A climate informed model for nonstationary flood risk prediction: Application to Negro River at Manaus, Amazonia

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SUMMARY

Historically, flood risk management and flood frequency modeling have been based on assumption of stationarity, i.e., flood probabilities are invariant across years. However, it is now recognized that in many places, extreme floods are associated with specific climate states which may recur with non-uniform probability across years. Conditional on knowledge of the operating climate regime, the probability of a flood of a certain magnitude can be higher or lower in a given year. Here we explore nonstationary flood risk for the streamflow series of the Negro River at the city of Manaus in Brazil by investigating climate teleconnections associated with the interannual variability of the peak flows. We evaluate attributes and the fit of a generalized extreme value (GEV) distribution with nonstationary parameters to the annual peak series of the Negro River stages. The annual peak flood occurs between May and July and its magnitude depends on the Negro River stage at the beginning of the year and on the previous December sea surface temperature (SST) of a region in the tropical Pacific Ocean. A statistically significant monotonic trend is also observed in the peak level series. The indexing of the parameters of a GEV distribution to the NINO3 index and to the observed river stage at the beginning of the year reveals a changing flood hazard for the city, with the joint occurrence of high values associated with La Niña conditions in the previous December and high river stages in January preceding the flood season. The proposed model is shown to be useful for quantifying the changing flood hazard several months in advance for Manaus, thus providing an early flood alert system for the city and may be an important tool for the dynamic flood risk management for the region.

1. Introduction

Traditionally, flood frequency analysis has been the primary tool to provide information (e.g. flood quantiles) for flood risk management (e.g. Stedinger et al., 1992; Loucks et al., 1981; Chow et al., 1988). Usually, flood frequency analysis has a local basin perspective and is based on the assumption that floods are the consequence of a random process such that are independent and identically distributed. This approach has become overall the standard for the design of structural (e.g. levees, reservoirs, etc.) and non-structural (e.g. delimitation of inundation zone) flood control measures across the world. However, this assumption has been questioned on the basis that climate, land use and other factors that determine flood occurrence are likely changing with time (Milly et al., 2008).

Recent advances in the understanding of the flood mechanisms and associated large scale climate patterns (see, for instance, Hirschboeck, 1988; Hirschboeck et al., 2000; Kahana et al., 2002; Lima and Lall, 2009; Prudhomme and Genevier, 2011; Nakamura et al., 2013 and the references therein) have shown that particularly extreme floods in a given place may have distinct signatures which may be associated with persistent and distinguished climate states, notably anomalies in the sea surface temperature (SST) and the occurrence of large scale moisture transport in the low atmosphere (e.g. see Lavers et al., 2012), also known as atmospheric rivers. These findings suggest that floods may come from a mixture of probability distributions (not necessarily in the same family of distributions) which may persist for some period of time. This relatively new hypothesis for flood origins and characteristics suggests that the current flood risk management practices may
benefit from extended approaches of flood frequency modeling that incorporates a global view (Merz et al., 2014) of the main physical processes, which can be achieved, for instance, by integrating climate information into the flood frequency analysis.

Some recent studies have identified nonstationarities in streamflow and flood series, translated in terms of monotonic (e.g. Clarke, 2002) or polynomial/cyclical (e.g. Jain and Lall, 2001) trends, and closely associated with climate variability (e.g. Andrews et al., 2004; Jain and Lall, 2000; Towler et al., 2010a) or land-use changes (e.g. Vogel et al., 2011; Changnon and Demissie, 1996; Bronstert et al., 2002). Flood frequency modeling of such nonstationary series have been based mainly on the assumption that the underlying distribution parameters, particularly the position and scale parameters, are linear or nonlinear functions of a time-indexed covariate, which might be the time itself (e.g. Clarke, 2002; Cunderlik and Burn, 2003) or some other time related index (e.g. Kwon et al., 2008; Villarini et al., 2009). The use of such approaches has been facilitated by the development and availability of specific software products for analysis and modeling of flood series and extreme events in geophysics considering nonstationary distributions (e.g. Rigby and Stasinopoulos, 2005; Gilleland and Katz, 2011).

In this nonstationary framework, the probability of flooding changes over time – it can be greater or smaller than the flood hazard assumed under stationary conditions (e.g. Lima and Lall, 2009; Villarini et al., 2009). The work of Olsen et al. (1998) appears in the literature as one of the first attempts to extend the concept of return period and flood risk under nonstationary conditions. More recently, Salas and Obeysekera (2014) provided a review of these concepts and suggested a unified framework for application in water resources engineering considering monotonic trends and regime changes as examples of nonstationarities in flood events.

In Brazil, extreme rainfall and floods have become a major concern in recent years due to an apparent increase in the frequency, magnitude and impacts associated with such events in several regions across the country. Considering this nonstationary setting of flood events and a changing climate, we explore an approach for dynamic flood risk management for the city of Manaus, Brazil. We analyze and model the stage level series of the Negro River gauge station at the city of Manaus in the context of climate teleconnections associated with the peak flows. In the next section we present the hydroclimatic data and perform an initial exploratory analysis of the data set. In Section 3 we discuss and present the nonstationary flood frequency model and associated estimates. The results are presented in Section 4 with an overview of the potential use of the proposed model as a tool for short term flood risk management in the city of Manaus. Some concluding remarks are offered in Section 5.

2. Hydroclimate dataset and initial exploratory analysis

Manaus is the capital of the Amazonas state in Brazil and is located in the central part of the Amazonia rain forest (Fig. 1). The Negro River flows along the southwestern portion of Manaus and has been responsible for major floods in the city due to its natural variability and low slope of the terrain, which amplifies its floodplain. Historical series of daily stage at the Negro River streamflow gauge (drainage area = 712,000 km²) located in the port of Manaus (60° 36' 48" W, 3° 8' 12" S, see Fig. 1) is provided by the Brazilian National Water Agency (ANA). The series covers the period from 1903 to 2011 and has a few missing data points that do not compromise the study presented here.

The evaluation of the daily series for each year separately shows a well defined seasonal cycle for the daily stage (Fig. 2), with a marked interannual variability and one curve significantly below the others, reflecting an extremely dry year. Due to the large size and time of concentration of the Negro River basin, the river stage evolves very slowly through the year. A tendency of higher values of river stages in the order of 36 cm is also observed for the second half of the record period (see red and blue lines in Fig. 2). The annual peak stages tend to occur, on average, in the beginning of June, with a variability around one month (left panel of Fig. 3). The peak flow timing (right panel of Fig. 3) shows a statistically significant (p-value = 0.07646 for a Mann–Kendall test, significance level α = 10%) trend, such that peak flows have been occurring later in the year. An initial analysis (not shown here) does not indicate a statistically significant association between tropical Pacific based climate covariates and the observed trend in the timing of the peak.

2.1. Annual maximum series of daily river stages

The annual maximum daily peak flow series is shown in Fig. 4. There is no significant auto correlation up to 20 years lag time (not shown here) and a simple fit of an ordinary linear regression to the data (red line in Fig. 4) shows evidence of a monotonic, increasing trend, which is confirmed by the Mann–Kendall test for monotonic trends (τ = 0.159, p-value = 0.014768). A standard wavelet analysis (Torrence and Compo, 1998) applied to the annual maximum data did not reveal a period that was significant over the full record (not shown here). Since this is a low level sediment river (Richey et al., 1986), one expects minimal changes in the riverbed geometry (Richey et al., 1989) over the 1903–2011 period.

The extreme low flow registered in 1926 also appears in other hydrological studies in the region (see Fig. 2 of Richey et al. (1989)) and is associated with a severe and broad dry season accompanied by fires in the vegetation (Sternberg, 1987). It has a minor effect in the statistical analysis performed here, particularly in the parameter estimates, and deleting it from the data set does not change the main results and conclusions obtained in this study. Hence we keep it throughout the analysis and modeling of this work.

3. Nonstationary flood frequency modeling

3.1. Model formulation

The literature on nonstationary flood modeling in recent years seems to have veered towards the use of the Generalized Extreme Value (e.g. Katz et al., 2002; Clarke, 2002; Towler et al., 2010b) or other parametric distributions (e.g. Villarini et al., 2009), with the parameters informed by covariates or by time. The motivation is that a simple, parsimonious model is available using a standard distribution, which can be justified on some grounds (GEV as a natural distribution for block maxima (Coles, 2001), or Lognormal from empirical considerations (e.g. Jain and Lall, 2000)). These parametric models are typically fit considering a linear or generalized linear relationship between the model parameters and exogenous climate predictors. As an alternative, semiparametric (e.g. Jain and Lall, 2000; Sankarasubramanian and Lall, 2003) and nonparametric (e.g. Aplin and Stedinger, 2000) models consider that the target distribution may correspond to an unknown mixture of marginal probability distributions and/or the relationship between the exogenous climate predictor and the response of the flood may not be linear. These methods seek to estimate a conditional quantile or density function that is more flexible than the parametric choice, and are hence much more adaptive with respect to the data. The parametric models can be fit using the traditional or the generalized maximum likelihood methods (e.g. El Adlouni et al., 2007; Martins and Stedinger, 2000) as well as fully Bayesian methods to develop uncertainty distributions for any of the
quantities forecast (e.g. Renard et al., 2006; Kwon et al., 2008; Liang et al., 2011). Semiparametric and nonparametric models are usually fit using local polynomials, kernel and quantile regression based approaches, which may require bootstrap techniques to derive confidence intervals for the estimates. A discussion on the limitations and advantages of these fitting methods in semiparametric and nonparametric models is provided by Sankarasubramanian and Lall (2003). We refer the reader to Khaliq et al. (2006) for a review of parametric and nonparametric methods applied for nonstationary frequency analysis of hydro-meteorological data.

Both approaches are useful to study a particular data set and since the main goal of this work is to provide a new tool for flood risk management in the region, we adopt the classical GEV distribution to model the annual peak series of the Negro River at the city of Manaus. Mathematically, if we assume that $q_i$ represents the annual maximum peak stage at year $i$ for the Negro River streamflow gauge (Fig. 1), then under some conditions, the extreme value theory (see for instance Coles (2001)) postulates that $q_i$ follows a GEV distribution $g$ with stationary parameters $\mu$ (location), $\sigma$ (scale) and $\xi$ (shape):

$$q_i \sim g(\mu, \sigma, \xi).$$  \hspace{1cm} (1)

where the cumulative distribution function of $g$ can be written as:

$$G(x) = \exp \left\{-\left[1 + \xi \left(\frac{x - \mu}{\sigma}\right)\right]^{-1/\xi} \right\}.$$  \hspace{1cm} (2)

Given the observed time series record of $q_i$ (Fig. 4), the parameters $\mu$, $\sigma$ and $\xi$ can be estimated using standard procedures of maximum likelihood estimation (Coles, 2001). It is important to notice that as the size of the available record decreases, the uncertainty in the estimates increases, particularly for the shape parameter $\xi$, and other options, such as the generalized maximum likelihood approach (e.g. Martins and Stedinger (2000)), could be used.

If we assume that the location parameter changes over time, then its value for year $t$ can be modeled as a function of $k$ predictors $x_1, x_2, \ldots, x_k$:

$$\mu(t) = f(x_1(t_1), x_2(t_2), \ldots, x_k(t_k)),$$  \hspace{1cm} (3)

where $t_1, t_2, \ldots, t_k$ indicate the respective time of the predictors, which can refer to monthly or seasonal values within or before the year $t$.

Similarly, it is also reasonable to assume that the scale parameter may undergo temporal changes, which can be formulated as:
Fig. 2. Seasonal and interannual variability of daily river stage (each gray line represents the daily river stage series for each year in the 1903–2011 record period). The red and blue lines show the average seasonal river-stage for the periods 1903–1956 and 1957–2011, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Left: Density of timing (day of year) of annual maximum peak levels. Right: Time series of peak flow timing with an ordinary linear regression fit to the data (red curve). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

\[ \sigma(t) = f_2(x_1(t_1), x_2(t_2), \ldots, x_k(t_k)) \]

where the condition \( f_2(\cdot) > 0 \) must be satisfied.

Changes over time in the shape parameter \( \xi \) are hard to account for small data sets. Even in the stationary case, estimates may differ significantly from the parameters (e.g., Martins and Stedinger (2000)). Hence, in order to avoid a high uncertainty in the estimates of \( \xi \), we will keep it stationary in time.

We assume a linear trend for the functional form of \( f_1 \) and \( f_2 \) for the sake of a simple and parsimonious model for the location and scale parameters. In the case of the scale parameter \( \sigma(t) \), we also use the log link function to guarantee that \( \sigma(t) > 0 \) in the codomain of \( f_2 \). Empirical evidences presented in the next section do also support our assumption of linearity for \( f_1 \) and \( f_2 \).

For comparison purposes, we evaluate the fit of a standard normal distribution to the annual maximum data considering a time-varying mean conditioned on the selected predictors and also assuming a linear trend. Finally, a stationary Log-Pearson 3 (LP3) distribution, usually recommended for extreme events in hydrology (Stedinger et al., 1992), is also included in this study to model the frequency of the peak stage series. We refer the reader to Rao and Hamed (2000) for mathematical details of the normal and LP3 distributions.

### 3.2. Predictors

In a first attempt to identify climate teleconnections associated with the interannual variability of the annual maximum series (Fig. 4), we use the extended NINO3 index (Kaplan et al., 1998; Reynolds and Smith, 1994) as representative of anomalies in the sea surface temperature (SST) across the tropical Pacific Ocean. 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. During El Niño years (NINO3 > 0), annual peak levels tend to be below the average (left panel of Fig. 5), while during La Niña events the tendency is reversed. This finding is in agreement with previous studies that associated a decrease in summer and autumn rainfall over the Amazonia following a December El Niño due to a shift in the subsiding branch of the Walker circulation to the Amazonia region (see, for instance, Richey et al., 1989; Grim, 2003; Grimm, 2004 and the references therein). The Pearson correlation coefficient of these data is \( -0.42 \) (\( p \)-value = 4.57 × 10\(^{-5} \)) for the null hypothesis of the true correlation equals to zero.

An exploratory analysis also shows that the annual peak level has a statistically significant positive correlation with the river stage recorded on the first of January (right panel of Fig. 5) of the same year, with a Pearson correlation coefficient equals to 0.29 (\( p \)-value = 0.002146, significance level \( \alpha = 5 \%)\). It is possible that the nonstationarity or the trend is primarily due to continuous changes in river morphology or land use, and using the value of the stage at the beginning of each year is effective in addressing the impact of such changes on the peak flow.

Based on the associations seen in Fig. 5, we explore nonstationary probabilistic models for the annual maximum peak stage series by indexing the location and scale parameters (Eqs. (3) and (4)) to the covariates: (i) previous December NINO3 index \( (x_1) \) and (ii)
river stage on the first of January of year \( t (x_t) \). These two predictors are uncorrelated (Pearson correlation = 0.12, \( p \)-value = 0.227) and respond to around 30% of the interannual variability of the peak stages. We believe that restrict the predictors in (3) and (4) to only these two covariates will lead to a parsimonious model and will suffice to show the applicability of the proposed model as a novel tool for flood risk analysis and management in the region.

A set of stationary models are also fit to the data to evaluate the gain, in terms of modeling, in adopting nonstationary distribution models. A summary of the models used here is shown in Table 1. Note that a linear trend is assumed for \( f_1 \) and \( f_2 \) in Eqs. (3) and (4). Models 1–3 are also referred as the Gumbel distribution, since the shape parameter \( \xi \) in the GEV model is equal to 0. Models 1, 4 and 9 are the classical stationary Gumbel, GEV and Log-Pearson 3 distributions, respectively. Models 2, 5 and 8 have a time-varying location but stationary scale parameters. Finally, models 3, 6 and 7 have both location and scale parameters changing over time. Note also that the shape parameter is static for the GEV and LP3 models.

### 3.3. Model fit, selection and diagnostic

For models 1–8 in Table 1, maximum likelihood estimates as suggested in Coles (2001) are obtained. For model 9 (LP3), we use the L-moments method as recommended by some authors (e.g. Hosking and Wallis, 1997; Rao and Hamed, 2000) to estimate its parameters. In a first attempt to choose a model among those in Table 1 that provides the best balance between model complexity and model fitting to the data, we use the Bayesian Information Criterion (BIC) as a model selection tool. Mathematically, the BIC is defined as (Schwartz, 1979):

\[
\text{BIC}(j) = -2 \cdot \log(L(j)) + k(j) \cdot \log(n),
\]

where \( j = 1, 2, \ldots, 9 \) refers to the models shown in Table 1, \( L(j) \) is the maximized likelihood function of model \( j \), \( k(j) \) is the number of estimated parameters for model \( j \) and \( n \) is the sample size.

The goal here is to find the model \( j \) with minimum value of BIC, i.e., the model that maximizes the fit to the data, expressed in (5) as \( L(j) \), with a small number of parameters \( k(j) \), which can be interpreted as model complexity. The use of BIC as a criterion for model selection appears in statistics textbooks (e.g. Hastie et al., 2001) and has been also used in related works (e.g. Villarini et al., 2009; Furrer and Katz, 2007; Roth et al., 2012).

The BIC obtained for each fit is presented in Fig. 6. Based on this model selection criterion, which tends to penalize more complex models more than the also common Akaike Information Criterion (AIC, Hastie et al., 2001), the model which includes both covariates in the location parameter regression and the NINO3 index in the scale parameter trend (model 6) presents the best fit. Thus, we choose model 6 for the nonstationary flood frequency analysis for Negro River. The diagnostic plot shown in Fig. 7 confirms that model 6 is appropriate for the data. The maximum likelihood estimates and associated \( p \)-values (based on the normality approximation of the estimators – see Coles (2001) for more details) obtained for the parameters of model 6 are shown in Table 2. Note that, based on the \( p \)-values, the null hypothesis of the parameters equal to zero is rejected for all parameters but \( \beta_0 \) at the \( \alpha = 5 \% \) significance level. Additionally, a likelihood ratio test (Coles, 2001) of model 6 versus model 4 (the classical stationary GEV) as the null model rejects model 4 in favor of model 6 at the 5\% significance level (\( p \)-value = 1.89e−10).

### 4. Results

#### 4.1. Nonstationary flood quantiles and dynamic flood hazard estimation

Since both the location and scale parameters of model 6 vary with time (indexing by \( x_1 \) and \( x_2 \)), one can estimate nonstationary flood quantiles for any specified probability and year. Fig. 8 displays the observed annual maximum daily stage and the nonstationary flood quantiles \( q_{2.5}, q_{50}, q_{90}, q_{97.5} \), which are associated with the exceedance probabilities 97.5\%, 50\%, 10\% and 2.5\%, respectively. These quantile estimates are obtained using the one-fold (or leave-one-out) cross-validation procedure, which can be described as: (i) for the first year of the record, the parameters of model 6 are estimated using the \( n – 1 \) remaining data (observed river stages and predictors), where \( n \) is the total number of years in the record; (ii) the estimated model is used to predict the nonstationary flood quantiles for the first year given the observed

### Table 1

<table>
<thead>
<tr>
<th>Model</th>
<th>Distribution</th>
<th>Location</th>
<th>Scale</th>
<th>Shape</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>GEV</td>
<td>( \mu )</td>
<td>( \sigma )</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>GEV</td>
<td>( \mu(t) = \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \sigma )</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>GEV</td>
<td>( \mu(t) = \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \log(\sigma) = \beta_0 + \beta_1 \cdot x_1(t_1) )</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>GEV</td>
<td>( \mu )</td>
<td>( \sigma )</td>
<td>( \xi )</td>
</tr>
<tr>
<td>5</td>
<td>GEV</td>
<td>( \mu(t) = \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \sigma )</td>
<td>( \xi )</td>
</tr>
<tr>
<td>6</td>
<td>GEV</td>
<td>( \mu(t) = \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \log(\sigma) = \beta_0 + \beta_1 \cdot x_1(t_1) )</td>
<td>( \xi )</td>
</tr>
<tr>
<td>7</td>
<td>GEV</td>
<td>( \mu(t) = \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \log(\sigma) = \beta_0 + \beta_1 \cdot x_1(t_1) + \beta_2 \cdot x_2(t_2) )</td>
<td>( \xi )</td>
</tr>
<tr>
<td>8</td>
<td>Gaussian</td>
<td>( \mu_0 + \mu_1 \cdot x_1(t_1) + \mu_2 \cdot x_2(t_2) )</td>
<td>( \sigma )</td>
<td>–</td>
</tr>
<tr>
<td>9</td>
<td>LP3</td>
<td>( \mu )</td>
<td>( \sigma )</td>
<td>( \gamma )</td>
</tr>
</tbody>
</table>
predictors for this year; (iii) the procedure is repeated until all $n$ years are used as the forecast target. For comparison, the stationary flood quantile associated with the 10% exceedance probability (i.e. the 10 year return period quantile) estimated from model 4 (stationary GEV) is also shown in Fig. 8 (dashed blue line).

The nonstationary, cross-validated flood quantile (red line) tends to reproduce the patterns of the observed data. The Pearson correlation coefficient is 0.50 ($p$-value $= 3.1\times 10^{-8}$ for the null hypothesis of true correlation equals to zero). The $q_{90}$ flood quantile (blue line) shifts up to 2 m from its stationary counterpart (dashed blue line) and also follows closely the observed river stages (black line), which tend to stay within the $q_{2.5}$ and $q_{97.5}$ nonstationary quantiles (gray region in Fig. 8), with just 6 events (5.5 % of the total number of years) outside this interval. It is also interesting to note that the length of the interval defined by the $q_{2.5}$ and $q_{97.5}$ quantiles, which represents the dispersion of the nonstationary probability distribution of the annual maximum river stage, changes across the years, with the largest values associated with $x_1 > 0$ (i.e. El Niño conditions). Thus, we see that the predictors used inform changes in both the location and the scale of the distribution, and that the conditional coverage of the flood stage series is 94.5% versus the expected 95% over the period of record under cross validation, which shows that the model is very well calibrated.

From the perspective of dynamic flood risk analysis, if we consider, for instance, the river stage quantile ($= 29.15$ m) obtained from stationary model 4 for the 10 year return period, i.e. the river stage associated with the 10% exceedance probability, one can obtain from model 6 the nonstationary exceedance probabilities associated with this river stage value. As shown in the left panel of Fig. 9, the dynamic flood risk assumes values that oscillate around the expected 10% value (average = 9.3%), but can be as high as 60%, particularly in the years following La Niña events (right panel of Fig. 9) and when the river stage is relatively high in January. Thus, even in the presence of nonstationarity, a candidate reference level can first be estimated using the traditional stationary analysis that may have been used for levee design or flood plain mapping, and then the likely risk of overtopping the levee or inundating the T-year flood plain can be assessed using this predictive model, a few months prior to the flood season. This lead time would be sufficient to explore some additional preparation or adaptation measures, and to do a benefit-cost analysis of those measures using traditional statistical decision theory methods.
4.2. An early flood alert system

As a tool for flood risk management, the model proposed here could be used to complement the flood alert and warning system for Manaus and the surrounding region already operated by the Geological Survey of Brazil (CPRM), which starts its river stage forecasts on March 31st (http://www.cprm.gov.br/). For instance, in the beginning of January, with available information for the river stage and the previous December NINO3 index, one could use model 6 to predict the river stage associated with (for example) the 0.1 exceedance probability, and use available tools (e.g. Christian et al., 2013; Neal et al., 2013; Bernini and Franchini, 2013; Zhang et al., 2014) to define inundation zones associated with this risk level, which in turn could be used to guide short term flood control measures and disclose target flood alerts and preparedness (e.g. Sene, 2008).

Alternatively, the nonstationary model could be used to issue an early flood alert (binary response forecast) when a pre-defined flood hazard is achieved for a certain threshold of the river stage. For instance, if we define the 28.5 m as the threshold value for the river stage (which could be associated with a large increase in property losses once this level is achieved during the flood season), one could issue a flood watch in January when the nonstationary exceedance probability associated with the 28.5 m river stage is above some maximum allowed flood hazard, which in turn could be defined in order to maximize a certain performance measure of the forecast model (e.g. Probability of Detection or hit rate, Brier Skill Score, Peirce’s Skill Score, Critical Success Index, area beneath the relative operating characteristic, etc. We refer the reader to Mason (2003) for more details) or some economic benefit associated with the value of the forecast (Sene, 2008).

As an illustrative example of the potential use of the proposed model for flood alerts for the city of Manaus, we evaluate the model performance for different values of river stage thresholds and flood hazards by looking at the area $A_0$ beneath the relative operating characteristic, which is a graph of the hit rate $H$ versus the false alarm rate (FAR) and has been used for the purpose of measuring forecasts accuracy (e.g. Mason, 2003). Onefold cross-validated results for $A_0$ as a function of flood hazard and river stage threshold is shown in Fig. 10. A value of $A_0 = 1$ indicates a perfect forecast model, while $A_0 = 0.5$ indicates a random forecast with no skill. A measure of $A_0 < 0.5$ indicates the same level of discrimination capacity of a model with $A_0$ flipped over 0.5, but calibrated in the wrong direction (Mason, 2003). Note that for practically all points $A_0 > 0.5$, which indicates a moderate level of skill for the proposed model. Maximum values of $A_0$ are found along the main diagonal of Fig. 10. Note also that for river stage thresholds outside the range of the historical data there is no objective way to estimate $A_0$.

The probability of detection (or hit rate, discrimination measure $H$) associated with the values of river stage thresholds tends to decrease as the tolerable flood hazard increases (left panel of Fig. 11). The false alarm rate (FAR) tends to oscillate between 30% and 100% (right panel of Fig. 11), with an increase as the threshold for the river stage increases. In a hypothesis test framework, with the null hypothesis of no occurrence of a flood event (river stage greater than the threshold), the hit rate can be seen as the power of the test (i.e. the probability of reject a correct null hypothesis) for a given flood hazard threshold, whereas the false alarm rate is analogous to the probability of rejecting a correct null hypothesis (i.e. the probability of a type I error) (Mason, 2003; Wilks, 2006).

As an example of model application for the 2014 flood season, considering the observed values of $x_1 = 0.237$ (NINO3 index for December 2013) and $x_2 = 22.24$ m (river stage at first January 2014), the nonstationary exceedance probabilities associated with the river stage flood quantiles (red line in Fig. 12) are relatively close to the static counterpart obtained from model 4 (stationary GEV). If, for instance, we consider a 29.15 m (= stationary 10-year return period quantile) river stage threshold and a tolerable flood hazard specified as 10%, then the nonstationary probability of exceeding 29.15 m is 10.05%, which is very close to the nominal design level from the stationary model but still would imply an early flood alert for the 2014 season. For these values, the cross-validated performance of the flood alert system (from Figs. 10 and 11) is $A_0 = 0.66$, $H = 67\%$ and FAR = 85\%, suggesting that the model is informative in this range. In fact, by July 2014, the actual river stage had already crossed 29.40 m (from http://www.portodemanaus.com.br/ which provides near real time river stage data).

Fig. 10. Cross-validated area $A_0$ beneath the relative operating characteristic as a function of flood hazard and river stage thresholds.
5. Summary

The primary objective of this paper was to demonstrate that a relatively simple model of the peak river stage can be developed using readily available tools and climate indicators, and be informative for dynamic flood risk management. The particular series selected at Manaus, on the Negro River, has been of interest for quite some time for its nonstationarity (Brillinger, 1989; Brillinger, 1994). We find that using the January stage of the river at the gaged location is effective in addressing part of the monotonic trend in the stage due to geomorphic and land use change factors, while the NINO3 index is informative as to the climate effects on regional precipitation and streamflow that were indicated also in prior research. The model identified using the GEV distribution with time varying location and scale parameters informed by the two predictors is shown to be effective in cross-validated performance, with high correlation of the cross-validated median and 90th percentile with the observed series that were not included in the model, and excellent coverage of the observations by the time varying, cross validated 2.5% and 97.5% quantiles of the stage. The reliability of performance of the model as to the prediction of selected percentiles of the peak stage was further tested using standard prediction performance metrics and shown to be quite good.

Finally, we discussed the potential application for early alert of floods at selected thresholds and for selected years with anomalous observed floods, again in a leave one out validation setting and illustrated when it would be appropriate to issue a clear flood watch that a certain level may be exceeded or not. An economic or decision theoretic application to specific actions that could be taken was not presented, since the detailed potential loss and cost of adaptation information is not available to us. However, such an illustration could be readily developed using techniques that are well described in the literature for risk based flood design (e.g. Tung and Mays, 1981; Al-Futaisi and Stedinger, 1999).

In forthcoming work, we expect to take a regional approach to nonstationary flood frequency analysis, in a hierarchical Bayesian framework, with automatic identification of regionally relevant predictors and the application of such a model to reduce uncertainties in at site estimation of nonstationary flood risk.

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