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CLIMATE INFLUENCES ON THE FLOOD HAZARD ACROSS BRAZIL

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ABSTRACT: Flood risk management and flood frequency analysis have relied on the stationary and independence assumptions of random events, whereas the probability associated with a given flood is constant across time. However, climate variability and land use changes may impose significant modifications in the physical processes associated with extreme rainfall-runoff events in a given region which in turn may alter the flood hazard for short or long periods. In this case, identification of the key climate variables associated with the flood hazard variability is particularly important if one wants to assess the impacts of climate change on the flood risk. Here we explore the hypothesis of a time varying flood hazard for several streamflow gauges in leading locations across Brazil by analyzing historical streamflow series and large scale climate teleconnections associated with their interannual variability. Particularly, we define the flood hazard as the probability of the daily flow to exceed some pre-defined threshold value, e.g., the 90th daily streamflow percentile. For each year and gauge, the number of days in which the daily streamflow exceeds the threshold value is then stored. In order to consider only time independent flood events, we decluster the daily streamflow series by taking only flood events in which the inter-arrival time is greater than three days. The interannual variability in the number of flood events for each site is then associated with climate variability in a Poisson regression framework, whose covariates are representative of ENSO, of the meridional position of the Intertropical Convergence Zone (ITCZ) and of the monsoon system over South America. The spatial distribution of the regression estimates are then used to depict a quantitative view of the most sensitive regions in Brazil in terms of flood risk changes due to ENSO, ITCZ and monsoon variability. Finally, the implications of potential future changes of such large scale climate systems on the flood risk in the country are discussed.

Key Words: Flood Frequency Analysis, Flood Risk, Poisson Regression, Climate

1. INTRODUCTION

Floods are indeed one of the most interesting phenomenons in hydrology. The understanding of its spatio-temporal patterns are of practical importance for the society as a whole and their scientific studies along the years have also contributed to the advance of other fields in science such as theoretical statistics (e.g. the introduction of the extreme value theory by Gumbel in 1958) and climate (e.g. the study of floods in a hydroclimate perspective introduce by Hirshboeck in the 1980's). Traditionally, the empirical study of local and regional flood occurrence also known as flood frequency analysis has been the main tool to understand some of the spatial and temporal patterns of such extreme events and to provide, among other things, crucial information (e.g. flood quantiles) for flood risk management. Usually, when local data of flood events in available, a probability model is fit to block maximum or peak over threshold (POT) streamflow series and flood quantiles can be obtained for any desired frequency or return period (see for instance Stedinger et al., 1993). For ungauged basins, when local data is few or not available (prediction in ungauged basins - PUB, see Gupta et al., 2007), then flood flow and its attributes from gauged basins are used to estimate flood parameters in the ungauged basins. This process, also known as regional flood frequency analysis, has been subject of several studies (see, for instance Stedinger et al.,1993, and the references therein) and still poses some relevant challenges (Gupta et al., 2007). In both local and regional flood frequency analysis is common to assume that the flood generation mechanism is random and stationary in time, which in turn will imply stationary distribution parameters and a constant flood hazard along the years.

Since the stationary assumption may not hold in basins subject to significant urban development or under global climate changes, several attempts have been made to identify non-stationarities in flood flow series (e.g. Clarke, 2002; Cunderlik and Burn, 2003; Jain and Lall, 2001; Jain and Lall, 2000; Kwon et al., 2008; Milly et al., 2008). Some of those studies have associated time trends in flood frequency and magnitude with large scale climate forcings (Olsen et al., 1999; Jain and Lall, 2000; Andrews et al., 2004) while others have attributed those trends to human-induced changes in the basin attributes (e.g. Milly et al., 2008). Non-stationary models for local flood frequency analysis have as basis the assumption that the underlying distribution parameters, particularly the position and scale parameters, are linear or non-linear functions of a time-indexed covariate, which might be the time itself or some other time related index (e.g. Clarke, 2002; Cunderlik and Burn, 2003). A common approach in regional flood frequency analysis under non-stationary conditions has been the extension of the non-stationary local flood frequency analysis to ungauged basins (e.g. Cunderlik and Burn, 2003). Note that in this non-stationary framework the concept of return period is vague, losing its formal definition (Lima and Lall, 2009), and the associated flood risk changes over time - it can be greater or smaller than the risk assumed under stationary conditions (Lima and Lall, 2009). Some recent studies (e.g. Salas and Obeysekera, 2014; Obeysekera and Salas, 2013) have focused on the development of a new framework for a non-stationary flood risk and have proposed methodologies to incorporate it into the design of flood control measures.

Statistical analysis and models for flood events are often criticised by their lack of physical basis. Flood hydroclimatology, as defined by Hishboeck (1988) as "the study of the climate context of floods, i.e., an understanding of the long term variation in the frequency, magnitude, duration, location and seasonality of floods as determined by an interaction of evolving regional and global ocean and atmospheric circulation patterns", brings however a good opportunity to understand the causal chain of extreme floods and include this understanding in any flood frequency analysis. A significant number of papers (see, for instance, Hirschboeck et al., 2000; Kahana et al., 2002; Prudhomme and Genevier, 2010 and the references therein) has taken the framework of flood hydroclimatology to identify flood mechanisms and associated climate patterns.

Here we develop a statistical model to estimate the non-stationary, summer season (December to March) flood hazard across Brazil as a function of large scale climate indices that are known to influence the rainfall and streamflow patterns across the country. A Poisson regression model is proposed to estimate the flood risk, defined as the probability of occurring at least one streamflow event in the summer season above a given threshold value, for 44 streamflow gauges in the country. After this introduction, this article is organized as follows. In the next section we present the hydroclimate data and the region under study. In section 3 we present the theoretical basis for the Poisson regression model. Finally, the results obtained are presented and discussed in section 4.

2. HYDROCLIMATE DATA AND REGION OF STUDY

Naturalized series of mean daily flow for 44 streamflow gauges located in Brazil (Fig. 1) are provided by the National Operator of the System (ONS), which is responsible for the operational policy of most hydropower reservoirs in Brazil. Beyond the generation of electrical energy, most of these reservoirs are also used for flood control, water supply and agriculture. Roughly 60% of the gauges have flood data available that goes back to 1931. The streamflow data available for most gauges covers the period from January/1931 to December/2009. Drainage areas range from 2,588 to 823,555 km^2. Series of flood events for the austral summer months (December through March), which is the main flood season across all sites (Lima and Lall, 2011), are obtained for each site by counting the number of days in the season in which the daily flow exceeds some pre-specified threshold, which is defined here as a flood quantile of low exceedance probability (e.g. the 90^{th} flood quantile – see more details in section 3). As in partial serial analysis (e.g. Lang et al., 1999), only independent flow events are considered. In our case, we decluster the daily streamflow series by taking only flood events when the inter-arrival time is greater than three days.

In order to account for the influence of large scale climate on the flood risk associated with the streamflow data displayed in Fig. 1, we define several climate indexes to be used as covariates in the Poisson regression model. The climate indexes are defined based on interpolated data of sea surface temperature (SST) anomalies from the Tropical Pacific and Atlantic oceans (Kaplan et al., 1998; Reynolds et al., 1994) and based on seal level pressure (SLP) and 850hPa geopotential heights from the NOAA NCEP-NCAR Reanalysis data set over the South America and South Atlantic regions. Both data are provided by the International Research Institute for Climate and Society (IRI) and are available at http://iridl.ldeo.columbia.edu/SOURCES/.KAPLAN/.EXTENDED/.v2/.ssta/ and at http://iridl.ldeo.columbia.edu/expert/SOURCES/.NOAA/.NCEP-NCAR/.CDAS-1/.MONTHLY/.Intrinsic/. The Climate data sets cover the period from January 1949 to December/2009.

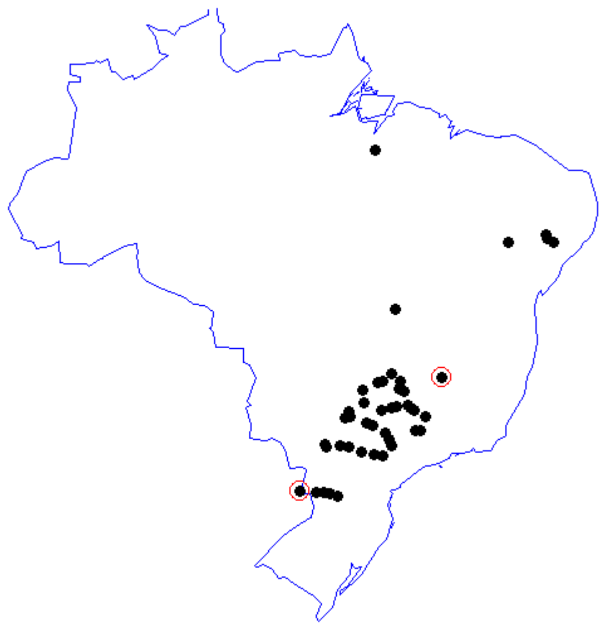

Figure 1: Location across Brazil of the streamflow gauges used in this work. The red circles show the location of the Itaipu (bottom left) and Três Marias (middle right) streamflow gauges used to evaluated the proposed model.

2.1 Climate Predictors

Climate predictors for the number of flood events for each site and summer season are obtained by defining climate indexes from the climate data described above. In order to take into account the effects of the El Niño Southern-Oscillation (ENSO) on the frequency of flood events across Brazil (e.g. Grimm et al., 1998; Lima and Lall, 2011), we use the NINO3 index as a measure of variability of the SST over the tropical Pacific. The NINO3 index is defined as the monthly mean sea surface temperature (SST) anomalies (with annual cycle removed) averaged over the area 5°N-5°S latitude, 150°W-90°W longitude. The influence of the meridional position of the Intertropical Convergence Zone (ITCZ) on the number of floods events is taking into consideration through a predictor derived from the tropical Atlantic SST meridional gradient, also known as Atlantic dipole and defined as the difference between the spatially average SST anomalies over the tropical North Atlantic (5.5°N- 23.5°N and 15°W-57.5°W) and tropical South Atlantic (20°S-0° and 30°W-10°E), as identified in many studies (e.g. Moura and Hastenrath, 2004) to be associated with changes in rainfall patterns over Brazil. Changes in the streamflow interannual variability associated with anomalies in the SST in the subtropical Atlantic Ocean are considered by taking as climate predictors the first two principal models of variability obtained from Principal Component Analysis (PCA – see, for instance, Wilks, 2005) of the SST anomalies over the region delimited by 70°W-20°E and 0°S-60°S. The first two principal components explain around 50% of the data variability.

The effect of atmospheric circulation patterns on the flood events across Brazil is considered by defining climate predictors associated with the monsoon circulation over South America. Two predictors are obtained from the first two principal components (PCs) of the gridded sea level pressure anomalies over the area delimited by 80°W-20°E and 0°S-60°S. Two other climate predictors are obtained from the first two PCs of the 850 hPa geopotential height over the same area. These two PCs explain roughly 48% of the data variability and, given their importance in the proposed model (see next section), we show in Figure 2 the loadings (eigenvectors) associated with them. The first loading (Top panel on Fig. 2), which explains 28% of the data variability, shows a unique pattern of variation centered on 20°W-50°S. The second mode responds to 20% of the data variance and is associated with a kind of see-saw structure, with the two poles centered along the 55°S latitudinal band.

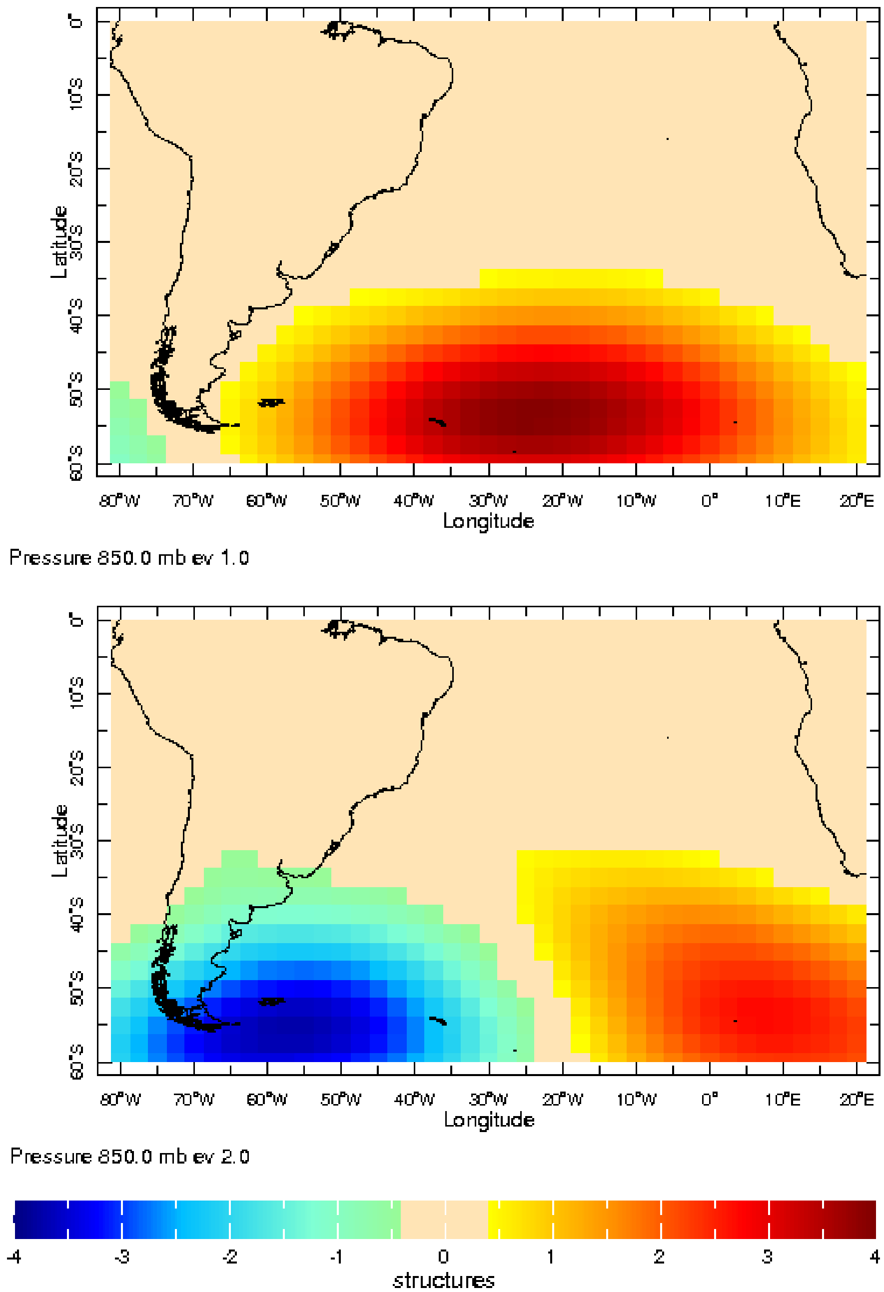

Figure 2: First (top) and Second (bottom) loadings associated with the principal components (PCs) of the 850 hPa geopotential height field.

3. THE POISSON REGRESSION MODEL

The use of large scale climate information in flood frequency analysis is evaluated in this work through a Poisson regression model for the seasonal (DJFM) number of flood events for each site. Here we choose to model the number of events exceeding the 90% percentile threshold of the seasonal maximum series, which is equivalent to count the number of events in which the daily flow exceeds the 10-year return period flood quantile. This particular choice of threshold is intended to illustrate the model and can be changed according to the application.

Mathematically, if Y_{ij} denotes the random variable number of floods events that occur in summer season i for site j, then the Poisson homogeneous distribution can be defined as:

$$P(Y_{ij} = y) = \frac{e^{-\lambda_j} \lambda_j^y}{y!} \, , \qquad [1]$$

where λ_j is the expected number of occurrences for a given interval for site j and y is the number of occurrences (0, 1, 2, 3, …).

In a changing climate, we can also assume that the λ_j parameter is no more stationary in time but a function of some large scale climate predictor x indexed by a time variable i, which may represent some climate state on a month before or during the respective summer season. By doing so, we explicitly account for the climate influence on the frequency of flood events. A Poisson regression model can then be applied:

$$\log(E(Y_{ij} \mid x_i)) = a_j + b_j x(i) \, , \qquad [2]$$

which implies:

$$P(Y_{ij} = y \mid x(i)) = \frac{e^{-\lambda_{ij}} \lambda_{ij}^y}{y!} \text{, where} \qquad [3]$$

$$log(\lambda_{ij}) = a_j + b_j x(i). \qquad [4]$$

Here we assume that there is no overdispersion, i.e., the expected value and the variance of Y_{ij} are equal. In order to verify this assumption, we apply a regression based test for overdispersion (Cameron and Trivedi, 1990) and, for a significance level α = 5%, the null hypothesis of equidispersion ($E(Y_{ij}) = Var(Y_{ij})$) is not rejected for any site. We also assume that, given the climate predictor $x(i)$, the random variables Y_{ij} are independent in both time and space.

It is reasonable to assume that a skilful climate predictor x has to carry some information of important climate variables responsible for most of the rainfall and streamflow variability across Brazil. The expansion of [2] to include all climate predictors presented in section 2.1 would be a logical choice given the knowledge of climate teleconnections in Brazil, however, an excessive number of predictors (correlated or not) in [2] would lead to a poor fitting and consequently deteriorate the ability of the model to predict the flood hazard. That being said, we limit the number of predictors in [2] through a preliminary analysis of cross-correlation between the average number of flood events across all sites and the value of the climate predictors at the eleven months (January-November) that anticipate the summer season (December through March) and at December of the concurrent summer season. The results (not shown here) pointed out to three important predictors to consider: December NINO3 index, December Atlantic dipole and October second leading mode of the PC associated with the 850 hPa geopotential height field, whose spatial patterns are shown in Fig. 2.

The final model for the frequency of extreme flood events on the summer season over all sites analyzed here can be written as:

$$\log(\lambda_{ij}) = a_j + b_j x_1(i) + c_j x_2(i) + d_j x_3(i)\,, \qquad [5]$$

where the covariates are explained in table 1.

Table 1: Covariates used in model [5]

Covariate	Description	Time index i
x_1	NINO 3 index	December of concurrent summer season
x_2	Tropical Atlantic Dipole	December of concurrent summer season
x_3	PC2 of Geopotential Height at 850 hPa	Previous October

4. RESULTS

4.1 Spatial Distribution of Poisson Coefficients

Maximum likelihood estimates (MLE) for all three parameters (b, c and d) in Eq. [5] are shown in Figure 3. The spatial distribution of the b coefficient associated with the NINO3 index shows (left hand panel of Fig. 3) a spatial homogeneity across all sites, although not all estimates are statistically significant (solid circles) at the 10% significance level. The spatial pattern of the c coefficient (middle panel of Fig. 3) shows a high heterogeneity and no statistically significant estimate, which suggests a weak influence of the dipole index on the frequency of extreme events across the country. The influence of the atmosphere circulation on flood events can be seen in the spatial distribution of the d parameter (right panel of Fig. 3), which displays a high degree of homogeneity and an elevated number of statistically significant parameters, particularly in the Paraná basin.

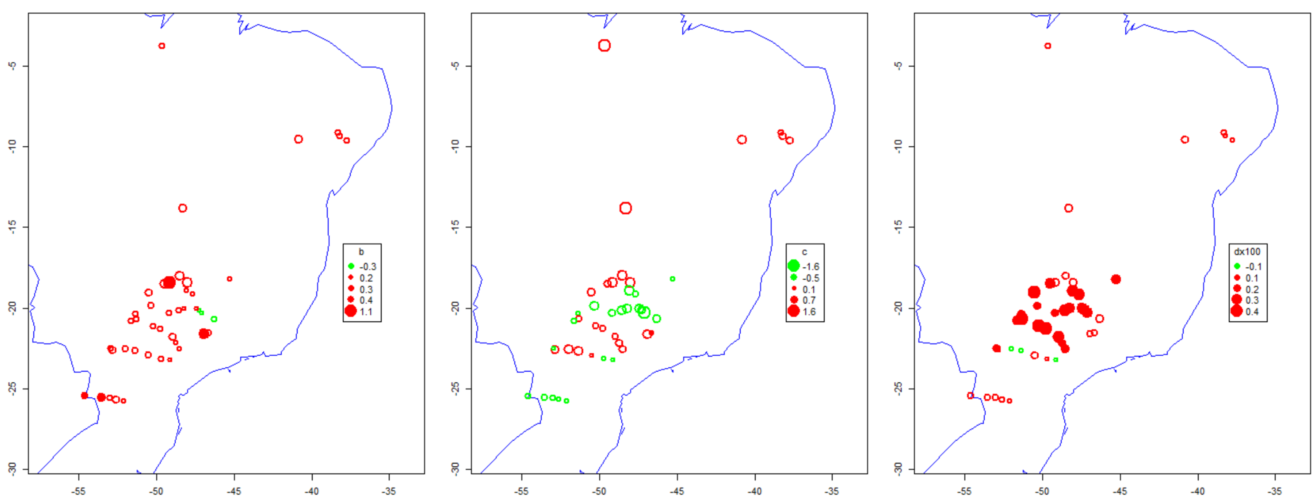

Figure 3: Spatial Distribution of Poisson Parameter Estimates. Filled circles are statistically significant.

4.2 Example of Flood Hazard Estimation as a Function of Climate

In order to better quantify the flood hazard as a function of large scale climate, we estimate, for each site, the probability of occurrence of at least one event using the Poisson regression model (Eqs. [3] and [5]). Since the c parameter is not statistically significant for all sites, we fit the Poisson model having only the covariates x_1 and x_3 , and then calculate $P(Y_{ij} > 0)$ for a range of values of x_1 and three fixed values of x_3 related to 10^{th}, 50^{th} and 90^{th} percentiles of its historical values. Note that, for a stationary Poisson process, the probability $P(Y_{ij} > 0)$ depends on the value of the threshold chosen in order to count the number of flood events.

As illustrative of the model utility, we show in Figures 4 and 5, respectively, the probability $P(Y_{ij} > 0)$ for the Itaipu and Três Marias streamflow gauges (see location in Fig. 1), which are flood prone regions and rely on reservoir operation policies as a flood control measure for the downstream areas. For values of NINO3 close to zero (neutral conditions in tropical Pacific), the flood hazard tends to be close to what is expected based on the historical data and on the stationary assumption, with a moderate increase in the risk for state 3 of x_3, which is associated to extreme values (90^{th} percentile) of this covariate, more precisely to an enhancement of the dipole structure of the 805 hPa geopotential height along 55°S (bottom panel of Fig. 2). As the December conditions in the eastern Tropical Pacific switches to El Niño, the associated flood risk increases and fluctuates around 25% for a mild El Niño (x_1 = 1.5) and crosses 75% for the most extreme El Niño event that occurs in December 1997 (x_1 = 3.68). In general, the uncertainty band associated with the flood hazard increases (in %) as x_1 gets lower, being also larger for state 3 of x_3.

The flood risk for the Três Marias gauge (Fig. 5) shows a weak association with ENSO, with a gentle increase in the risk for higher values of x_1. However, independent of x_1, the flood risk more than double from state 1 to state 3 of x_3, with an associated increase in the uncertainty band. In fact, all eight flood events identified for the Três Marias gauge occurred for $x_3 > 0$ (Fig. 6), while five events took place when $x_1 > 0$.

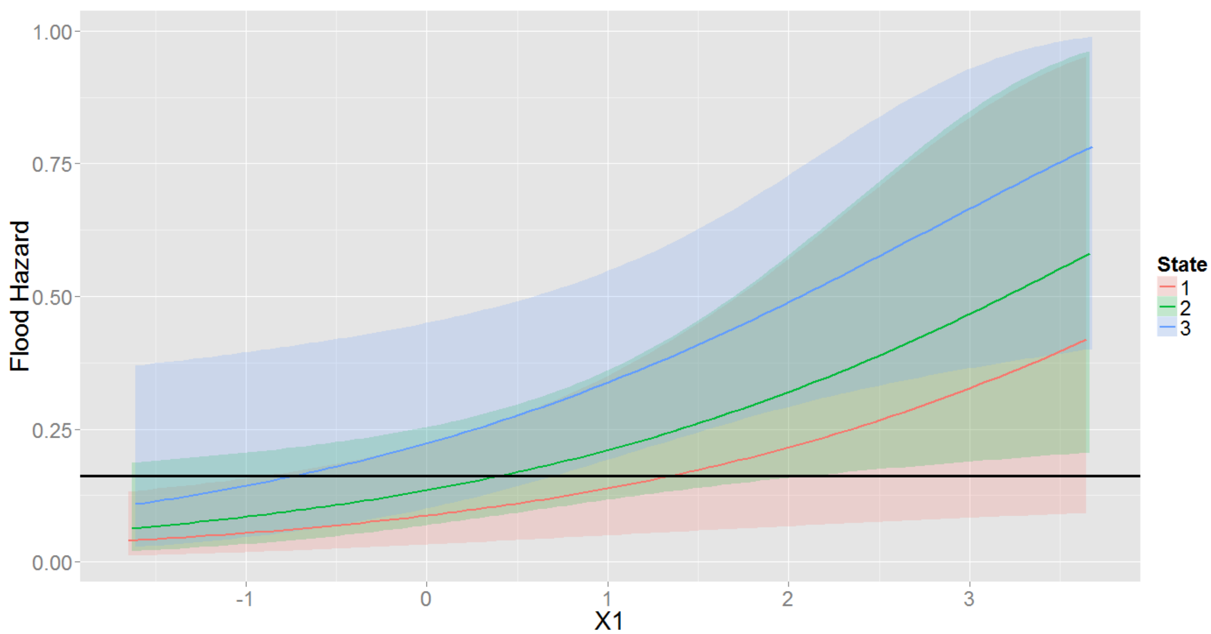

Figure 4: Flood hazard for the Itaipu streamflow gauge as a fuction of the NINO3 index (predictor x_1). The three states correspond to the 10^{th}, 50^{th} and 90^{th} percentiles of the historical values of the x_3 covariate. The horizontal black line shows the stationary flood hazard based on the historical, average frequency of flood events. The shaded regions depict the 95% confidence interval for the respective probabilities

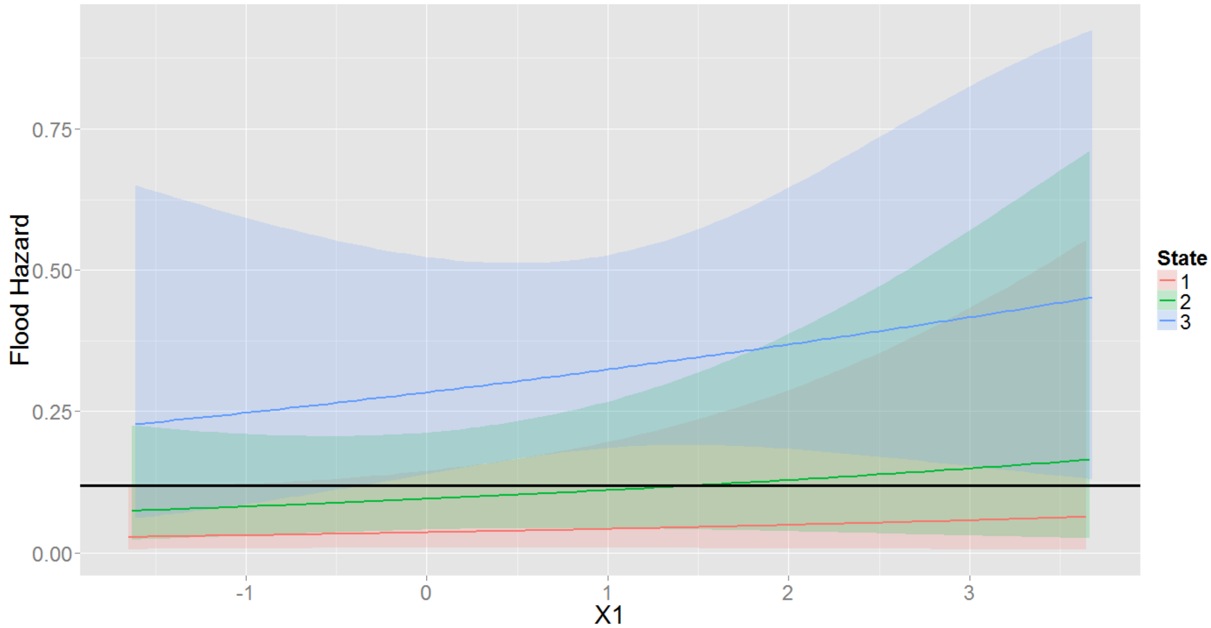

Figure 5: As in Fig 4, but for the Três Marias streamflow gauge

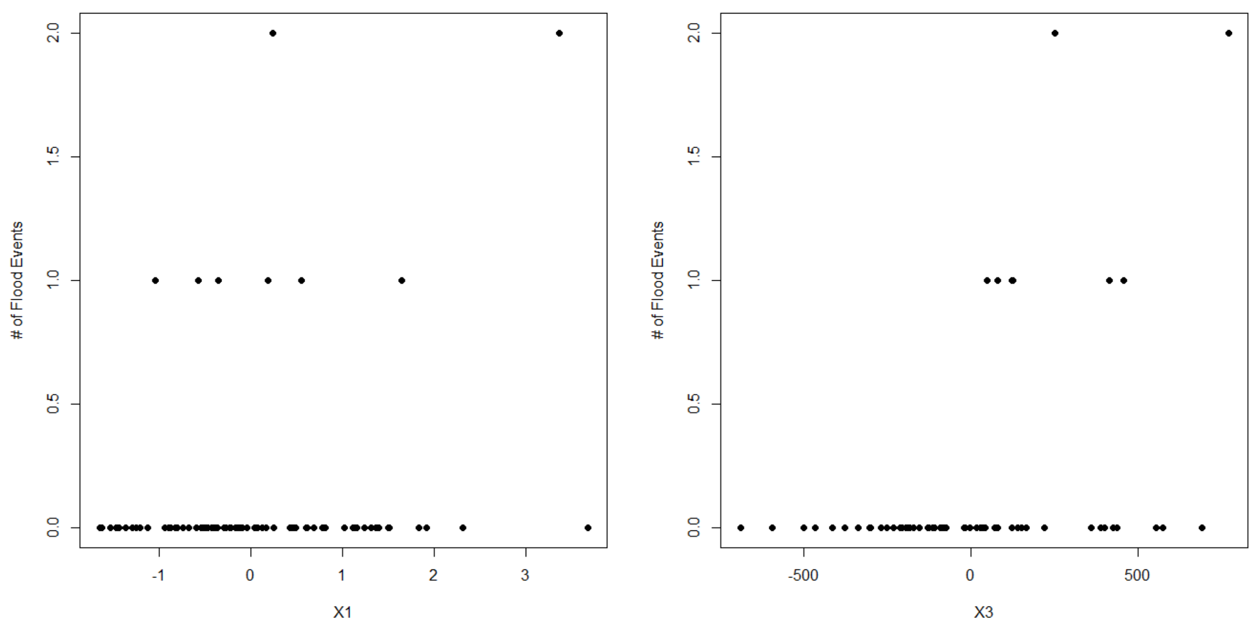

Figure 6: scatter plot of x_1 (left) and x_3 (right) versus the number of flood events for the Três Marias streamflow gauge.

4.3 Non-Stationary Flood Hazard and Future Changes

As a non-stationary process, the flood hazard for most streamflow gauges analyzed here changes every summer season as a function of the covariates x_1 and x_3, which represent large scale climate associated with the SST in the eastern tropical Pacific (i.e. ENSO) and a seesaw pattern of variability of the 850 hPa geopotential height (Fig. 2) in the southern Atlantic. For instance, Figure 7 depicts the temporal changes in the flood hazard estimated by the model as the probability of occurrence of at least one flood event with magnitude greater than the 90th percentile of the summer season maximum flow on the Itaipu streamflow gauge. It is interesting to note that the flood risk can be much higher than what is expected from a homogeneous Poisson process (i.e. a static flood risk, horizontal black line in Fig. 7). The question that pops up is how this curve will change as the climate system, particularly x_1 and x_3, evolve into the future? A simple Mann-Kendall test (e.g. Wilks, 2005) on the x_1 and x_3 series shows no evidence of any monotonic trend in both cases, so no immediate threat related to increasing or decreasing trends in the predictors is found.

Future projections of ENSO from General Circulation Model (GCMs) simulations in general do not show (e.g. Philip and van Oldenborgh, 2006) any preference across models for a particular state (El Niño, Neutral or La Ninã), so in this case it is not straightforward to access future changes in the flood hazard across Brazil due to changes in the magnitude and frequency of ENSO. On the other hand, future changes in the statistics of x_3 may change the flood hazard. Here we perform a simple sensitivity analysis in order to evaluate how potential changes in the mean and variance of x_3 affect the flood risk for the Três Marias streamflow gauge. For simplicity, we keep the x_1 statistics as observed in the historical record. The simulation procedure is done as follows:

- 1000 samples of length 60 years are obtained for x_3 considering a normal distribution and changes in the historical statistics of mean and variance of x_3. Simulation of x_1 is obtained through bootstrapping (with replacement) the historical series of x_1;

- The flood hazard (probability of at least one flood event during the summer season) for each season is calculated considering the model (Eq. [5], without x_2) fit with the historical data (Fig. 5);

- For each sample of 60 years, one counts the number of seasons in which the flood risk is greater than 50%. The average number of seasons is obtained by averaging the 1000 simulations;

- The entire process is repeated for each different value of mean and variance of x_3.

The results obtained are depicted in Figure 8. Changes in the mean value of x_3 lead to only small changes in the flood risk. On average, just one summer season in the 60-year block has a flood risk greater than 50%, which is still less than what is obtained in the historical record (= 2, see Fig. 7). On the other hand, a linear increase in the number of seasons is observed as the variance changes from 50% to 300% of its historical value.

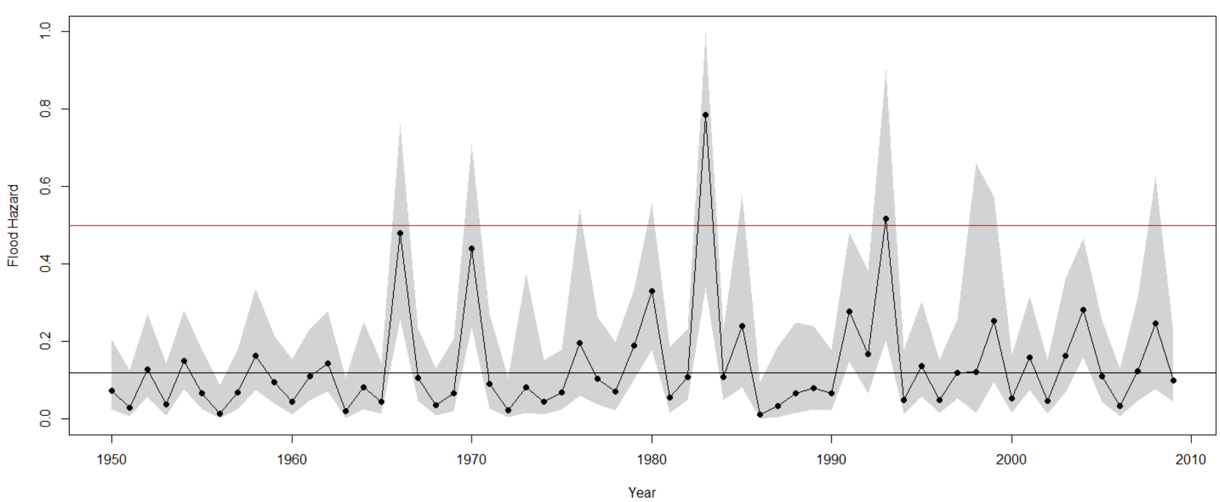

Figure 7: Probability of occurrence of at least one flood event with magnitude greater than the 90th percentile of the seasonal (summer) maximum flow on the Itaipu streamflow gauge. The shaded region in grey is the 95% confidence interval. The black horizontal lines shows the static flood risk based on the frequency of events and a homogeneous Poisson model. The red line shows flood hazard = 50%.

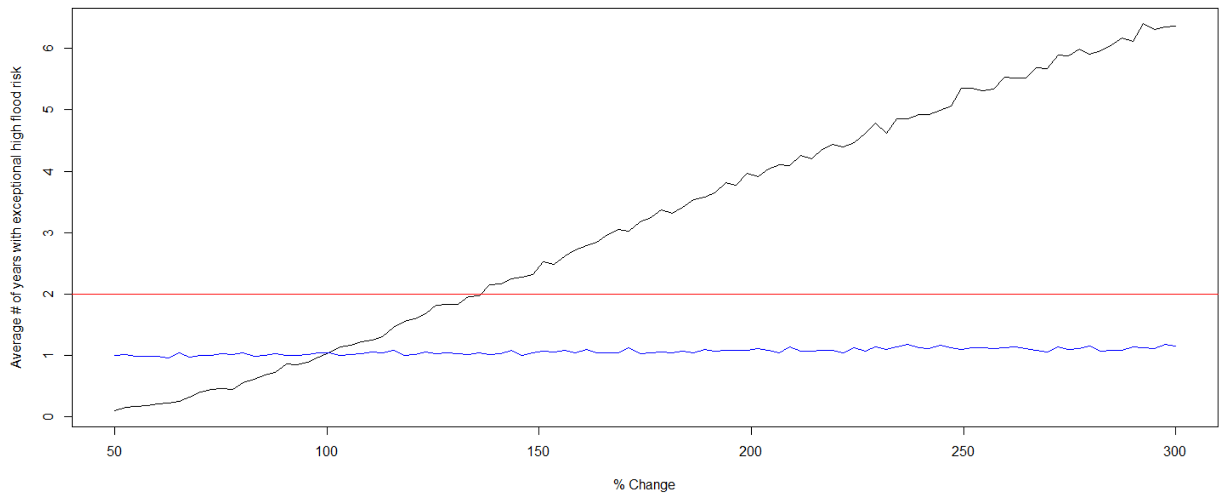

Figure 8: Average number of summer seasons (over 1000 samples) in a 60-year period in which the flood hazard is greater than 50% as a function of % changes in the historical mean (blue curve) and variance (black curve) of x_3. The horizontal red line shows the number of seasons in the historical record (Fig. 7).

5. CONCLUSIONS

In this work we proposed a model to estimate the non-stationary, summer season flood hazard across Brazil as a function of large scale climate indices that are known to influence the rainfall and streamflow patterns across the country. For a given season, the flood hazard for 44 streamflow gauges in the country was defined as the probability of occurring at least one flood event, which in turn was defined for this work as a streamflow magnitude above the 90th flood quantile of the seasonal maximum series of each gauge (i.e., the empirical 10-year return period flood quantile). A Poisson regression model was proposed to estimate the flood risk having as covariates the concurrent December NINO3 and tropical Atlantic dipole indexes and the previous October second PC associated with the 850 hPa geopotential height field over the South America and South Atlantic regions.

Based on the spatial distribution of the Poisson regression estimates, high values of the NINO3 index were associated with an increase in the frequency of flood events for most of the sites, although for only 16% of them the regression coefficient was statistically significant at the 10% significance level. The coefficients associated with the tropical Atlantic dipole index were not statistically significant, suggesting that the influence of this climate variable may be limited to changes in the average rainfall, with no influence in extreme events. The predictor associated with the 850 hPa geopotential height field shows a strong influence on several sites, particularly those located in the southeast region. The estimates were statistically significant for roughly 50% of the sites. Other potential predictors associated with SST anomalies over the South Atlantic and with SLP anomalies over South American and South Atlantic were also evaluated but did not show any statistically significant association with the interannual variability of the number of flood events for the streamflow gauges analyzed here.

As an illustrative example of the model use, we estimate the flood hazard for two flood prone regions: the Itaipu and Três Marias streamflow sites, located, respectively, in the Paraná and São Francisco basins. The climate risk related to the flood events of these sites was estimated considering the range of the previous December NINO3 index and three states of the 850 hPa geopotential height derived index: the 10th (state 1), 50th (state 2) and 90th (state 3) empirical percentiles. For the Itaipu gauge, a tremendous increase in the flood risk, compared with its stationary counterpart, is observed when the NINO3 index is above zero (warm ENSO events), with risk values even higher than 50%, particularly for states 2 and 3 of the 850 hPa geopotential height index. The flood risk for the Três Marias streamflow gauge is less sensitive to changes in NINO3, as expected given the diffuse effect of ENSO on the rainfall patterns across the San Francisco basin, but tends to more than double when the 850 hPa geopotential height index switches from state 1 to state 3. Particularly, all summer seasons in which there was at least one flood event in the Três Marias gauge were marked by positive values of x_3 in the previous October.

The use of a Poisson regression model with time-varying covariates led to a non-stationary flood hazard, which for some summer seasons can be more than double the static risk, as illustrated for the Três Marias streamflow gauge. Changes in the future risk were evaluated by a sensitive analysis considering simulations of x_1 through bootstrapping the historical series and of x_3 assuming incremental changes in the mean and variance of its historical statistic. The results show that the frequency of seasons that experience a high flood risk (>50%) tends to be very sensible to changes in the variance of x_3, which reinforces the need to improve the monitoring and prediction of this variable, particularly its variability. The inclusion of other predictors in the model and an increase in the number of sites to be evaluated will be theme of future research. Assessing changes in the flood risk associated with projected changes in x_3 will be also researched.

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