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# A Univariate Extreme Value Analysis and Change Point Detection of Monthly Discharge in Kali Kupang, Central Java, Indonesia

Sandy H. S. Herho<sup>a,\*</sup>

<sup>a</sup> Department of Geology, University of Maryland, 8000 Regents Dr #237, College Park, 20742, United States Corresponding author: <sup>\*</sup>herho@terpmail.umd.edu

*Abstract*—Kali Kupang plays an important role in the life of the people of Pekalongan and its surrounding areas. However, until recently, not many hydrological studies have been carried out in this area. This study presents how Extreme Value Analysis (EVA) can predict future extreme hydrological events and how a dynamic-programming-based change point detection algorithm can detect the abrupt transition in discharge events variability. Using the annual block maxima, we can predict the upper extreme discharge probability from the generalized extreme value distribution (GEVD) that best fits the data by using the Markov Chain Monte Carlo (MCMC) algorithm as a distribution fitting method. Metropolis-Hasting (MH) algorithm with 500 walkers and 2,500 samples for each walker is used to generate random samples from the prior distribution. As a result, this discharge data can be categorized as a Gumbel distribution. The changepoint location of the annual standard deviation of this discharge data in the mid-1990s is detected by using the pruned exact linear time (PELT) algorithm. Despite some shortcomings, this study can pave the way for using data-driven algorithms, along with more traditional numerical and descriptive approaches, to analyze hydrological time-series data in Indonesia. This is crucial, considering an increasing number of hydro climatological disasters in the future as a consequence of global climate change.

Keywords- Hydrological extreme; change point detection; block maxima; MCMC; PELT.

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## I. INTRODUCTION

Kali Kupang, locally known as Kali Loji, flows from the confluence of the Retno Sumilir tributaries located at the foothills of the Mount Rogojembangan - Petungkriyono, which is administratively located on the border of Banjarnegara and Pekalongan districts to its estuary, which is located in the Java Sea, north of the city of Pekalongan. Kali Kupang is also called the Masin river because this river passes through a village called Masin, which is located in Warungasem, Batang district. This Masin village is referred to in classical Javanese Hindu history [1] as the Mo-Ho-Sin kingdom or the Mahasin kingdom. This kingdom was a Hindu kingdom in Java that developed in the 10th century AD. According to Ma-Huan, a secretary to Admiral Zheng He [2], settlements in the Sampangan village area began Pekalongan's development as an inter-island port time; Kali Kupang was designated as its base. It is not known who is the ruler in this Pekalongan harbor area. At that time, Pekalongan was still part of the vacant land of the Cirebon sultanate. In the Cirebon Kertabumi script by Wangsakerta in 1485, the Pekalongan area was once led by the Wu Hang family, a great harbormaster who controlled trade traffic at the Pekalongan port. During the reign of the Islamic Mataram sultanate, around the 17th century AD, Pekalongan became a rich area. A large amount of money and abundant rice production sent to the kingdom's center made Pekalongan an important part of the territory of the Mataram sultanate [2].

Meanwhile, during the Dutch colonial period in the early 18th century AD until the 20th century AD, many merchant ships from various nations such as China, Arabia, India, and Europe docked at Kali Kupang until they passed the *Vereenigde Oostindische Compagnie* (VOC) guard post, namely Fort Peccalongan. This is evidenced by the many graves of sailors from various archipelago regions, such as Bugis, Madura, Malay, and Kalimantan [1]. The tombs of these sailors are located in the forest near Kali Kupang in the Arab village of Suguhwaras [2]. This was proven when Sayid Husein bin Salim, an Islamic scholar, and trader from Hadramaut, built the Waqaf mosque in 1854 AD. Many tombs are found with tombstones made of sea shells [2]. Entering the era of 1830 after the Diponegoro war, when Pekalongan

became a sugar-producing area for the Dutch kingdom, sugar exports to Europe also went through this Pekalongan port where Kali Kupang served as a transit point for Dutch trading ships before sailing back to Europe [2]. In the 18th to 20thcentury batik trade era, many merchant ships entered the Loji area. The ship unloaded its cargo around Sugihwaras, because this area is a Batik market near Kali Kupang [2]. Kali Kupang was also used as a berth for fishing boats until the early 1980s, before the Nusantara fisheries port were built in Pekalongan [2]. Due to the historical facts mentioned above, Kali Kupang plays a very important role in the lives of the people of Pekalongan and the surrounding area. In this study, I would like to examine the extremes and changes in the variability of the Kali Kupang flow.

### II. MATERIALS AND METHOD

## A. Dataset

This study uses the average monthly discharge at Pagarukir station (7.03056°S, 109.76111°E) (Fig. 1) from July 1975 to November 2009. These data were obtained from the Global Data Runoff Centre (GRDC) database (https://www.bafg.de/GRDC/ accessed 17 May 2022) operated by GRDC at the German Federal Institute of Hydrology (BfG) in Koblenz, Germany.



Fig. 1 Map of the study region highlights the region's hydrological station (red circle).

## B. Exploratory Data Analysis

Because there is 13.56% of missing data from the average monthly discharge time series, it is necessary to interpolate. This study uses a shape-preserving piecewise cubic Hermite interpolation scheme [3], one of the interpolation methods that can smooth the curves at each data point [4]. To simplify the numerical calculation process, I use the **pandas** library [5] in the Python computing environment to implement this interpolation scheme for the missing data. In order to discover the annual pattern of this time series, the data are averaged for each month throughout the period. To characterize the location and variability of these data, measurements of skewness and kurtosis. I use the Fisher-Pearson coefficient of sample skewness as follows,

$$g_1 = \frac{m_3}{m_2^{3/2}} \tag{1}$$

Meanwhile, to measure the kurtosis of the sample, the following equation is used,

$$g_4 = \frac{m_4}{m_2} - 3 \tag{2}$$

where  $m_i$  is the moment coefficient defined as follows,

$$m_{i} = \frac{1}{N} \sum_{n=1}^{N} (x_{n} - \bar{x})^{i}$$
(3)

In this study, skewness and kurtosis are measured automatically using the **scipy** library [6] in the Python computing environment. A normality test must be carried out to ensure that these data do not come from a normal distribution. Due to the relatively small number of samples, I use the Shapiro-Wilk test [7] on this data [8]. The Shapiro Wilks test is used to identify whether a random variable is normally distributed. This test is often applied in regression analysis to check the normality assumption of random error. The first step in the Shapiro-Wilk test is to determine the null hypothesis and the alternative hypothesis, namely:

- H<sub>0</sub>: The population follows a normal distribution,
- H<sub>1</sub>: The population does not follow a normal distribution.

Then, I determine the significance value of  $\alpha$ , which in this case is 0.05. Then, the data are sorted from smallest to largest and divided into two groups for conversion in the Shapiro-Wilk test. Then, the statistical value of the Shapiro-Wilk test is calculated using the following equation,

$$T_3 = \frac{1}{D} \left[ \sum_{i=1}^n a_i (x_{n-i+1} - x_i)^2 \right]$$
(4)

where,

$$D = \sum_{i=1}^{n} (x_i - \bar{x})^2$$
(5)

In this case,  $a_i$  is the Shapiro-Wilk test coefficient determined automatically, without a table, using the **scipy** library [6] in the Python computing environment.

## C. Extreme Value Analysis

Extreme events in insurance, economics, climatology, hydrology, and telecommunications are indicated by a very high (maximum) and very low (minimum) observed value. The interesting thing is to determine the probability (maximum and minimum) of rare events (tail distribution). One of the statistical methods used to study the tail behavior of the distribution is extreme value analysis (EVA). EVA focuses on the behavior of a distribution's tail region to determine the probability of extreme values [9]. An extreme value is derived from an event that occurs very rarely, is often declared an outlier, and is ignored but has a large impact. The study of the distribution tail shows that in some cases, the hydrological data has a heavy tail distribution [10]-[15]; that is, the tail of the distribution decreases slowly when compared to the Gaussian distribution. According to the central limit theorem (CLT), the Gaussian distribution is the limit distribution of the sample mean. The Fisher-Tippet-Gnekendo theorem is analogous to the CLT and uses the tail index to unify the possible characterizations of the density function of the extreme value distribution [9]. Coles [9] states that there are two methods for identifying extreme values, namely taking the maximum/minimum value in a certain period,

which is often referred to as the block maxima/minima (BM) method, and taking values that pass a threshold value, called the peaks over threshold (POT) method. In this analysis, I use the annual block maxima approach (365.2425 days).

This is done considering the ease and simplicity of this method compared to using POT. I purposely do not use block minima analysis because of the possibility of constraints on the elevation limit of the riverbed elevation that require recalibration [16]. I can determine the generalized extreme value distribution (GEVD) that fits the data through this BM method. The BM method is one of the EVA methods that can identify extreme values based on the highest value of observation data grouped by a certain period, which in this study is the value of average monthly discharge in 365.2425 days. Samples of extreme values taken based on BM can be grouped as Gumbel, Fréchet, or Weibull distributions. The combination of these three distributions into one family is referred to as the GEVD distribution. The following equation defines the cumulative distribution function (CDF) of the GEVD,

$$F(x;\mu,\sigma,\xi) = \begin{cases} exp\left\{-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)^{\frac{-1}{\xi}}\right)\right\}, -\infty < x < +\infty, \left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right); \\ exp\left\{-exp\left(-\frac{x-\mu}{\sigma}\right)\right\}, -\infty < x < +\infty, \xi = 0. \end{cases}$$

The GEVD is flexible in modeling different extreme behavior with three distribution parameters ( $\theta = (\mu, \sigma, \zeta)$ ). The location parameter ( $\mu$ ), with  $-\infty < \mu < +\infty$ , is a parameter that determines the distribution center. The scale parameter ( $\sigma$ ), with  $\sigma > 0$ , determines the size of the deviation around the location parameter. The shape parameter ( $\zeta$ ) governs the behavior of the GEVD tail. GEVD is divided into three types when viewed based on the value of the shape parameter ( $\zeta$ ), namely type I (Gumbel) if  $\zeta = 0$ , type II (Fréchet) if  $\zeta > 0$ , and type III (Weibull) if  $\zeta < 0$  [9].

Since the number of extreme values in the average monthly discharge data is relatively small, which only covers the maximum value for 35 years, so to stabilize the fitting distribution process, I use a Bayesian perspective [17], namely by using the Markov Chain Monte Carlo (MCMC) method which is considered more stable for determining the  $\hat{\theta} = (\hat{\mu}, \hat{\sigma}, \hat{\xi})$  Parameters are compared to the maximum likelihood estimation method commonly used for large samples [18].

MCMC is a method for generating random variables based on Markov chain [19]. With MCMC, a correlated random sample sequence is obtained, i.e. the  $j^{\text{th}}$  value of the  $\{\theta_j\}$ sequence is sampled from a probability distribution that depends on the previous value of  $\{\theta_{j-1}\}$ . The exact distribution of  $\{\theta_j\}$  is generally not known, but the distribution at each iteration in the sequence of sample values will converge to the true distribution for a sufficiently large value of j. Therefore, if the updated sample size is large enough, then the last group of values sampled in the sequence, e.g.  $\{\theta_{P+1}, \theta_{P+2}, \theta_{P+3}, ...\}$ will approximate a sample originating from the desired GEVD [20]. P is usually referred to as the burn-in period.

There are two main algorithms used in MCMC: the Metropolis-Hastings algorithm and the Gibbs sampling algorithm. This study uses the Metropolis-Hasting (MH) algorithm to generate random samples from the prior distribution [21]. The MH algorithm needs a proposal distribution  $p(\theta|\theta_j-1)$  to generate random sample candidates. The basic steps of this algorithm are as follows (21),

- Take the initial value, which is θ<sub>0</sub> for iteration j = 1, and generate θ\* ~ p(θ|θ<sub>j-1</sub>).
- 2. Generate a random sample u from the uniform distribution U[0, 1].

3. If 
$$u < \min\left(1, \frac{p(\theta^*|X,y)p(\theta_{j-1}|\theta^*)}{p(X,y|\theta^*)p(\theta^*|\theta_{j-1})}\right)$$
, then take  $\theta_j = \theta^*$ .  
4. But if  $u > \min\left(1, \frac{p(\theta^*|X,y)p(\theta_{j-1}|\theta^*)}{p(\Phi^*|X,y)p(\theta_{j-1}|\theta^*)}\right)$  then take  $\theta_i = \theta_{i-1}$ .

4. But if  $u > \min\left(1, \frac{1}{p(X,y|\theta^*)p(\theta^*|\theta_{j-1})}\right)$ , then take  $\theta_j = \theta_{j-1}$ .

5. Repeat steps 1 to 3 up to the desired amount.

The statistic used to measure the degree of dependence between successive retrievals in a Markov chain is autocorrelation. Autocorrelation measures the correlation between two sets of simulated values  $\{\theta_j\}$  and  $\{\theta_{j+L}\}$ , where *L* is the lag or number that separates the two sets. For a certain hyperparameter  $\theta_i$ , the autocorrelation value in the *L*<sup>th</sup> lag can be calculated by the following equation,

$$r_{iL} = \left(\frac{M}{M-L}\right) \left[\frac{\sum_{i=1}^{M-L} (\theta_i - \bar{\theta})(\theta_{i+L} - \bar{\theta})}{\sum_{i=1}^{M} (\theta_i - \bar{\theta})}\right]$$
(7)

where M is the size of the random sample. This study uses the **emcee** library [22] to perform the MCMC computation, which is a built-in from the **pyextremes** library [16] to perform GEVD fitting using the MCMC method. **Emcee** uses the ensemble samplers with affine invariance method to run the MH algorithm [22], which is proven to be significantly faster than the standard MH algorithm on highly skewed distribution [23]. Therefore, there are the term walkers, which are the members of the ensemble. These walkers are like separate MH chains. In this study 500 walkers are used, with 2,500 samples for each walker.

By using GEVD parameters obtained from MCMC fitting, recurrence intervals (RI) can be calculated from the extreme upper values for the annual average monthly discharge in Kali Kupang. RI is defined as the maximum value in the future period [9]. In the context of this study, RI is the maximum average monthly discharge expected to be exceeded once in a certain period. The maximum value is expected to be exceeded once in a period of k with period p. The average monthly discharge will reach the maximum value of  $R_k^p$  once. The estimated RI is expressed through the following equation,

$$\hat{R}_{k}^{p} = \begin{cases} \hat{\mu} - \frac{\hat{\sigma}}{\hat{\xi}} \left\{ 1 - \left( -ln\left(1 - \frac{1}{k}\right) \right)^{-\hat{\xi}} \right\}, \hat{\xi} \neq 0 \\ \hat{\mu} - \hat{\sigma}ln\left\{ -ln\left(1 - \frac{1}{k}\right) \right\}, \hat{\xi} = 0 \end{cases}$$
(8)

## D. Change Point Detection

The abrupt change in the average monthly discharge data is determined by using the pruned exact linear time (PELT) algorithm developed by Killick et al. [24]. This algorithm has been widely used and is quite successful in detecting changes in the mean and variance of hydrological data in various regions [25 - [30]. This algorithm is based on dynamic programming methods that are both fast and exact, nor does it rely on certain statistical assumptions. This algorithm works on a simple principle as follows,

$$\min_{\tau,k} \left[ \sum_{j=0}^{k} \mathcal{C} \big( y_{\tau j+1:\tau j+1} + \beta \big) \right]$$
(9)

where y is the time series vector of the annual standard deviation of the average monthly discharge, C(.) is the cost function,  $\beta$  is the penalty term used to avoid overfitting, and  $\tau$  is the vector of change point locations, which in this case I just use a single change point location in order to detect an abrupt transition in the standard deviation. I use **ruptures** library [31] in the Python computing environment to automate the calculation.

### III. RESULTS AND DISCUSSION

The result of implementing the shape-preserving piecewise cubic hermite interpolation scheme is shown in Fig. 2. Based on this interpolated data, the annual hydrological cycle in Kali Kupang (Fig. 3) is consistent with the precipitation study conducted by [32] which grouped Central Java into region A with one peak and one trough. This pattern is due to the strong influence of the northwest monsoon from November to March (NDJFM) and the southeast monsoon from May to September (MJJAS) [32].



Fig. 2 Shape-preserving piecewise cubic hermite interpolation of average monthly discharge (red line). Uninterpolated data points mark with x.



Fig. 3 Annual cycle of average monthly discharge.

The skewness and kurtosis values in this data are 1.313 and 2.146, respectively. This shows that the tail of this distribution is longer towards the right-hand side of the curve  $(g_1 > 0)$  and is a flat distribution, where the values are moderately spread out or known as the platykurtic distribution  $(g_4 < 3)$ . It appears from the results of this calculation that these average monthly discharge data are not normal, which can also be seen in the distribution graph in Fig. 4. The statistical value of the Shapiro-Wilk test is 0.886, with p < 0.05, so the null hypothesis can be rejected, therefore these data do not come from a Gaussian distribution.



Fig. 4 Distribution of average monthly discharge.

Fig. 5 shows extreme values by using BM approach. The MCMC trace and corner plots of this EVA can be seen in Fig. 6. Through this MCMC computation, I get the parameter values,  $\hat{\mu} = 6.818$ ,  $\hat{\sigma} = 3.456$ , and  $\hat{\xi} = 0$ , so it can be concluded that the extreme upper value of this average monthly discharge can be classified into Gumbel distribution. The graphic visualization of this distribution is shown in Fig. 7. The summary of RI can be seen in Table 1.



Fig. 6 Annual block maxima parameter estimation using MCMC. (a) Trace plot for GEVD parameter estimation. The corner plot (b) shows all the one and two-dimensional projections of the posterior probability distributions of GEVD parameters.



Fig. 7 Diagnostic plots of average monthly discharge RI: (a) return level (shaded region corresponds to 95% confidence interval, (b) histogram with fitted GEVD density, (c) probability, (d) quantile.

 TABLE I

 AVERAGE MONTHLY DISCHARGE RI VALUES

Return Period (years)	Return Value (m³/s)	Lower CI (m <sup>3</sup> /s)	Upper CI (m³/s)
2	8.0879	6.807	9.688
5	12.008	10.340	14.756
10	14.603	12.552	18.222
25	17.883	15.297	22.665
50	20.315	17.315	25.979
100	22.730	19.312	29.285

A visual graph of change point in this discharge data is shown in Fig. 8. There appears to be a change in discharge variability after the mid-1990s. This change may have occurred because manufacturing-based development began to be encouraged at the end of the New Order era in the 1990s [33]. With the increase in the manufacturing industry [34], it is possible to trigger population density in the area around the Kali Kupang watershed which causes various causes of changes in discharge variability [35; 36; 37]. However, this can also be caused by the artifacts of filling in missing data that often occurred in the 2000s, so further analysis is needed.



Fig. 8 Change point detection with PELT algorithm. The y-axis is the annual standard deviation of the average monthly discharge in Kali Kupang displayed on a logarithmic scale.

## IV. CONCLUSION

In this study, univariate EVA and PELT change point detection are carried out on average monthly discharge data in Kali Kupang. The computational results of EVA using a Bayesian perspective succeeded in showing the RI values drawn from the Gumbel distribution. This may be used as a basis for decision-making for regional governments that are traversed by the Kali Kupang watershed, namely Banjarnegara regency, Batang regency, Pekalongan city, and Pekalongan regency to implement related infrastructure planning [e.g., 38; 39; 40]. The computational results of change point detection using the PELT algorithm are able to detect abrupt shifts in the annual standard deviation from the average monthly discharge in the mid-1990s, to be precise in 1995.

However, this study has many shortcomings that need to be corrected. The main thing to do is to collect data on other stations, which unfortunately cannot be found on the GRDC database. This must be done because the Kali Kupang watershed is quite wide with an area of 18,022.193 ha. However, if there is no data for any station, it may be possible to simulate discharge using a numerical model, such as HEC HMS [e.g., 41; 42; 43; 44]. In addition to that, there are other problems because there is no data from other stations in the same watershed, it is not possible to use double-mass curves [45], which are popularly used by hydrologists to replace the missing data. I have to interpolate missing data. This interpolation process is prone to cause time series artifacts, so further analysis of missing data imputation is required [e.g., 46; 47; 48]. Furthermore, discharge data, like other hydroclimatological data [49], generally are not stationary, therefore adjustments are needed using non-stationary EVA (50). Unfortunately, pyextremes does not yet have this feature, so it is necessary to rewrite the code or switch to the extRemes package [18] in the R computing environment which already has the capability to perform non-stationary EVA. Improvements in this study need to be made considering the vitality of Kali Kupang for the lives of the people of Pekalongan and its surrounding areas. The potential use of data-driven computational methods [51] in this study can be further developed to anticipate extreme hydrological disasters that are likely to occur more in the future [52].

#### CODE AND DATA AVAILABILITY

Data are available through the cited sources throughout the article. Python scripts used in this study are accesible at https://github.com/sandyherho/kaliKupangDisch.

#### **COMPETING INTEREST**

I declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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