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Mitigating infectious disease risks through non-stationary flood frequency analysis: a case study in Malaysia based on natural disaster reduction strategy

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Abstract

The occurrence of floods has the potential to escalate the transmission of infectious diseases. To enhance our comprehension of the health impacts of flooding and facilitate effective planning for mitigation strategies, it is necessary to explore the flood risk management. The variability present in hydrological records is an important and neglecting non-stationary patterns in flood data can lead to significant biases in estimating flood quantiles. Consequently, adopting a non-stationary flood frequency analysis appears to be a suitable approach to challenge the assumption of independent and identically distributed observations in the sample. This research employed the generalized extreme value (GEV) distribution to examine annual maximum flood series. To estimate non-stationary models in the flood data, several statistical tests, including the TL-moment method was utilized on the data from ten stream-flow stations in Johor, Malaysia, which revealed that two stations, namely Kahang and Lenggor, exhibited non-stationary behaviour in their annual maximum streamflow. Two non-stationary models efficiently described the data series from these two specific stations, the control of which could reduce outbreak of infectious diseases when used for controlling the development measures of the hydraulic structures. Thus, the application of these models may help prevent biased prediction of flood occurrences leading to lower number of cases infected by disease.

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Introduction

On a global scale, flooding stands as the foremost item of natural catastrophes therefore representing a significant environmental problem confronting numerous countries in the twenty-first century (Abaya *et al.*, 2019; Ochani *et al.*, 2022). Overflow of water bodies, such as rivers, streams, and main channels leads to floods (El-Mousawi *et al.*, 2023) making them a significant cause of natural disasters with a substantial impact on fatalities worldwide. This is particularly evident in the state of Johor, situated in the southern part of Peninsula Malaysia, which experiences floods twice a year during the monsoon seasons from late May to September and from November to March. Notably, as of March 5th, 2023, Johor had the highest number of flood victims (50,596) accommodated in 268 temporary relief centres across its ten districts. Other affected states included Pahang and Melaka, while Selangor and Negeri Sembilan had already begun recovery at this time (Malaymail, 2023).

Flooding in major agricultural producing regions can result in significant damage to plants, fences, and livestock. Crop losses due to adverse weather conditions, saturated soils, and delays in harvesting are compounded by transportation disruptions caused by flooded roads (Caldas-Alvarez *et al.*, 2022; Mohr *et al*., 2023; Romali & Yusop, 2021). These natural extremes contribute to a higher global death charge and have a substantial economic impact on infrastructures (Ludwig *et al.*, 2023; Prasad & Francescutti, 2017; Pregnolato *et al.*, 2017). For health impacts, flooding brings to physical injuries, respiratory infections, mental health, cases of poisoning, and infectious diseases (French *et al*., 2019; Okaka & Odhiambo, 2019).

Infectious diseases occur during the flood events because floods transport many different pieces of material that can include harmful germs and numerous studies have explored the relationship between flooding and spread of infectious diseases (Brown & Murray, 2013; Okaka & Odhiambo, 2018; Shokri *et al.*, 2020). Throughout history, floods have been associated with the spread of infectious diseases caused by waterborne pathogens. Brown and Murray (2013) have compiled a list of infectious diseases resulting from flood events in various countries worldwide between 1983 and 2011. This issue persists to the present day, with new diseases continuing to emerge as a consequence of flooding. The primary health concerns associated with floods are waterborne diseases (Gleneagles, 2022; Ho *et al.,* 2022; Shafii *et al.*, 2023) and vector-borne diseases (Barteit *et al.*, 2023; Gleneagles, 2022). Waterborne diseases occur when floods contaminate drinking water sources (Brown & Murray, 2013). This has shown an increasing trend from 1980-2006, which coincides with increasing number of flood events globally (Adikari & Yoshitani, 2009). Furthermore, floods also serve as breeding habitats for mosquitoes thereby increasing the incidence of mosquito-borne diseases, including typhoid fever, cholera, leptospirosis, dengue fever, malaria, and others (Okaka & Odhiambo, 2018). According to a report from the World Health Organization (WHO), Malaysia reported 52,977 cases of dengue fever in the span of January to November 2022 alone (Gleneagles, 2022). In addition to these diseases, flood victims are also susceptible to mental health illnesses such as post-traumatic stress disorder, depression, and anxiety (El-Mousawi *et al.*, 2023).

It is crucial to prevent infectious diseases due to flood events, something which is not solely the responsibility of public health managers but also hydrologists when related to flooding. In order to limit and control the risks of future floods, control measures, such as construction of dams, risk management, institutional measures as well as public education should be initiated alongside suitable operational guidelines since improved flood prediction could help reducing the severity of disease outbreaks. This could be gained from accurately estimating quantile magnitudes of flooding since necessary upgrades and improvements would mitigate the occurrence of increasingly frequent flood events. Most researchers investigating flood risk assessment have employed flood frequency analysis (FFA) to estimate quantile magnitudes of flooding (Badyalina *et al.*, 2022; Mondal *et al.*, 2023; Pan *et al.*, 2022).

In FFA, the maximum flows that exceed specific thresholds at each return time are crucial in designing hydraulic structures, such as dams and weirs. This approach aids measuring the stationary properties of river systems (Hirabayashi *et al.*, 2013; Kuriqi & Ardiçlioglu, 2018 ; Zalnezhad *et al.*, 2022). However, growing concerns revolve around irregular climate change patterns leading to increased risks of flooding and severe hydrological events (Badyalina *et al.*, 2021; Ishak & Rahman, 2019; Ishak *et al.*, 2013; Yao & Soro, 2021). Weiskopf *et al.* (2020) and Diaz *et al.* (2019) have projected that climate change, influenced by human activities, heightens vulnerability in ecosystems. The warmer air induced by climate change can lead to potential extreme rainfall and subsequent flooding events. The evolving climate pattern necessitates adjustments in the frequency of data sampling with reference to mean and variance (Chen *et al.*, 2021; Khaliq *et al.*, 2006). As a result, the analysing of probability and parameter distributions under non-stationary conditions has evolved over time. Assuming stationarity for non-stationary sample records may no longer be valid due to the potential impact of climate change on flood events (Mat Jan *et al.*, 2020; Salas & Obeysekera, 2014; Vasiliades *et al.*, 2015). Several studies have explored risk factors associated with violations of the stationarity principle (Cunderlik & Burn, 2003; Milly *et al.*, 2008; Villarini *et al.*, 2009), but alternative methods are necessary for estimating time-dependent distribution parameters for non-stationary data.

This study explored the behaviour of the non-stationary flood frequency analysis model in order to find the precise information and reliable flood prediction estimates. The insights gained from this research would contribute to a deeper understanding of the connection and fundamental mechanisms behind the emergence of infectious disease outbreaks in the aftermath of floods. This knowledge is essential to shape informed policy decisions in reducing the spreading of infectious disease (Brown & Murray, 2013). The significance of non-stationary assumptions of the generalized extreme value (GEV) distribution was applied in estimating extreme events through the application trimmed L-moments (TL-moments), which are generalizations of L-moments that give zero weight to extreme observations.

Materials and Methods

Data description

Johor is known as one of Malaysia's most precipitation-rich states. Typically, the intensity of rainfall peaks towards the end of the year, after the May through September period, a pattern known as the Southwest Monsoon season. In 2006, Malaysia encountered a substantial deluge, culminating in unforeseen floods in Johor. This intensified flooding can largely be attributed to unprecedented rainfall caused by global climate change. Consequently, this study systematically scrutinized a sequence of annual maximum flow data from various stations in Johor to assess the viability of employing non-stationary assumptions using FFA. The investigation leveraged secondary data gathered from ten stream-flow stations situated in Johor, Malaysia. To yield significant flood quantile estimations, the stream-flow data must encompass a minimum duration of 15 years or more. The pertinent particulars for each station used in this research are succinctly summarized in Table 1. For enhanced geographical comprehension of the station placements, Figure 1 depicts the map illustrating the positioning of stream-flow stations across Johor, Malaysia.

Operational framework

Figure 2 provides an overview of the research flow. The study initiates by revisiting the development of the GEV model while considering non-stationary scenarios. Subsequently, the TL-moments method was employed to estimate the model's parameters. To analyse real data, an assessment of the data series trend was conducted, aimed at comprehending potential changes in the stream-flow series. Following this, the goodness of fit of the model was assessed to determine the significance of specific stationary or non-stationary model estimations. To evaluate the model's stationarity, statistical tests, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), were employed. Additionally, graphical diagnostic tests are applied to the observed data. As a result, the most suitable GEV distribution model was selected for the non-stationary stream-flow station to estimate the flood discharge of each station (Figure 2).

The non-stationary GEV model

The GEV distribution is a commonly utilized tool for analysing flood frequency in extreme events (Badyalina *et al.*, 2021; Badyalina *et al.*, 2022; Guru & Jha, 2014), with the GEV distribution's three parameters derived from three distinct probability distribution functions: Frechet, Gumbel and Weibull as describes by Coles (2001). The cumulative distribution function (CDF) for the GEV distribution is expressed as follows:

$$F(x) = \exp\left[-\left(1-\frac{k(x-\xi)}{\alpha}\right)^{1/k}\right],\ k \neq 0 \qquad \text{(Eq. 1)}$$

$$F(x) = \exp\left[-\exp\left(-\frac{x-\xi}{\alpha}\right)\right],\ k = 0$$

where x denotes the observed flood series, with ξ, α, and k representing the location, scale and shape parameters, respectively.

Traditionally, the GEV parameter model is characterized by its time-independent nature (constant) (Coles, 2001). When a trend is detected within a data series, specific parameters of the non-stationary model transform into time-dependent variables. However, the shape parameter remains constant due to the challenges associated with precise estimation (Coles, 2001). In this study, three non-stationary models incorporating time (t) as time-dependent covariate are presented and detailed in Table 2.

Earlier research efforts, as observed in studies by Gado and Nguyen (2016a,b) and Mat Jan *et al.* (2020), employed an exponential function in lieu of a linear function for the scale parameter within the NSGEV2 model. However, for the sake of simplicity, the present study adheres to the original parameterization involving a linear trend in time for the scale and location parameters. By retaining the linear approach, this study aimed to mitigate complexity while maintaining a manageable and interpretable framework.

Table 1. Characteristics of gauging sites for annual maximum flow series in Johor.

Station	Period	No. of years	Catchment area (km²)	Latitude	Longitude
Sayong	1987-2020	33	624	01° 48' 15" N	103° 40' 10" E
Pengeli	1996-2020	24	143	01° 49' 15" N	103° 37' 15" E
Sembrong	1990-2020	30	186	01° 56' 20" N	103° 09' 40" E
Kahang	1988-2020	32	587	02° 15' 05" N	103° 35' 15" E
Muar	1976-2020	44	3130	02° 33' 20" N	102° 45' 50" E
Segamat	1976-2020	44	658	02° 30' 25" N	102° 49' 05" E
Parit Madirono	2004-2020	16	1840	01° 41' 30" N	103° 16' 15" E
Johor	1975-2020	45	1130	01° 46' 50" N	103° 44' 45" E
Linggui	2005-2020	15	209	01° 53' 45" N	103° 41' 30" E
Lenggor	1971-2020	49	207	02° 15' 30" N	103° 44' 10" E

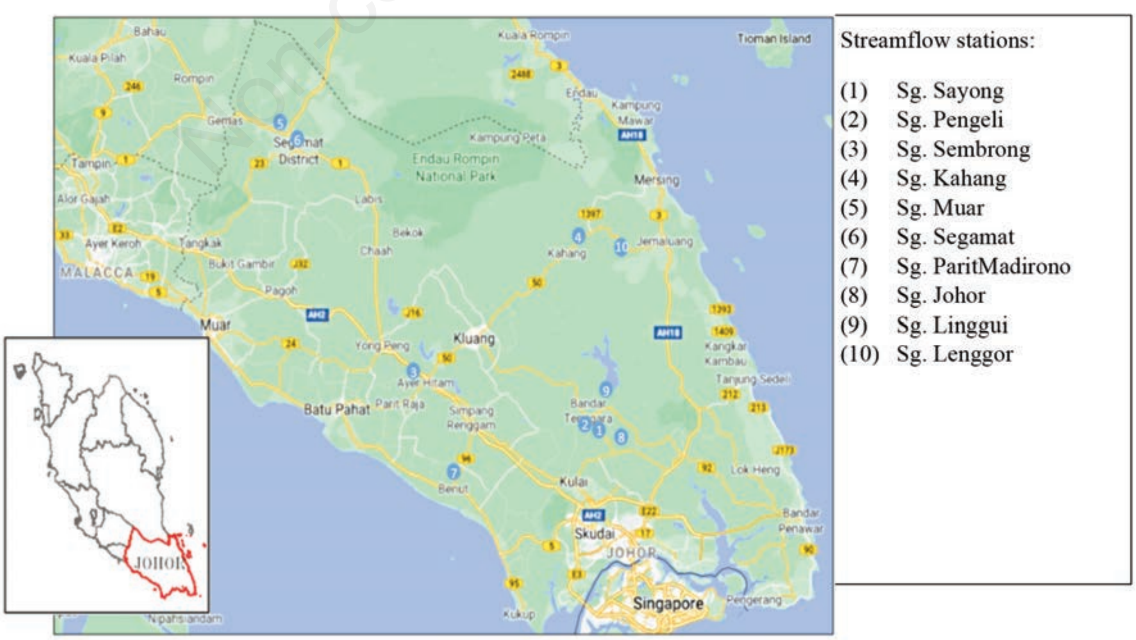

Figure 1. The geographical placement of stream-flow stations in Johor, Malaysia.

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Application of the TL-moment approach for the GEV distribution

According to Elamir and Seheult (Elamir & Seheult 2003), the r^{th} trimmed TL-moment is expressed as follows:

$$\lambda_r^{(t_1,t_2)} = \frac{1}{r}\sum_{k=0}^{r-1}(-1)^k \binom{r-1}{k} E(X_{r+t_1-k:r+t_1+t_2})\; r = 1,\ 2, \qquad \text{(Eq. 2)}$$

where $\lambda_r^{(t_1,t_2)}$ refers to r^{th} trimmed TL-moment and $E\,(X_{r+t_1-k:r+t_1+t_2})$ is expectation of order statistics. For each r, the conceptual sample size increases from r to $r+t_1+t_2$ and works only with the expectations of the r order statistics $X_{t_1+1:r+t_1+t_2}, \ldots, X_{t_1+r:r+t_1+t_2}$ by trimming the t_1 smallest and t_2 largest from the conceptual sample (Elamir and Seheult, 2003). Note that TL-moments can be reduced to L-moments when $t_1 = t_2 = 0$. The expectation of order statistics can be written as follows (Hosking & Wallis 1997):

$$E(X_{r:n}) = \frac{n!}{(r-1)!\,(n-r)!}\int_0^1 x(F)F^{r-1}(1-F)^{n-r}dF \qquad \text{(Eq. 3)}$$

where $F(x)$ denotes the CDF for x, $x(F)$ the inverse CDF of x calculated at the probability, with r and n non-negative integers. The expectation of order statistics can also be defined in term of β_r; where $\beta_r = \int_0^1 x(F)F^r dF$ (Greenwood *et al.,* 1979).

The non-stationary parameter in the GEV distribution both for the L-moment and the TL-moment can be obtained based on the relationships between the non-stationary condition of the series and the moments of the sample time series (Gado & Nguyen, 2016a). The quantile functions for NSGEV1, NSGEV2, and NSGEV3 models take the following form:

$$\begin{aligned}
&\text{NSGEV1: } x(F,t) = \xi(t) + \frac{\alpha}{k}[1-[-\ln(F)]^k]\\
&\text{NSGEV2: } x(F,t) = \xi(t) + \frac{\alpha}{k}[1-[-\ln(F)]^k]\\
&\text{NSGEV3: } x(F,t) = \xi(t) + \frac{\alpha(t)}{k}[1-[-\ln(F)]^k]
\end{aligned} \qquad \text{(Eq. 4)}$$

where $x(F)$ and $x(F,t)$ are quantile estimations of the stationary and non-stationary GEV model at T-years return period; F = 1-1/T.

Analysis of the stream-flow data series

According to some studies, the record for the hydrological data are censored and non-normally distributed (Bouza-Deano *et al.* 2008; Sadri *et al.* 2016). The non-parametric Mann-Kendall (MK) and Spearman's Rho (SR) test have been widely used to identify the existence of a trend in environmental data series (Pohlert 2020).

The Mann-Kendall (MK) test

The power of the monotonic relationship between two variables x and y is quantified through the *tau*, $\tilde{\tau}$ measured in both tests suggested by Kendall (1975). In order to estimate the *tau*, $\tilde{\tau}$ in the test, variable x was assigned as time and variable y as the annual maximum stream-flow for this study (Mann, 1945). This test is commonly known as the MK test. It is highly effective in identifying monotonic patterns due to its simplicity, reliability, and ability to handle missing values below a detection threshold (Ahmad *et al.* 2015; Ishak *et al.* 2013; Ren *et al.* 2019). Given the hypothesis for MK test as H_0 = *without monotonic trend in the data series* and H_1 = *the data series follow a monotonic trend*, the statistic for the MK test is given by:

Data series follow a monotonic trend

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\text{sgn}(x_j - x_i), \text{sgn}(x) = \begin{cases}+1, x>0\\ 0, x=0\\ -1, x<0\end{cases} \qquad \text{(Eq. 5)}$$

where x_i and x_j are the data points at times i and j (j>i), n the number of data points and estimated *tau*, $\tilde{\tau}$ given by:

$$\tilde{\tau} = \frac{2S}{N(N-1)} \qquad \text{(Eq. 6)}$$

and the standardized test statistic Z given by:

$$Z = \begin{cases} S - 1/\sqrt{Var(S)} & S>0\\ 0 & ,S=0\\ (S+1)/\sqrt{Var(S)} & S<0\end{cases} \qquad \text{(Eq. 7)}$$

The Spearman's Rho (SR) test

Spearman's Rho test is a rank-based test commonly used to determine monotonic trend (Chen *et al.* 2019; Mehmood *et al.* 2019; Tan & Gan 2015). Given the hypothesis as H_0 = A the sample data set $\{x_i,\ i = 1, 2, \ldots, n\}$ is independent and identically distributed (IID) and H_1 = A positive or a negative trend exist in the

Table 2. The parameters for GEV non-stationary models

Model	Scale (α)	Location parameter $\xi(t)$	Shape (k)
NSGEV1	constant	$\xi_0 + \xi_1 t$	constant
NSGEV2	$\alpha(t) = \alpha_0 + \alpha_1 t$	$\xi_0 + \xi_1 t$	constant
NSGEV3	constant	$\xi_0 + \xi_1 t + \xi_2 t^2$	constant

NSGEV, generalized non-stationary extreme value.

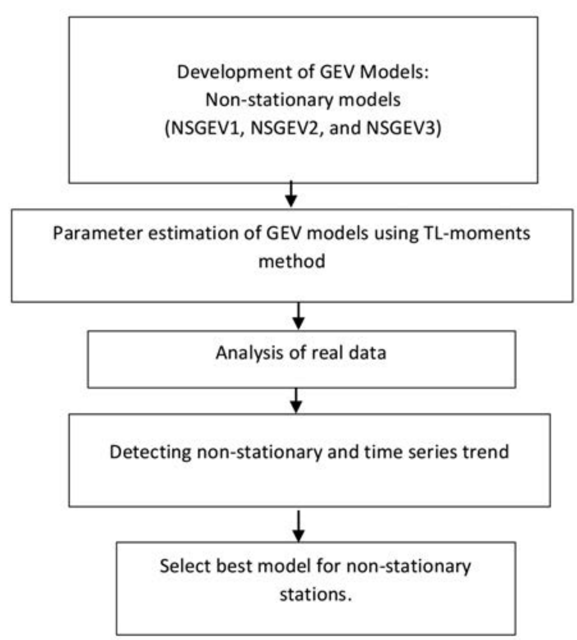

Figure 2. Flowchart of the research undertaken.

data series, the test statistic, Z for SR test is given by Sneyers (1990):

$$Z = r_s\sqrt{n-1} \quad \text{(Eq. 8)}$$

where Spearman's rank r_s is defined as follows:

$$r_s = 1 - \frac{6[\sum_{i=1}^{n}(R(x_i) - i)^2]}{(n^3 - n)} \quad \text{(Eq. 9)}$$

where $R(x_i)$ is the rank of the i-th observation x_i in the sample size n.

The augmented Dickey-Fuller (ADF) test

The ADF test typically used to test the existence of unit roots in the series (difference stationary), which was first suggested by Dickey and Fuller (1979) and updated by Said and Dickey (1984). This test is performed to check if mean values and variances of a series vary with time, which is known as non-stationary time series. The ADF test is an 'augmented' version of the Dickey Fuller test that extends the test equation as follows:

$$y_t = c + \beta t + \alpha y_{t-1} + \Phi \Delta Y_{t-1} + e_t \quad \text{(Eq. 10)}$$

which becomes a model equation with high order regressive process:

$$y_t = c + \beta t + \alpha y_{t-1} + \Phi_1 \Delta Y_{t-1} + \Phi_2 \Delta Y_{t-2} + \ldots + \Phi_p \Delta Y_{t-p} + e_t \quad \text{(Eq. 11)}$$

where y_{t-1} is lag 1 of time series and Dy_{t-1} refers to difference of the series at time (t-1). The hypothesis of the ADF test is H_0 = *the time series data are not stationary*, and H_1 = *the time series data are stationary.*

Selection of preferential model and diagnostic

In the context of non-stationary flood frequency analyses, a significant challenge arises in selecting the most suitable model when multiple competing models are developed for a single time series of flood data. Consequently, the need for an effective approach to model selection in non-stationary flood estimation methods becomes paramount (Ouarda & El-Adlouni, 2011). In this study, the AIC and the BIC were employed to facilitate the selection of the optimal non-stationary models. The former is defined as a calculated value obtained by summing a constant and the relative difference between the unknown true likelihood function of the data and the likelihood function of the fitted model. Consequently, a lower AIC value signifies that the model is considered to be in closer agreement with the underlying truth. The AIC for a model (Akaike, 1974) is typically expressed in the following manner:

$$\text{AIC} = -2\log(L) + 2p \quad \text{(Eq. 12)}$$

where L is the likelihood function and p is the number of parameters in model. The BIC serves as an approximation of the validity of a prediction based on the posterior probability. A lower BIC value indicates a higher likelihood that a model represents the true underlying structure and is expressed as follows (Schwarz, 1978):

$$\text{BIC} = -2\log(L) + \log(n)\,p \quad \text{(Eq. 13)}$$

where L is the likelihood function, p the number of parameters in the model and n the sample size.

The primary goal of the diagnostic plot is to determine the optimal model based on all plotted data points. The ideal model should exhibit a strong fit with the data station, as this plot's sensitivity relies heavily on the accuracy of the fitted model (Coles, 2001). The accuracy of the non-stationary GEV model is assessed through an investigation involving graphical tests, which include probability plots and quantile plots to be applied to standardized data with restricted fitted parameter values (Coles, 2001). The probability and quantile plots involve a comparison between the empirical distribution function and the predicted values are generated by the fitted distribution function model. In the event that the fitted model aligns well with the observed data, the lines within the probability plot should closely follow the unit diagonal line. This diagonal line signifies a theoretical one-to-one relationship (Serago & Vogel, 2018), with a large distance indicating model failure (Coles, 2001).

Results

Trend and non-stationary detection test

The outcomes of the Mann-Kendall, Spearman's Rho test, and the Augmented Dickey-Fuller (ADF) test for each of the examined streamflow stations are presented in Table 3, which displays the outcomes derived from the MK, SR and ADF tests for the ten

Table 3. The result of trend and non-stationary analysis.

River	MK		SR		ADF	
	Test result	p-value	Test result	p-value	S/NS	p-value
Sayong	-0.1394	0.8891	-0.1750	0.8621	NS	0.4811
Pengeli	-1.7611	0.0782	-1.7154	0.1008	**S**	**0.0385**
Sembrong	0.2855	0.7753	0.4549	0.6516	NS	0.8238
Kahang	-2.0919	**0.0364**	-2.2918	**0.0299**	NS	0.4777
Muar	0.1517	0.8794	0.1937	0.8470	**S**	**0.0168**
Segamat	-1.1025	0.2703	-1.1293	0.2642	**S**	**0.0498**
Parit Madirono	-1.5323	0.1254	-1.6344	0.1244	NS	0.9871
Johor	0.0880	0.9298	0.1357	0.8927	**S**	**0.0427**
Linggui	1.0887	0.2763	0.9452	0.3618	NS	0.4435
Lenggor	-2.1119	**0.0347**	-2.1964	**0.0330**	NS	0.4914

MK, Mann-Kendall test; SR, Spearman's Rhotest; ADF, augmented Dickey-Fuller test; S, stationary outcome; NS, non-stationary outcome; bold test for p-value, statistical significance.

stream-flow stations within Johor. Merely two out of the ten stations, namely Kahang and Lenggor, exhibited a noteworthy negative trend (p = 0.05) within their stream-flow data according to the MK and SR tests. In the case of the ADF test, it became evident that six out of the ten stations, namely Sayong, Sembrong, Kahang, Parit Madirono, Linggui, and Lenggor, were deemed non-stationary. It is noteworthy that the stations identified with significant trends also demonstrated non-stationary characteristics. The presence of a discernible trend direction within the data series points towards non-stationary behaviour in the respective stream-flow data stations (López & Francés, 2013). Subsequent analyses (trend and non-stationary detection tests) will exclusively focus on data that exhibits trends and non-stationary behaviour underscoring the significance of non-stationary models.

Model selection

The objective of non-stationary flood frequency analysis is to enhance the precision of flood prediction. Consequently, the process involves selecting the most appropriate candidate models. In this study, model efficiency is gauged by comparing the AIC and BIC test values among all non-stationary models. The outcomes of the AIC and BIC tests for river stations displaying non-stationary behaviour (*i.e.* the NSGEV1, NSGEV2, and NSGEV3 models) are outlined in Table 4. The selection of the optimal model hinges on the attainment of the lowest AIC and BIC values. To identify the robust model for each station, the AIC and BIC test results for every model were systematically compared. The model exhibiting the smallest AIC and BIC values was considered the most efficient as demonstrated in Table 4.

The Sayong station, the NSGEV2 model stands out with the lowest AIC and BIC values in comparison to other models. Consequently, the NSGEV2 model emerges as the robust fitted model based on the test outcomes. A similar assessment is conducted for other stations, leading to the identification of preferred models. It is pertinent to note that the smaller AIC and BIC test values observed for all models at the Parit Madirono station can be attributed to the relatively diminutive stream-flow data series. The favoured model for each station is listed in Table 5 facilitating a logical presentation of the results.

Table 5 shows that the most optimal fitting model for each of the preceding stream-flow stations, selected through the criterion of the lowest AIC and BIC values. Additionally, it is noteworthy that both the Kahang and Lenggor stations exhibit robust trends, substantiated by significant results in the trend test at the 1% significance level. It is pertinent to acknowledge that these two stations manifest their trends with distinct models, specifically NSGEV1 and NSGEV3, respectively. The findings show that the trend in the model, characterized by the location parameter's dependency on time, elucidates a portion of the data's variance. Consequently, the deviations around these trend-based models are diminished compared to those around the stationary model (Šraj *et al.*, 2016). The differences in the results are due to the tendency of the BIC test in selecting the more complex models than the AIC test (Panagoulia *et al.*, 2014). However, four stationary stations, *i.e.* Pengeli, Muar, Segamat and Johor, preferred the SGEV model as their optimal model due to non-detected, non-stationary behaviour in the observed data.

The estimated flood discharge can be predicted for each station based on the selected model as presented in Table 6. This refers to the flood magnitude for T = 20, 50 and 100 years. From the table, Sungai Parit Madirono exhibited the smallest, estimated river flows for return periods of 20, 50 and 100 years, with values of 1.393, 2.003 and 2.545 m³/s, respectively. These flow estimates are indicative of the river's hydrological characteristics and its vulnerability to flooding. It is important to note that smaller catchment areas naturally deliver less water into the river during rainfall events, which can affect the river's response to precipitation and the potential for flooding and reduced risk of infectious disease transmission. However, Sungai Segamat exhibits significantly larger estimated flood discharges for the given return periods, with values of 752.041, 1205.395 and 1511.016 m³/s, indicating a high-

Table 4. Results for model likelihood tests for stream-flow stations in Johor.

Station name	Dataset size	Test	GEV0	GEV1	GEV2	GEV3
Sayong	45	AIC	368.426	364.597	**360.761**	365.801
		BIC	372.915	370.583	**368.243**	373.284
Pengeli	33	AIC	**274.436**	275.482	274.502	274.966
		BIC	**278.723**	280.665	280.981	281.445
Sembrong	39	AIC	286.549	288.453	290.424	**279.167**
		BIC	290.851	294.189	297.594	**286.337**
Kahang	49	AIC	423.353	420.315	421.100	**419.367**
		BIC	427.750	**426.178**	428.429	426.696
Muar	50	AIC	**612.373**	612.717	612.900	613.364
		BIC	**618.109**	620.365	622.460	622.924
Segamat	50	AIC	**647.071**	648.819	649.959	650.726
		BIC	**652.807**	656.467	659.519	660.287
Parit Madirono	16	AIC	27.127	27.424	28.878	**-25.464**
		BIC	29.445	30.515	32.741	**-21.601**
Johor	45	AIC	**562.291**	567.025	567.923	563.147
		BIC	**570.711**	574.252	576.956	572.180
Linggui	15	AIC	149.552	144.995	**72.949**	120.579
		BIC	151.676	147.827	**76.490**	124.119
Lenggor	49	AIC	579.166	572.270	573.892	**570.025**
		BIC	584.841	579.837	583.351	**579.484**

Models with the lowest AIC and BIC values (in bold text) were considered the most efficient.

er risk of flooding. While these values are associated with the river's hydrology, it's essential to note that factors beyond catchment area size, such as topography, land use and rainfall patterns also play a significant role in determining the risk of flooding in the area.

A graphical assessment is presented to validate the performance of the fitted models for each station. This evaluation focuses on two stations that exhibited significant trends namely, *i.e.* the Kahang and Lenggor stations as illustrated in Figures 3 and 4. The intent was to observe how well the data aligns with the diagonal line on the probability and quantile plots, indicative of a favourable fit of the GEV model to the stream-flow station.

In Figure 3a, representing the Kahang station with the SGEV model, the data points spread along a linear line, albeit with some deviations from the diagonal on the probability and quantile plots. On the other hand, Figures 3b, d depict the points of the non-stationary models (NSGEV1, NSGEV2, and NSGEV3), demonstrating satisfactory scattering along the diagonal line. This provided substantial confidence in the validity of the fitted models, particularly the NSGEV model. Figure 4 corroborates these findings, displaying data points that closely adhere to the linear line on both the probability and quantile plots across all models. Hence, the accuracy of the GEV fitted model is well-established, particularly evident in the case of the NSGEV3 model as exemplified by the fitted model of the Lenggor station.

Discussion

In Malaysia, heavy floods predominantly occur during the monsoon season. In early 2023, the Drainage and Irrigation Department (DID) reported that 15 rivers in Johor, three in Pahang, two in Negeri Sembilan, and one each in Selangor, Melaka, and Sarawak had exceeded danger levels (Haizan & Mamat, 2023). These floods result in the release of garbage and other waste materials from surrounding areas, the dispersion of which poses a significant risk of spreading various infectious diseases. Therefore, accurately assessing flood magnitudes and prediction of flood events, including the frequency of recurrences, have become of paramount importance.

Table 5. Best model for stream-flow stations in Johor.

Station	Trend test	ADF test	Best model AIC	Best model BIC
Sayong		NS	NSGEV2	NSGEV2
Pengeli		S	SGEV	SGEV
Sembrong		NS	NSGEV3	NSGEV3
Kahang	*	NS	NSGEV3	NSGEV1
Muar		S	SGEV	SGEV
Segamat		S	SGEV	SGEV
Parit Madirono		NS	NSGEV3	NSGEV3
Johor		S	SGEV	SGEV
Linggui		NS	NSGEV2	NSGEV2
Lenggor	*	NS	NSGEV3	NSGEV3

ADF, augmented Dickey-Fuller test; AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; SGEV, generalized stationary extreme value model; NSGEV, generalized non-stationary extreme value model; *significant trend at the 1% significance level.

Streamflow modelling

The goal of the non-stationary FFA was to establish a fitting model capable of comprehending the non-stationary behaviour evident in the annual maximum flow data. The initial step involved assessing the trend and non-stationary behaviours present within the data series. To accomplish this, trend detection tests were applied, specifically the MK and SR tests, both of which can identify monotonic trends within the data. These non-parametric trend detection tests offer advantages such as calculation independence from distribution assumptions and resilience against missing data (Hipel & McLeod, 2005). In contrast, the non-stationarity test serves to detect alterations in the mean values and variances of data

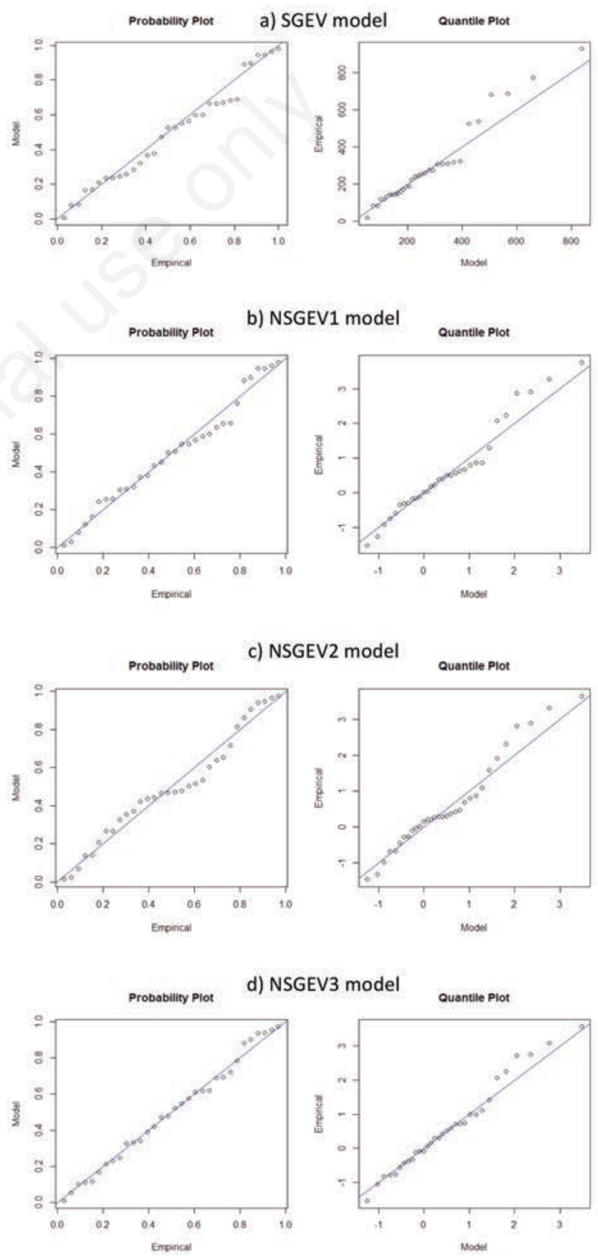

Figure 3. Fit diagnostics for different models applied to the Kahang station.

series over time, and their use in time series analysis aids in validating certain models. For optimal model selection, the BIC test tends to favour less complex models compared to the AIC test (Panagoulia *et al.*, 2014). As observed by Gado and Nguyen (2016b), the model chosen by the BIC test is better suited for estimating flood quantiles within the historical record. This is because the primary objective of the BIC test is to identify the most fitting model for the data series (Gado & Nguyen, 2016b).

In light of the above criteria, the appropriate non-stationary GEV model was selected for each station based on the AIC and BIC tests. Notably, the NSGEV2 model, featuring linear functions of time for location and scale parameters while maintaining a constant shape parameter, emerged as the most suitable model for Sayong and Linggui stations. Conversely, the NSGEV1 model, with a linear function of time for the location parameter and constant scale and shape parameters, was deemed the best fit for the Kahang station. The NSGEV3 model, characterized by a quadratic function of time for the location parameter, was selected for the Sembrong, Parit Madirono, and Sembrong stations.

The selection of the NSGEV1 and NSGEV3 models as the optimal fits indicated that transfer functions represented in the location parameter are more appropriate, considering the linear or quadratic function of time indicated by the trend test. The selected models for each non-stationary station were then employed to estimate parameters and predict flood quantiles for specific return periods. The results underscore the importance of accounting for changes over time in flood frequency analysis, as assuming flood quantiles as stationary data yields high uncertainties in estimation. This case study sheds light on the necessity of considering non-stationarity in hydrology management planning, reducing human vulnerability and the risk of infectious diseases exposed to flood-related hazards.

This evaluation, involving rigorous criteria concerning data, distribution models and methods employed, showed a notable relationship between the MK and SR tests for the Kahang and Lenggor rivers highlighting strong evidence of decreasing trends in stream-flow for both stations as indicated by negative values. Notably, six river stations – Sayong, Sembrong, Kahang, Parit Madirono, Linggui and Lenggor – displayed signs of non-stationary behaviour with regard to stream-flow. Non-stationary behaviour, implying the breakdown of independence, emerges in hydro-meteorological data due to disturbances in river basins, often induced by climate change (Milly *et al.*, 2008; Vasiliades *et al.*, 2015; Xiong *et al.*, 2015).

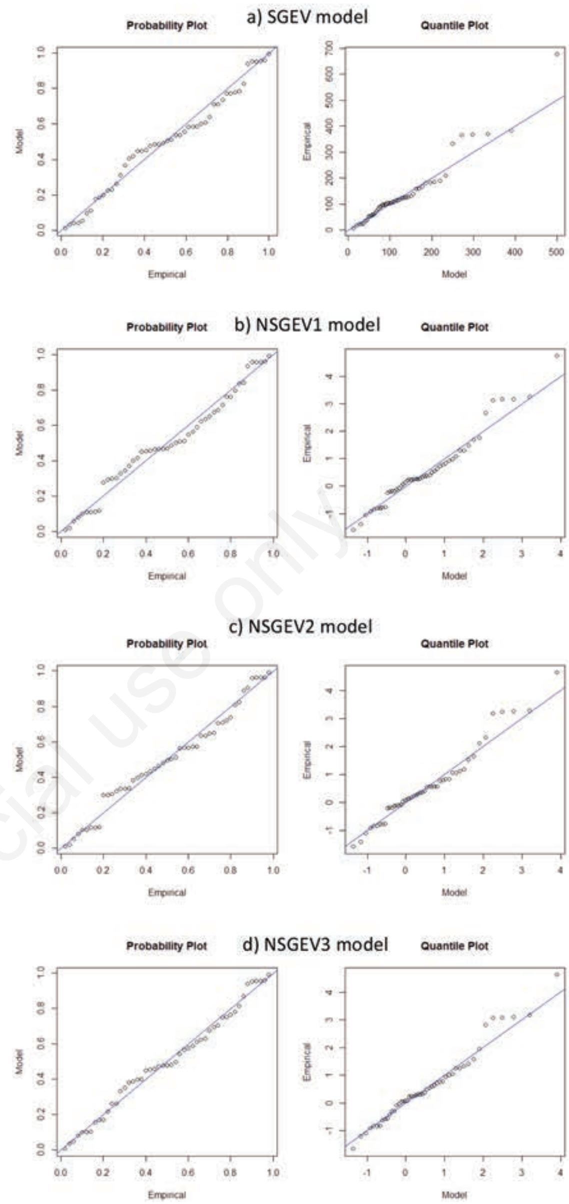

Figure 4. Fit diagnostics for different models applied to the Lenggor station.

Table 6. Quantile estimates of the best model for each station.

Station	Danger level (m)	Catchment area (km^2)	Best model	Estimated flood discharge (m^3/s)		
				20	50	100
Sayong	11.5	624	NSGEV2	197.285	380.112	553.341
Pengeli	24.0	143	SGEV	152.379	293.002	483.807
Sembrong	3.7	130	NSGEV3	66.003	75.831	81.439
Kahang	14.5	587	NSGEV1	510.944	712.602	865.329
Muar	9.1	3,130	SGEV	445.193	550.865	635.994
Segamat	7.2	658	SGEV	752.041	1205.395	1511.016
Parit Madirono	3.0	2	NSGEV3	1.393	2.003	2.545
Johor	9.8	1,130	SGEV	528.787	678.115	779.807
Linggui	24.0	209	NSGEV2	120.632	214.958	291.586
Lenggor	37.0	207	NSGEV3	222.054	365.741	497.644

Risk of infectious diseases

Floods elevate the potential risk of post-flood epidemics (Ding *et al.*, 2019) as they lead to dispersal of waste, debris, and food, which can contribute to the proliferation of rodent populations. Animal displacement is a common occurrence during flood events. Displaced domesticated animals, including rats, pigs, cattle and reptiles, frequently contaminate floodwaters and flood victims rescued from flooding may come into direct or indirect contact with contaminated water, which increases the risk of human infection. Effective flood control plays a crucial role in addressing the transmission of infectious diseases stemming from flood events. Health authorities' preparedness plans are imperative in mitigating flood-related risks and bolstering infection prevention and control preparedness plans (Apisarnthanarak *et al.*, 2013). Okaka and Odhiambo (2018) emphasize that the most effective way to address health risks caused by flooding is through planned adaptation strategies. These strategies involve constructing dams and related infrastructure to prevent riverbanks from overflowing and safeguarding sanitation facilities, ultimately reducing the risk of infectious disease outbreaks.

The issue of flooding and release of wastewater and effluents from reservoirs has drawn significant scholarly attention with respect to the substantial risk of spreading infectious diseases. The disease risk during and after floods include various afflictions, such as acute respiratory infections, conjunctivitis, leptospirosis, diarrhoea, dysentery, hepatitis A, cholera, typhoid fever, food poisoning, dengue, skin infections, measles, and hand, foot, and mouth disease (HFMD), as well as malaria and chickenpox (Flood Management Guidelines, 2008). The WHO (2023) has recently provided an update on the dengue situation in the Western Pacific, stating that Malaysia had 2,248 dengue cases in epidemiological week 33 of 2023, which was a decrease from the 2,487 cases reported in the preceding week. The cumulative total of dengue cases reported thus far stands at 75,928 cases, marking a substantial 115% rise when contrasted with the 35,330 cases recorded during the corresponding period in 2022. Additional analyses are required to better understand the link between flood risk patterns and the spread of infectious diseases in Malaysia, which will be the goal of a follow-up study.

Conclusions

The application of the TL-moments method for non-stationary modelling using the developed models is well-founded. The incorporation of non-stationary models in flood frequency analysis holds potential for predicting flood events. Given the critical nature of comprehensive responses to extreme climate events, this work contributes to flood risk management in reducing the risk of infectious diseases. Consequently, the implementation of effective plans devised by health authorities can play a pivotal role in managing and preventing the spread of infectious diseases during flood disasters. However, this research solely examined a non-stationary model with time as covariates. Further investigations are required to identify the most suitable model, considering non-stationary scenarios like incorporating climate indices or temperature as covariates using various estimation methods.

While existing literature comprehensively explores the historical link between floods and infectious diseases, the multifaceted nature of this issue necessitates future research directions. These include studying climate changes influence on disease dynamics, tracking long-term disease trends, evaluating the effectiveness of interventions, and investigating mental health implications among flood victims. In conclusion, these proposed research directions hold promise for advancing knowledge and improving strategies to mitigate the health impact of flooding events.

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