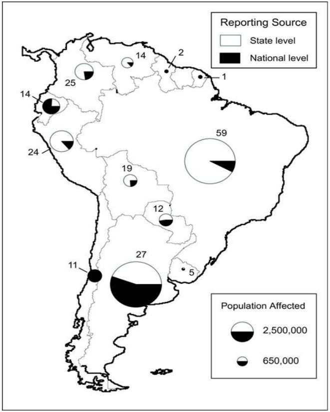
Presentation Outline

Introduction

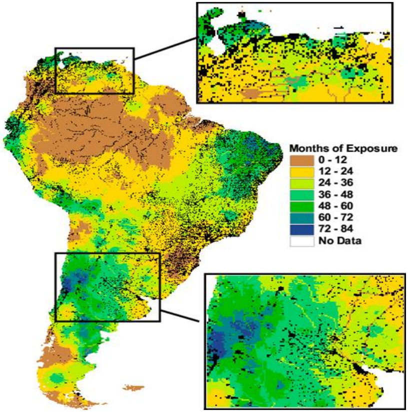
1. Present a retrospective analysis in where hazard, vulnerability and exposure are modeled using historical data during the period 1970–2006.
2. Model vulnerability, hazard and risk including uncertainty in all its components.
3. Describe a framework for risk mapping and present an application for Vargas state, Venezuela.

Reported events and People affected: South America 1960–2000



Source: Data from the Center for Research on the Epidemiology of Disasters (www.cred.be)

Population Exposure: South America 1960–2000



1. Extreme weather continues to preoccupy society with huges concerns on public safety and economic loses.
2. Attention has focused on global climate change and potential intensification on the water cycle elements as precipitation and river discharge.
3. It is the conjunction of geophysical and socioeconomic factors that shapes human sensitivity and risk to extreme weather events (Pielke and Sarewitz, 2005).
4. Several definitions of vulnerability and risk are available in the social and physical science literature. Working definitions are needed for modeling purposes.

Important concepts

Natural Hazard (H)

It is a natural phenomenon (Storm, Volcanic Eruption, Earthquake, etc.) causing damage to a population, ecosystem or unit of concern. This damage might potentially cause a disaster, when the levels of damage go beyond the response capability of the affected unit.

Important concepts

Vulnerability (V)

Downing *et al.* (1999) defines vulnerability as the degree of loss (from 0 to 100 %) in human casualties, property damage or interruption of an economic activity due to a damaging event on a given period and location.

Important concepts

Exposure (E)

It is the amount of infrastructure, population, ecosystem or environmental unit exposed to single or multiple hazards.

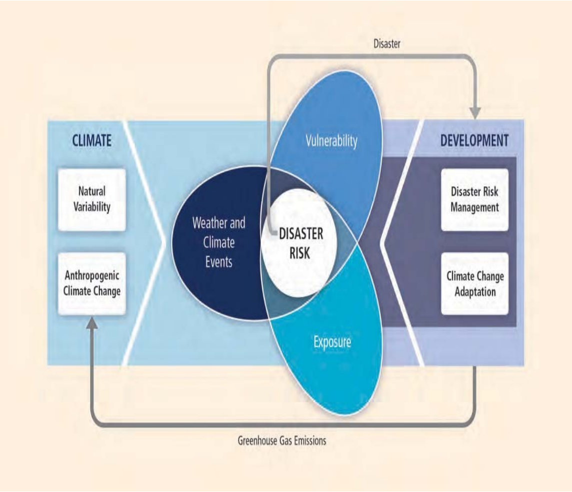
Important concepts

Risk (R)

Risk is defined as **the expected losses** due to a damaging event. It is the combination of the amount of damage caused for a particular hazard with the probability associated to this particular hazard. Normally is written as $R = E * V|H * P(H)$.

SREX IPCC Report

Managing the Risk to Extreme Events and Disasters (2012)



SREX Report Definitions

IPCC, 2012

- **Exposure**: The presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected.
- **Vulnerability**: The propensity or predisposition to be adversely affected.
- **Disaster Risk**: The likelihood over a specified time period of severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery.

SREX Report Definitions
IPCC, 2012

Probabilistic Risk Analysis

Defines risk as the product of the probability that some event (or sequence) will occur and the adverse consequences of that event.

$$Risk = Probability x Consequence$$

General Framework

We define the components of Risk following Downing *et al.* (1999)
Notation: For a given time t and location s, we define:

- $H_{t,s}$: Hazard (Rainfall anomalies in mm).
- $V_{t,s}$: Vulnerability or Loss Function (Number of People Affected per 100,000 inhabitants).
- $R_{t,s}$: Risk (Expected number of people affected).
- $E_{t,s}$: Exposure (Total population $\times$ 100,000 inhabitants).

General Framework

The **expected loss** conditioned on $H_{t,s}$ can be defined as

$$E[V_{t,s}|H_{t,s}].E_{t,s}$$

General Framework

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$$E[V_{t,s}|H_{t,s}].E_{t,s}$$

Finally Risk is defined as follows:

Risk

$$E_H[E_{V|H}[V_{t,s}|H_{t,s}].E_{t,s}] = E_{t,s}.\int_H E_{V|H}[V_{t,s}|H_{t,s}].P(H_{s,t})dH$$

We will be integrating out the above equation with respect to the Hazard $H_{s,t}$ and its Posterior Predictive distribution $P(H_{s,t})$.

General Framework

Vulnerability Model

- We model the total number of people affected per 100,000 inhabitants as a function of a set of co-variables as columns of the matrix X.
- We used reported counts of people affected for the period 1970–2006 by extreme rainfall related events. The values are aggregated counts on a monthly basis for the study region.
- Since we have an important presence of zero values (months with no events) or events with no casualties, we used a zero-inflated regression to model vulnerability.

General Framework

Vulnerability model

Let $Y_1, \ldots, Y_n$ be the observed values of the number of people affected due to an extreme rainfall event for a particular time t, $t = 1, \ldots, n$. Assuming the values of Y_t are independent, we have the Zero-Inflated Poisson model:

General Framework

Vulnerability model

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Zero-Inflated Poisson Regression (ZIP)

$$Y_t = \begin{cases} 0 & \text{with probability} \quad p_t + (1 - p_t) e^{-\lambda_t} \\ k & \text{with probability} \quad (1 - p_t) \dfrac{e^{-\lambda_t} \lambda_t^k}{k!} \end{cases}$$

General Framework
Vulnerability model

- Poisson mean vector $\lambda = (\lambda_1, \ldots, \lambda_n)$ satisfies

$$\log(x^\mathsf{T}\lambda) = B\beta$$

  x is the exposure vector of size n.
- Probability parameter vector $p = (p_1, \ldots, p_n)$ satisfies

$$\text{logit}\left(\frac{p}{1-p}\right) = G\gamma$$

G and B are covariate matrices, not necessarily sharing the same covariates. β and γ are unknown parameters.

General Framework

Vulnerability model

Another extension is the Zero Inflated Negative Binomial model

General Framework

Vulnerability model

Another extension is the Zero Inflated Negative Binomial model

Zero-Inflated Negative Binomial Regression (ZINB)

$$Y_t = \begin{cases} 0 & \text{with probability} \quad p_t + (1 - p_t) \dfrac{\theta^\theta}{(\lambda_t + \theta)^\theta} \\ k & \text{with probability} \quad (1 - p_t) \dfrac{\Gamma(k + \theta)}{\Gamma(\theta)\, k!} \dfrac{\lambda_t^k \, \theta^\theta}{(\lambda_t + \theta)^{k+\theta}} \end{cases}$$

with mean λ_t, shape parameter θ, and $\Gamma(\cdot)$ the Gamma function.

General Framework
Hazard Model

- A Hierarchical Bayesian Kriging model was fitted to monthly rainfall data of 27 locations from years 1970–2006 following Le and Zidek (2006).
- The Sampson and Guttorp method is used to consider non-stationarity conditions in the spatial covariance matrix.
- Posterior predictive simulations of total rainfall are obtained for each month, year and location in where rainfall data is estimated.

General Framework
Hazard Model

Hazard model

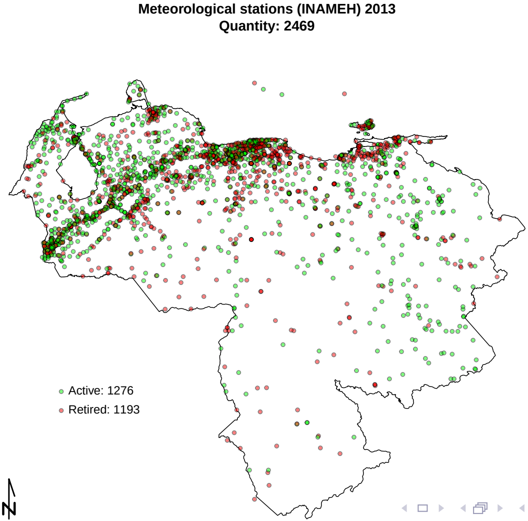
Monthly Rainfall Totals at ungauged (u) and gauged (g) locations $Y_t = \left(Y_t^{(u)}, Y_t^{(g)}\right), t = 1, \ldots, n$. Assuming Y_t are independent

$$Y_t \,|\, z_t, B, \Sigma \sim N_p\left(z_t B, \Sigma\right)$$

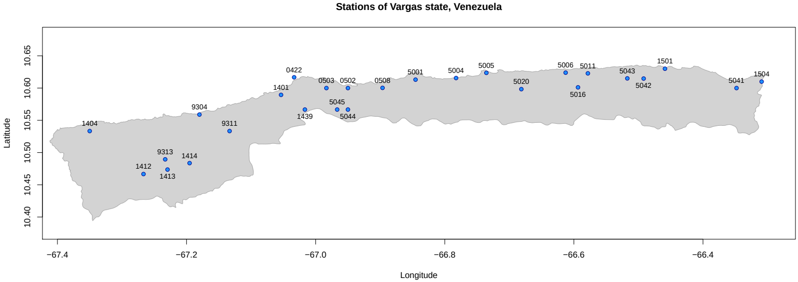
General Framework
Hazard Model

- $z_t = (z_{1t}, \ldots, z_{kt})$ is a k-dimensional vector of covariables.
- $B = \left(B^{(u)} \; B^{(g)}\right)$ is a $(k \times p)$ matrix of regression coefficients, where $p = u + g$.
- B and Σ are assumed to have conjugate priors: $B|\Sigma$ has a kp-dimensional Multivariate Normal and Σ has an p-dimensional Inverse-Wishart distribution.
- Given the hyperparameters defining the distributions of B and Σ, the joint posterior predictive distribution of $Y_f = \left(Y_f^{(u)'} \; Y_f^{(g)'}\right)$ conditional on the covariate vector z_f is fully characterized as the product of two Student's t-distributions, for $1 \leq f \leq n$.

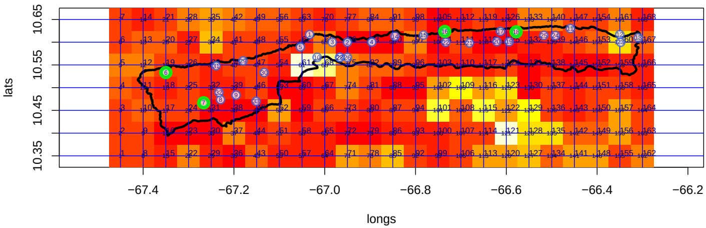
Monitoring Stations



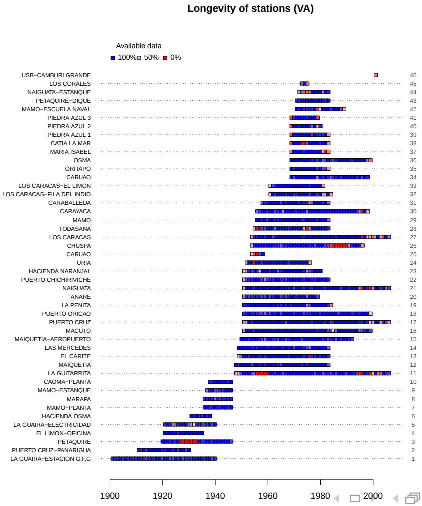
Particular case: Vargas state



Vargas state

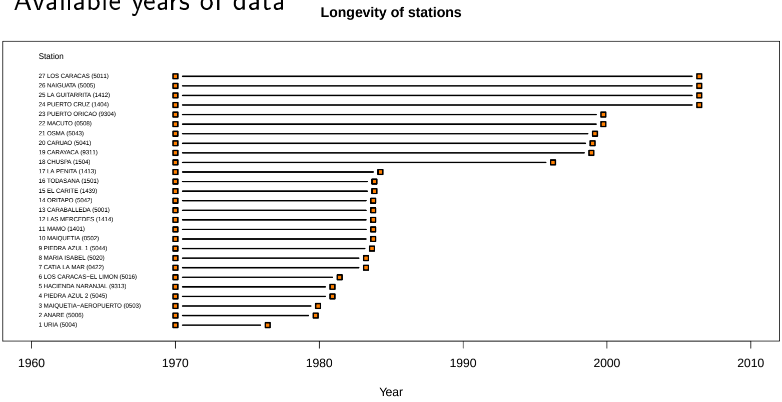


Station Data

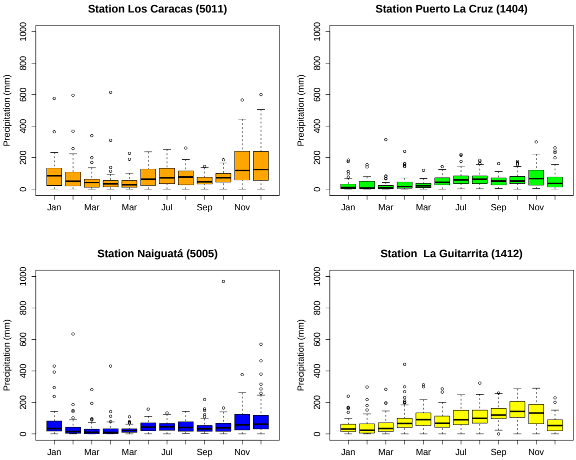


Station Data

Available years of data



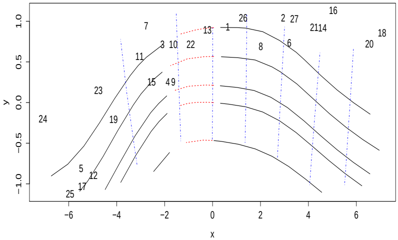
Station Data



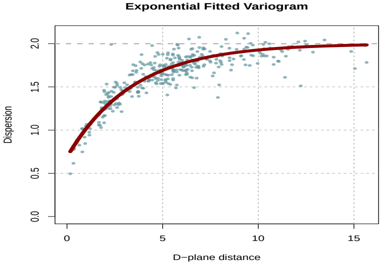
Hierarchical Kriging Model

Variogram fit in the Dispersion space (D-space)

D plane coordinates

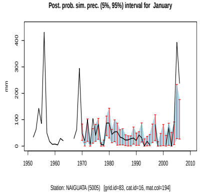


Exponential Variogram



Naiguata station (5005)

Jan



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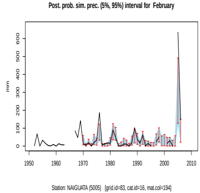

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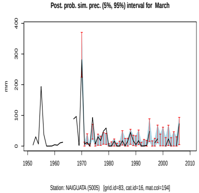

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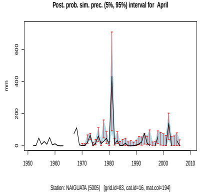

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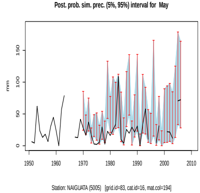

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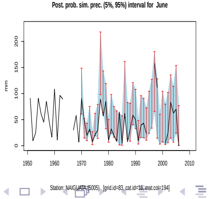

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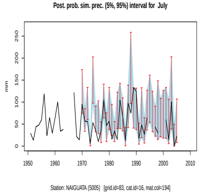

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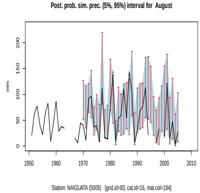

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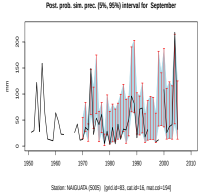

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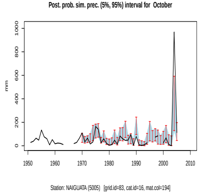

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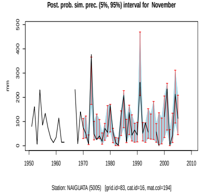

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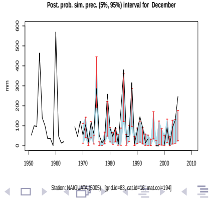
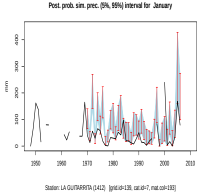


La Guitarrita station (1412)

Jan



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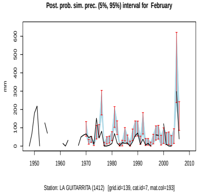

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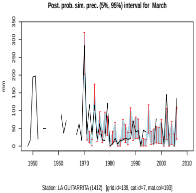

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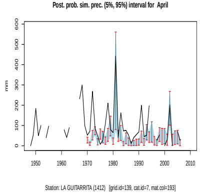

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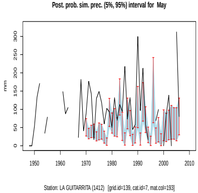

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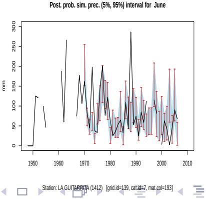

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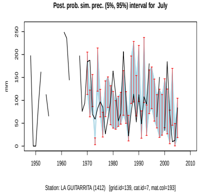

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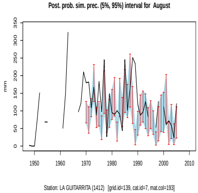

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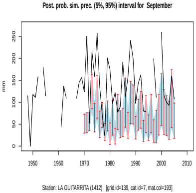

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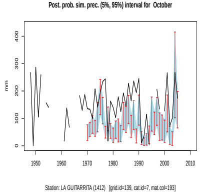

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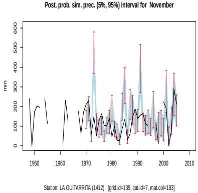

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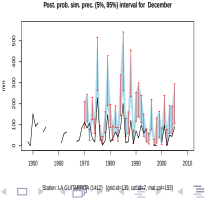
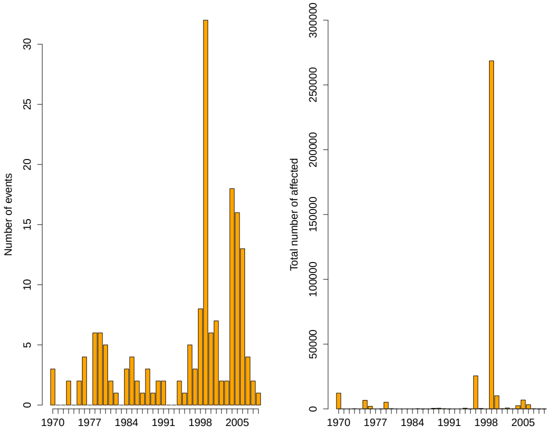


Vulnerability Model

Number of events and people affected in the period 1970–2009



Vulnerability Model for Vargas state

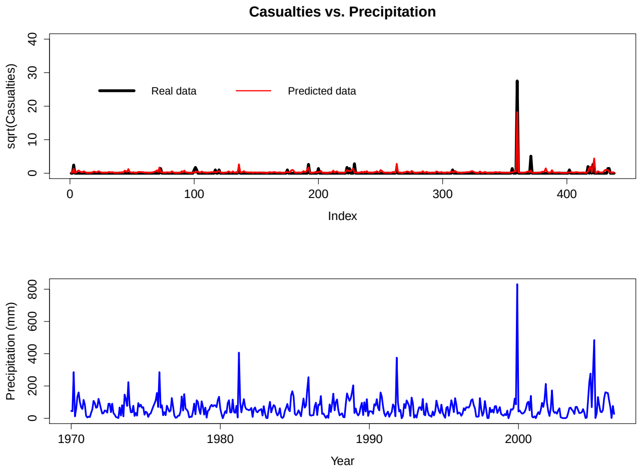
- Response Variable y: Number of Casualties.
- Model formula: $y \sim x_1 + \ldots + x_p \,|\, z_1 + \ldots + z_q$.
- $x_1, \ldots, x_p$: covariables included in the count model.
- $z_1, \ldots, z_q$: covariables included in the zero-inflation model.

	Model	AIC ZIP	AIC ZINB	p-Value Voung Test (ZIP vs. ZINB)
1	$y \sim \text{MEI} \,|\, 1$[1]	3141	322	0.012
2	$y \sim \text{MEI} + \text{PRECIP} \,|\, 1$	2490	**309**	0.020

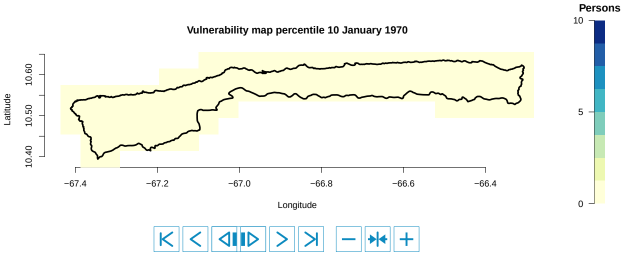
Number of zeros explained by model 2 ZINB: 414/451 (92 %).

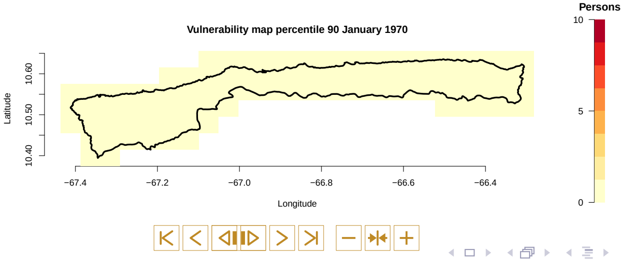
[1] A "1" means an intercept with no covariates has been used for the zero-inflation model.

Casualties vs. Rainfall

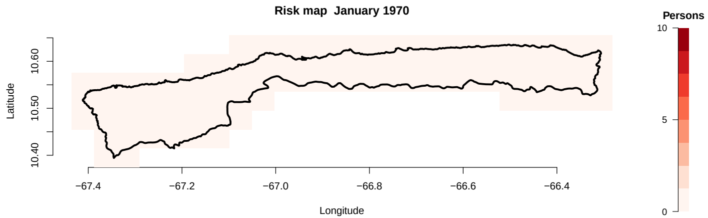


Vulnerability Maps





Risk Maps


Risk map January 1970
Latitude
10.60
10.50
10.40
−67.4
−67.2
−67.0
−66.8
−66.6
−66.4
Longitude
Persons
10
5
0

Future Work

1. This is work in progress. We apologize...
2. Changes of exposure with time were accounted for, but changes of exposure with space were not. This can be improved with higher resolution population data sets.
3. Uncertainty in the Vulnerability model parameters needs to be included in the model structure.
4. To estimate Risk we really need integration with respect to $P(V_{t,s}, H_{t,s})$, the joint probability distribution of Hazard and Vulnerability.
5. A fully Bayesian modeling approach will be implemented.

References

- Downing, T.E.; Olsthoorn, A.J. and Tol, R.S.J. (eds.) 1998. *Climate, Change and Risk*. Rouledge, New York.
- Pielke Jr R.A. and Sarewitz D. 2005 Bringing society back into the climate debate. Popul. Environ. 26, 255–268.(doi:10.1007/s11111-005-1877-6)
- Villalta, D.; Bravo de Guenni, L. and Sajo-Castelli, A. 2014. Risk Analysis to Extreme Rainfall: A retrospective approach (In Prep.).
- Vörösmarty, C.J; Bravo de Guenni, L.; Wollheim, W.M.; Pellerin, B.; Bjerklie,D.; Cardoso, M.; D'Almeida, C.; Green, P. and Colón, L. 2013. Extreme Rainfall, Vulnerability and Risk: a continental scale assessment for South America. Phil Trans R Soc A.371:20120408.


Thanks for your attention