ISSN 2278-3091
Volume 9, No.1.2, 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse0291.22020.pdf
https://doi.org/10.30534/ijatcse/2020/0291.22020

Flood Frequency Analysis of Annual Maximum of High Tides

Firdaus Mohamad Hamzah[1*,2], SitiHawaMohdYusoff[3,4], Mohd Tahir Ismail[5], MohdKhairulAmri Kamarudin[6], Norazman Arbin[7]

[1]Department of Engineering Education, Faculty of Engineering and Built Environment, UniversitiKebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.fir@ukm.edu.my
[2]Institute of Climate Change, UniversitiKebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.
[3]Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 Bangi Selangor Malaysia. hawa.yusoff@unisel.edu.my
[4]Department of Science and Biotechnology, Faculty of Engineering and Life Sciences, Universiti Selangor, 45600 Bestari Jaya, Selangor, Malaysia
[5]School of Mathematical Sciences, Universiti Sains Malaysia 11800 Minden, Pulau Pinang, Malaysia. m.tahir@usm.my
[6]Faculty of Applied Social Science (FSSG) and East Coast Environmental Research Institute (ESERI), Universiti Sultan Zainal Abidin, Gong Badak Campus, 21300 Terengganu, Malaysia. mkhairulamri@unisza.edu.my
[7]Department of Mathematics Faculty of Science and Mathematics UniversitiPendidikan Sultan Idris, 35900 Tanjung Malim, Perak Malaysia. norazman@fsmt.upsi.edu.my

ABSTRACT

Decision Support Systems have recently become popular in making decisions related to hydrological problems. In the annual cycle of hydrological data, the time series often exhibits spikes that rise far above the typical values in the time series. To capture this behaviour, the proposed decision support system which defined the class of distributions before a model selection toward the heavy-tailed distributions was used to represent the extreme sea level data. The objective of this study is to estimate the return period of maximum sea level at a particular location, since it is important for the planning, design, and management of coastal areas. The L-moment method is used to estimate the parameters for four probability distribution functions, namely Generalized Extreme Value (GEV), Generalized Pareto Distribution (GPA), Generalized Logistic Distribution (GLO), and Generalized Normal Distribution (GNO). The Kolmogorov-Smirnov (KS), is utilised to establish the adequacy of fitness of these probability distributions to the recorded data. The results of the KS test show that GEV is the most appropriate distribution for Port Klang station. Finally, the return value and return period was generated using the selected probability distribution function.
Keywords: Extreme value analysis, Kolmogorov-Smirnov test, Probability distribution, Return period, Sea Level.

1. INTRODUCTION

Flood is a natural disaster that frequently poses high physical risks and cause economic loss. Coastal cities located in low-lying [1], [2] areas are vulnerable to flood disasters. These cities are susceptible to coastal flooding as a result of sea level rise, storm surges and heavy rainfalls. [3–5]. Retreating mountain glaciers and ice caps, thermal expansion of ocean water, and the shrinking mass of the Greenland and Antarctic ice sheets are the main causes of sea level rise linked to climate change [6–8] pointed out that the rise in sea level is also brought about by the changes in terrestrial storage. Furthermore, [9] reported that the rate of global mean sea level rises from [1.5 to 1.9] mm/year between 1901 and 2010. The rate of sea level rise for the period between 1993 and 2010 is higher at [2.8 to 3.6] mm/year.

Estimation of maximum sea level data for a specific return period has been receiving increasing attention in recent years. Much statistical research has been carried out to estimate the statistics of extreme weather for related variables, such as precipitation [10], wind speed [11] and river discharge [12]. Extreme value analysis of near shore water level and their probability of exceedance are the principal parameters for coastal areas. [13] investigated extreme sea level by fitting a generalized extreme value (GEV) distribution to the data for sea level rise at Walcott, which is located on the east coast of the UK. [14] examined the extreme value of generalized Pareto distribution for the North Sea. A similar study by [15] has established that GEV distribution is able to generate reliable extreme sea level parameters for 655 locations around the world.

Malaysia has a long shoreline and most of the major cities are located near the coast. Two main factors have contributed to the rapid growth of coastal cities, namely fast-growing economy and high population density [16]. The demand for prime land has resulted in the construction of a large number of buildings on reclaimed lands. The wide shallow waters along the coastline have become prime candidate for reclamation [17]. Many of the larger cities with dense population and mega-urban region are located in coastal areas, for instance Kuala Lumpur, Putrajaya, and Penang [18]. Malaysia is strongly affected by the wet season during the

South-West (May–September) and North-East (November-March) monsoon. Convectional rainfall is a common occurrence during the inter-monsoon period. Land reclamation and monsoon season has made Malaysia vulnerable to sea level rise and extreme climate. Malaysia has experienced many flooding events that are related to high tide phenomena. Coastal areas are flooded during high tide and continuous heavy rainfall. Several areas in Selangor, such as Klang, Kuala Langat, Sepang, Kuala Selangor, and SabakBernam, are particularly vulnerable to high tide phenomenon. The high tide typically escalates between October and November during the monsoon seasons and inter-monsoon period during which tide could reach up to 5.3m high.

The focus of the present study is maximum sea level during high tides. Flooding events during high tide is a common phenomenon in Malaysia, especially during seasons of heavy rainfall. This paper discussed the L-moment approaches in flood frequency analysis of annual maximum sea level of Port Klang. The concept of this study is to identify the most appropriate probability distribution to the tidal data. There were 4 types probability distributions will be used namely, generalized extreme value (GEV), generalized Pareto distribution (GEV), generalized logistic distribution (GLO), and generalized normal distribution (GNO). After that, the return period of the extreme sea level will be estimated.

2. METHODOLOGY

In order to perform flood frequency analysis, the L-moment method was used by estimating the annual maximum high tide data. Only one maximum value of high tide was taken every year from 2004 until 2017. The process of study can be summarized by using flowchart in Figure 1.

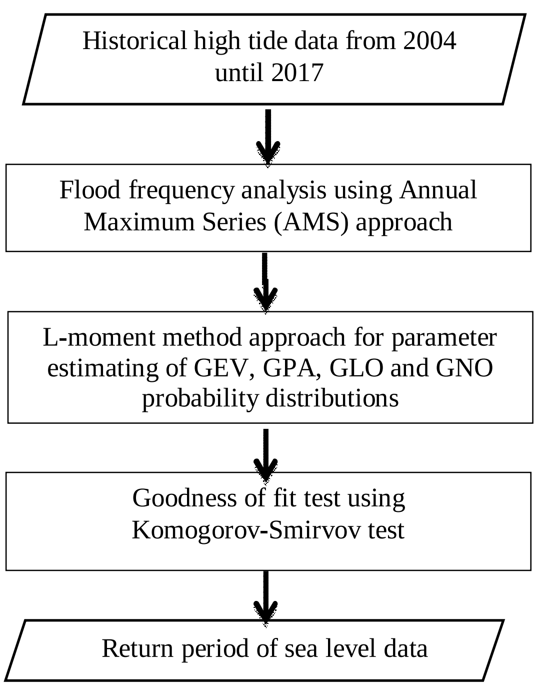

Figure 1: Flowchart of flood frequency analysis by using Annual Maximum Series (AMS) approach

2.1 L-Moment method

The L-moment method was used to estimate the sea level rise frequency analysis of annual maximum sea level data. The data employed is the largest value for each year of interest [19]. This method gives a more stable and realistic estimate of the shape parameter for a small sample size compared to other estimation methods [20–22]. The collection of historical sea level data is confined to certain stations due to loss of record, sensory problems, or disruption in the data collection activity [23]. The L-moment method is used to generate the parameter values for each probability distribution function such as measure of location, dispersion, skewness, kurtosis and shape of distributions. [24] defined the L-moment as linear combination of the probability weighted moments (PWM) of the ordered sample data. The L-moment technique is more accurate for small sample sizes and is more reliable since it is less sensitive to outliers. The equations employed in L-moment are as in [20].

2.2 Probability Density Function

In the annual cycle of high tide data, the time series often exhibits spikes that rise far above the typical values in the series. To capture this behaviour, the heavy-tailed distributions were used to represent the extreme sea level data. This study employs four types of probability distribution, namely, generalized extreme value (GEV), generalized Pareto distribution (GEV), generalized logistic distribution (GLO), and generalized normal distribution (GNO). Table 1 presents the probability density function for each distribution.

Table 1: Probability density function for each probability distribution

No.	Distribution	Probability density function
1.	GEV	$f(x) = \alpha^{-1} exp[-(1-\kappa)y - \exp(-y)]$ where, $y = -\kappa^{-1} log\left[1-\frac{\kappa(x-\xi)}{\alpha}\right]$, $\kappa \neq 0$ where ξ, α and κ are the location, scale and shape parameters, respectively.
2.	GPA	$f(x) = \alpha^{-1}e^{-(1-k)y}$ $y = -\frac{1}{k} log\left\{1-\frac{k}{\alpha}(x-\xi)\right\}, k \neq 0$ where ξ, α and k are the location, scale and shape parameters, respectively.
3.	GLO	$f(x) = \frac{\alpha^{-1}e^{-(1-k)y}}{(1+e^{-y})^2}$ $y = -\frac{1}{k} log\{1-\frac{k}{\alpha}(x-\xi)\}, k \neq 0$ where ξ, α and k are the location, scale and shape parameters, respectively.
4.	GNO	$f(x) = \frac{\kappa}{2\alpha\Gamma(\frac{1}{\kappa})} exp\left\{-\left(\frac{\lvert x-\xi\rvert}{\alpha}\right)^{\kappa}\right\}$ where ξ, α and k are the location, scale and shape parameters, respectively.

2.3 Goodness-of-fit tests

In this study the Kolmogorov-Smirnov (KS) Goodness-of-fit tests can be used to establish whether two samples belong to the same population or whether the probability distribution of a data belongs to a specific theoretical distribution. The goodness-of-fit tests based on empirical density function are used to measure the distance between the empirical and theoretical cumulative density functions [25], tests are used to test the goodness-of-fit. The KS test statistics is expressed as:

$$D = max_x|F(x) - F_n(x)| \qquad (1)$$

If $D \leq D_{1-\alpha}$, where $D_{1-\alpha}$is the critical value at a significant α, then the sample has the same distribution as the tested theoretical distribution. $F(x)$ is the cumulative distribution function of the theoretical distribution and $F(x_n)$ is the empirical distribution function.

2.4 Return period

Return period refers to the average number of trials (typically in years) to the first occurrence of an event with a magnitude greater than a predefined critical event [26]. Return period can be expressed as:

$$T_x = \frac{1}{P_x} \qquad (2)$$

$$F_x = 1 - \frac{1}{T_x} \qquad (3)$$

Where T_x corresponds to years of return period of such a design high sea level and P_x is an exceedance probability, where $P_x = P(X \geq x_T)$ of occurrence of the event $\geq x_T$. While F_x is the cumulative probability distribution function [27].

The return values were calculated using probability parameters. In order to calculate the return period of the sea level data, the inverse cumulative distribution function (quartile function) need to be derived from the probability density function. The following table in Table 2 presents quartile function for each distribution.

Table 2: Quantile function for each distribution.

No.	Distribution	Quantile function
1.	GEV	$x(F) = \xi + \frac{\alpha}{\kappa}\{1 - (-logF)^{\kappa}\}$, $\kappa \neq 0$
2.	GPA	$x(F) = \xi + \frac{\alpha}{k}\{1 - (1 - F)^{k}\},\ k \neq 0$
3.	GLO	$x(F) = \xi + \frac{\alpha}{k}\{1 - \{(1 - F)/F\}^{k}\},\ k \neq 0$
4.	GNO	$x(F)$has no explicit analytical form.

3. RESULT AND DISCUSSION

An attempt has been made to estimate the annual maximum sea level at Port Klang (PelabuhanKlang) tide gauge station by using four distributions. This tide station is located in the States of Selangor along the Straits of Malacca. The data for the station is plotted in Figure 2 and they show the time series plot for high tide at the Port Klang tide station. The series of annual maximum sea level is derived from the daily tide data for the period between 2004 and 2017. The highest daily annual maximum series (AMS) for sea level is 5.7 m at Port Klang.

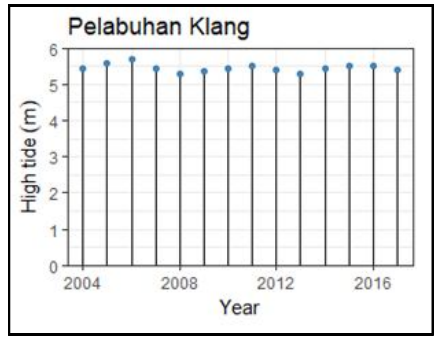

Figure 2: Time series plot of annual maximum sea level for Port Klang.

Table 3: L-moment statistics for maximum sea level at Port Klang tide gauge station.

L-location	L-scale	L-skewness	L-kurtosis	L-CV
5.454	0.061	0.109	0.258	0.011

The summary statistics for annual maximum sea level data is presented in Table 3. It can be seen that the mean for annual maximum sea level for the Port Klang station 5.454 m. Port Klang generally experiences more high tide throughout the 14 years. The standard deviation is low, indicating that the data points are quite close to the mean value. This is supported by the coefficient of variation value, where the values do not exceed 1.3% of the ratio between mean and standard deviation. The positive value of the parameter of skewness indicates that the distributions for Port Klang (0.109) are skewed to the right. The L-kurtosis, which measures the peak of distribution, is 0.258 for Port Klang.

Table 4: Parameter estimation using L-moment method for the four probability distributions for each tide station

Distribution	Parameter
	Port Klang
GEV	ξ =5.407, α = 0.095, κ = 0.098
GPA	ξ = 5.295, α = 0.255, κ = 0.608
GLO	ξ = 5.443, α = 0.059, κ = -0.109
GNO	ξ = 5.442, α = 0.105, κ = -0.223

In the present study, the fitness of the selected distributions (GEV, GPA, GLO, and GNO) was evaluated using goodness-of-fit test (Kolmogorov-Smirnov test). The parameters for the four probability distributions are computed using the L-moment method. The results are presented in Tables 4.

Table 5: Result of Kolmogorov-Smirnov goodness of fit test for high tide at Port Klang.

Distribution	Kolmogorov Smirnov	p-value
GEV	**0.181**	**0.246**
PE3	0.186	0.209
GLO	0.178	0.264
GNO	0.182	0.238

The goodness-of-fit test results can be used to make a better decision regarding the best fit model for Port Klang station. The null hypothesis H_0 for the goodness-of-fit test assumes that the data follow a specific distribution. Hence, if the P-value is greater than 0.05 at a significance level, the H_0 statement can be rejected. Table 5 shows that GEV distribution fits the data for Port Klang well with the Kolmogorov-Smirnov test giving a P-value of 0.246.

Table 6: Estimated return periods based on GEV distribution for Port Klang.

Return period (Year)	Return value (m)
1	5.515
5	5.605
10	5.660
20	5.709
30	5.735
40	5.753
50	5.767
60	5.778
70	5.787
80	5.795
90	5.801
100	5.807

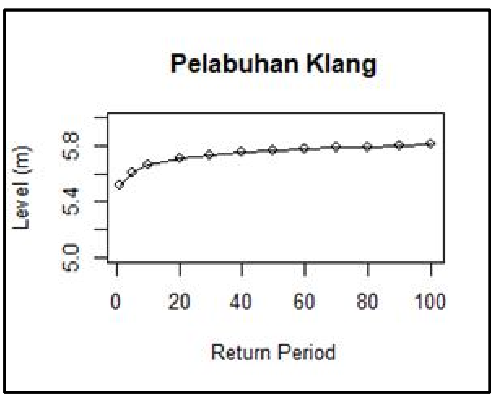

Figure 3: Plot of return period for Port Klang according to GEV distribution for the maximum sea level data.

Table 6 shows the estimated return periods for maximum sea level at Port Klang obtained via GEV distribution. The calculation of return values for each tide stations was carried out using the quantile function given in Table 2. GEV distributionwas used to construct the return period plot for Port Klang(Figure 3).

Port Klang is situated on the west coast of Peninsular Malaysia and about 40 km distance from Kuala Lumpur. It also plays an important role in economic development with a great commercial and industrial hub. Port Klang also become one of the busiest ports in the world and served as major commercial ports which are Northport, Southport, and Westport. [28]. Besides, Port Klang is the area for activities such as fisheries, transportation, navigation, and tourism [29].

From the year 2004 until 2017, Port Klang experienced frequent high sea levels with reading from 5.3 m to 5.7 m. As a result of this data sea level, the return period of 1-year will estimate the return value of 5.52 m, while the return period of 100-year will estimate the return value of 5.81 m. Since the Port Klang frequently experience coastal flooding, the high return value is good enough to give prevention and warning to people around the Port Klang areas. Besides that, coastal infrastructure management, flood risk and also federal flood insurance also depend on the estimation of the flood return period.[30]

Human factors can also contribute to coastal flooding, such as land reclamation, and development infrastructure that does not follow the right specification [18]. While physical factors such as sedimentation, erosion, heavy rainfall, storm surge, and astronomical tides, especially during high spring tide, can cause flooding to become worse [31]. When the number of victims was small and flood losses were minor, governments could deal with flood aid and recovery effectively. But today's flood disasters are more severe, with many more victims and much greater financial losses, and government aid is less effective [32].

A decision support system for flood management can give better output to decision-makers for manages the flooding. Prevention, mitigation, and preparedness for flood disasters should work forward to reduce the risk of life, property, social and economic activities and natural resources from natural hazards. Social support also an important asset as it helps to enhance the preservation or recovery of other valued resources from a disaster [33].

4. CONCLUSION

This paper has presented the return period estimation of annual maximum sea level in order to better understand the high tide phenomenon in Malaysia. The value for high tide was taken from the daily data recorded at the Port Klang (PelabuhanKlang) for the period from 2004 to 2017.

The following conclusions are drawn based on the findings of the study. Four probability distribution functions, GEV, GPA, GLO, and GNO, were used in this study. The parameters for each probability distribution functions were estimated using the L-moment method. The selection of suitable distribution was based on the results of the Kolmogorov-Smirnov (KS) goodness-of-fit test. The results of the KS tests showed that GEV is the most appropriate distribution for Port Klang station. The return period plots for Port Klang station were generated using GEV distribution.

The results obtained from this study show that the 100-year return period on Port Klang is 5.81m, based on annual maximum series high tide data. From the return period, it can help the government to provide decision support system such as flood early warning system to the authorities, and flood preparedness can be improved. Otherwise, the infrastructures, house and building, and the marine ecosystem such as algae, mangrove, and coral reefs also can be destroyed as a result of coastal flooding and consequent from this it can affect the fisheries, tourism industry and also economic development.

5. ACKNOWLEDGMENTS

The authors would like to thank the Earth Observation Centre, UniversitiKebangsaan Malaysia and the Department of Survey and Mapping Malaysia (JUPEM) for providing the data for this research. The authors wish to express their gratitude to the Yayasan Sime Darby (YSD) for supporting this research via research grants ZF-2017-008.

REFERENCES

1. Yong-Hoon Y, Sang OI, Young-Hyang P, Ki-Hyun K. **Climate variabilities of sea level around the Korean Peninsula**. *AdvAtmos Sci*. 21(4):617–26. 2004. https://doi.org/10.1007/BF02915729
2. Sukode S, Volume IJ, Sukode S, Gite PS, Agrawal H. **An Analysis of Flood Forecasting Criteria**. *Int J Adv Trends ComputSci Eng*. 4(1):1–9. 2015.
3. Hallett R, Johnson ML, Sonti NF. **Landscape and Urban Planning Assessing the tree health impacts of salt water flooding in coastal cities : A case study in New York City.** *Landsc Urban Plan*. 177(February 2017):171–7. 2018.https://doi.org/10.1016/j.landurbplan.2018.05.004
4. J.J.Lian, Xu K, Ma C. **Joint impact of rainfall and tidal level on flood risk in a coastal city with a complex river network : a case study of Fuzhou City , China.***Solid Earth. Hydrol Earth Syst Sci*. 17:679–89. 2013. https://doi.org/10.5194/hess-17-679-2013
5. Ng B, Chong EM. **Comparing Performance of Machine Learning Algorithms in a Flood Prediction Model with Real Data Sets.***Int J Adv Trends ComputSci Eng*. 8(3):375–82. 2019.
6. Mengel M, Nauels A, Rogelj J, Schleussner CF. **Committed sea-level rise under the Paris Agreement and the legacy of delayed mitigation action**. *Nat Commun*. 9(1):1–10. 2018. http://dx.doi.org/10.1038/s41467-018-02985-8
7. Khan AA. **Geoscience Frontiers Why would sea-level rise for global warming and polar ice-melt ?***Geosci Front*. 1–15. 2018. https://doi.org/10.1016/j.gsf.2018.01.008
8. Hamzah FM, Irfan MZ, Tajudin H, Toriman E, Abdullah SMS. **Assessment of rainfall trend at the airports using non-parametric statistics approach.** *Int J Adv Trends ComputSci Eng*. 8(1.6 Special Issue):290–5. 2019. https://doi.org/10.30534/ijatcse/2019/4381.62019
9. Church JA a, Clark PUU, Cazenave A, Gregory JMM, Jevrejeva S, Levermann A, et al. **Sea Level Change**. *Clim Chang. PhysSci Basis Contrib Work Gr I to Fifth Assess Rep Intergov Panel Clim Chang*. 1137–216. 2013.
10. Mailhot A, Lachance-Cloutier S, Talbot G, Favre A-C. **Regional estimates of intense rainfall based on the Peak-Over-Threshold (POT) approach**. *J Hydrol*. 476:188–99. 2013.http://linkinghub.elsevier.com/retrieve/pii/S0022169412009365
11. Kleinn J, Hall T. **Tropical cyclone return periods.***In: GIRO Conference, Liverpool*. 2011. https://doi.org/10.1201/b11332-240
12. Rutkowska A, Zelazny M, Kohnova S, Lyp M, Banasik K. **Regional L-Moment-Based Flood Frequency Analysis in the Upper Vistula River Basin , Poland**. *Pure ApplGeophys*. 174(2):701–21. 2016.
13. Chini N, Stansby PK. **Extreme values of coastal wave overtopping accounting for climate change and sea level rise**. *Coast Eng*. 65:27–37. 2012. http://dx.doi.org/10.1016/j.coastaleng.2012.02.009
14. Ross E, Sam S, Randell D, Feld G, Jonathan P. **Estimating surge in extreme North Sea storms.** *Ocean Eng*. 154:430–44.2018. https://doi.org/10.1016/j.oceaneng.2018.01.078
15. Hunter JR, Woodworth PL, Wahl T, Nicholls RJ. **Using global tide gauge data to validate and improve the representation of extreme sea levels in flood impact studies**. *Glob Planet Change*. 156:34–45. 2017. http://dx.doi.org/10.1016/j.gloplacha.2017.06.007
16. Wang W, Zhou W. **Statistical modeling and trend detection of extreme sea level records in the Pearl River Estuary**. *AdvAtmos Sci*. 34(3):383–96. 2017. https://doi.org/10.1007/s00376-016-6041-y
17. Kaparawi AR, Latif ZA. **Overview Of Coastal Reclamation Projects In Malaysia**. *Coast EngDiv Dep Irrig Drain Malaysia*. 1–11. 1996.
18. Yin S, Ghapar A, Kwang Y, Mat AN, Firth LB**. Land reclamation and arti fi cial islands : Walking the tightrope between development and conservation**. *Glob EcolConserv*. 12:80–95. 2017. https://doi.org/10.1016/j.gecco.2017.08.005
19. Vivekanandan N. **Flood frequency analysis using method of moments and L-moments of probability distributions.***Cogent Eng*. 2(1). 2015.http://dx.doi.org/10.1080/23311916.2015.1018704
20. Hosking JRM**. L-moments: analysis and estimation of distributions using linear combinations of order statistics**. Vol. 52, *Journal of the Royal Statistical Society. Series C (Applied Statistics)*. 52. 105–24.1990.
21. Hosking J, Wallis J. **Regional frequency analysis: an approach based on L-moments**. *Cambridge University Press*; 14–43. 1997.

22. Martins S, Stedinger JR. **Generalized maximum-likelihood generalized extreme-value quantile estimators for hydrologic data.***Water Resour Res.* 36(3):737–44. 2000. https://doi.org/10.1029/1999WR900330
23. Zhou CR, Y.F.Chen, .Huang Q, Gu SH. **Higher moments method for generalized Pareto distribution in flood frequency analysis.** *Earth Environ Sci.* 82. 2017.
24. Kim M, Baek S, Ligaray M, Pyo J, Park M, Cho KH**. Comparative studies of different imputation methods for recovering streamflow observation.** *Water (Switzerland).* 7(12):6847–60. 2015. https://doi.org/10.3390/w7126663
25. Esteves LS. **Consequences to flood management of using different probability distributions to estimate extreme rainfall**. *J Environ Manage*. 115:98–105. 2013.http://www.ncbi.nlm.nih.gov/pubmed/23246770
26. Gilroy KL, McCuen RH. **A nonstationary flood frequency analysis method to adjust for future climate change and urbanization**. *J Hydrol.* 414–415:40–8. 2012.http://dx.doi.org/10.1016/j.jhydrol.2011.10.009
27. Salas JD, Jayantha Obeysekera**. Revisiting the concepts of return period and risk for nonstationary hydrologic extreme events.***J HydrolEng ASCE.* 19:554–68. 2014.
28. Anor N, Ahmad Z, Abdullah J, Hafizah RN. **Road Network System in Port Klang, Malaysia and Impacts to Travel Patterns.***Procedia - SocBehav Sci*. 35:629–36. 2012.http://dx.doi.org/10.1016/j.sbspro.2012.02.130
29. Sany SBT, Salleh A, Sulaiman AH, Sasekumar A, Rezayi M, Tehrani GM**. Heavy metal contamination in water and sediment of the Port Klang coastal area, Selangor**, **Malaysia**. *Environ Earth Sci.* 69(6):2013–25. 2013 https://doi.org/10.1007/s12665-012-2038-8.
30. Buchanan MK, Oppenheimer M, Kopp RE. **Amplification of flood frequencies with local sea level rise and emerging flood regimes.** *Environ Res Lett.* 12(6). 2017.
31. Thuy VTT. **Storm Surge Modelling for Vietnam' s Coast**. 2003.
32. Ismail, M.G., Chan, N.W., Zakaria, N.A. and Ghani, A.A. **A review of standard operating procedures (sop) used in flood relief operations during the December 2014 flood in Pahang.***Proseedings Transformasi Sosial 2015. Fakulti Kemanusiaan, Seni & Warisan Universiti Malaysia Sabah*, 18–27. 2015
33. Ngai Weng Chan, Ranjan Roy, Chee Hui Lai &Mou Leong Tan. **Social capital as a vital resource in flood disaster recovery in Malaysia**. *International Journal of Water Resources Development*, 35, 619-637. 2018. https://doi.org/10.1080/07900627.2018.1467312