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Modelling Extreme Temperature in Malaysia Using Generalized Extreme Value Distribution

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***Abstract*—**Extreme temperature of several stations in Malaysia is modelled by fitting the monthly maximum to the Generalized Extreme Value (GEV) distribution. The Mann-Kendall (MK) test suggests a non-stationary model. Two models are considered for stations with trend and the Likelihood Ratio test is used to determine the best-fitting model. Results show that half of the stations favour a model which is linear for the location parameters. The return level is the level of events (maximum temperature) which is expected to be exceeded once, on average, in a given number of years, is obtained.

***Keywords*—**Extreme temperature, extreme value, return level.

I. Introduction

EXTREME weather may cause substantial damage to our lives through events such as droughts, floods and ecological disturbances as they affect human activities and the economy as well. Researchers are interested in developing appropriate statistical methods for extreme events that provide a significant help towards these problems. In the past few years, there have been several studies concerning extreme climatic events such as those by Flocas and Angouridakis [5], Katz et al. [14], Hurairah et al. [13], Gilleland and Katz [8], Siliverstovs et al. [17], Blain [1], and de Vyver [4].

Extreme Value Theory (EVT) is a branch of statistics that deals with asymptotic behaviour of extreme events. Its applications include the area of meteorology (see [6], [7] and [11]), hydrology (see [9]), ecological disturbances (see [14]), and finance (see [10]). The aim of EVT is to characterize rare events and tails of distributions.

The earliest application of EVT was by astronomers in rejecting outlying observation while Fuller in 1914 and Griffith in 1920 on applications and methods of mathematical analysis of EVT in flood flows and phenomenon of rupture and flow in solids, respectively [15].

A. Background

Present climate trends in Southeast Asia have been associated with increasing surface air temperature, attributed to global warming that contributes to changes in global climate patterns. The impact of global warming is felt in many aspects of human lives such as health, food supply, water supply and the environment (e.g. erosion of beaches, loss of habitats and species, and reduced diversity of ecosystems). For example, increasing intensity of forest fires in Southeast Asia is largely attributed to the rise in temperature and the decline in rainfall in combination with increasing intensity of land-use.

Although there has been some works on extreme value modelling of rainfall for Malaysia, none was dealing with extremes of temperature. In this paper, our focus is on extreme temperature in Malaysia. Located near the equator, the average temperature is about 80.6°F and is categorized as being hot and humid all year round. Daytime temperatures rise above 86°F year-round and night time temperatures rarely drop below 68°F. The country has abundant sunshine and solar radiation with an average of about 6 hours of sunshine every day. However, cloud cover cuts off a substantial amount of sunshine and solar radiation.

Malaysia consists of Peninsular Malaysia and East Malaysia. The climate of the Peninsular Malaysia is directly affected by the wind from the mainland, while the East is affected more by the maritime weather. The changes of climate are likely to have a significant effect on Malaysia. During north-eastern monsoon months, there are clear changes in temperature in the east coast of Peninsular Malaysia and in the northern and eastern seas of Sabah. Average monthly temperatures are high in April and May and low in December and January.

As climate variability increases due to global warming, it is expected that more extreme weather events will occur in Malaysia in the future. A report [2] revealed an increasing trend of the temperature in some areas such as Kuching, Kota Kinabalu, Kuantan and Petaling Jaya. Wan Hassan [18] reported that 31 out of 36 meteorological stations in Malaysia recorded highest maximum temperature during the 1990s and after.

B. Objective

Changes in temperature due to global warming affect Malaysia's weather just like it does to the rest of the world. The study on extreme temperatures in Malaysia will provide stakeholders with useful information and understanding about its trend and behaviour. Furthermore, necessary steps can be taken by relevant authorities to prepare the public for the impacts of weather changes due to extreme temperatures.

The objective of this study is to quantify and describe the behaviour of extreme temperature in Malaysia. Specifically,

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our aim is to apply the GEV distribution in modelling monthly maximum temperatures in Malaysia. An analysis of annual extreme temperatures on a sample of stations can be found in [12].

C. Description of Data

The data recorded at twenty-two meteorological stations in Malaysia are obtained from the National Climatic Data Center website which measured in degree Fahrenheit (°F). The data consists of average daily temperatures for the period of January 1981 to October 2012. The average daily temperature data is defined as the total amount of the temperatures collected for a particular day of a 24-hour observation starting from 08.00am on a particular day to 08.00am on the next day over the number of observation on that day. The selected meteorological stations are Bayan Lepas, Bintulu, Butterworth, KLIA, Kota Bharu, Kota Kinabalu, Kuantan, Kuching, Kudat, Labuan, Langkawi, Malacca, Mersing, Miri, Sandakan, SAS, SAAS, Senai, Sibu, Sitiawan, Subang and Tawau of which eight of them are located in East of Malaysia.

II. Research Methodology

The limiting distributions of large (or small) values in a random sample are used to obtain extreme value distributions. Suppose $X_1, X_2, ..., X_n$ are independent random variables with identical probability distribution and let $M_n = max(X_1, X_2, ...X_n)$. The Extremal Types Theorem states that if there exists normalizing constant $\{a_n > 0\}$ and $\{b_n\}$ such that

$$Pr\left(\frac{M_n - b_n}{a_n} \le z\right) = Pr(Z_n \le z) \to G(z) \text{ as } n \to \infty$$

where G is a non-degenerate distribution function, then the distribution of G belongs to either the Gumbel, Fréchet, or Weibull distribution. The combination of these three distribution families into a single-family model forms the GEV distribution [3], with cumulative function

$$G(z; \mu, \sigma, \xi) = \begin{cases} exp\left\{-\left[1+\xi((z-\mu)/\sigma)\right]^{-1/\xi}\right\}, & \text{for } \xi \ne 0,\ 1+\xi(z-\mu)/\sigma > 0, \\ exp\left\{-exp\left[-\frac{z-\mu}{\sigma}\right]\right\}, & \text{for } \xi = 0 \end{cases},$$

$\mu \in \mathbb{R}$, $\sigma > 0$ and $\xi \in \mathbb{R}$ are the location, scale and shape parameters, respectively. For notational convenience, the maximum of a sample $X_1, X_2, ..., X_n$ will be denoted by z and the standardized variable, $\{(z-\mu)/\sigma\}$ in the GEV distribution formed a distribution that does not depend on location μ and scale σ but only depends on shape ξ.

The classical GEV; $G(z; \mu, \sigma, \xi)$ model assumes that the three parameters of location, scale and shape are time-independent [3]. However, if trends are detected in the data sample, the non-stationary case where parameters are no longer constants but expressed as covariates (e.g. time), should be considered.

A. Selection Period and Stationary Test

The data on extreme values are grouped into blocks of equal length *n* and the maximum of each block form a series of block maxima, $M_{n,1}, M_{n,2}, ..., M_{n,m}$ to be fitted with the GEV distribution. A block represents the length of a period and the selection of block size is critical as too small block can lead to a bias and if too large, too few blocks maxima are generated, leading to a large estimation variance [3].

In this study, data of maximum temperature are blocked into monthly lengths. Modelling of GEV distribution needs the assumption of $X_{im}(i = 1, 2, ..., n)$ to have independent random variables with common distribution, F. The violation of the assumption will occur since seasonality will cause temperature data to vary accordingly. Failure to consider non-homogeneity into account, will affect the analysis of the data by producing inaccurate results.

It is essential that the stationarity assumption be fulfilled before the classical GEV can be fitted. The Mann-Kendall Trend Test is a test to determine if the values of a random variable follow a monotonic trend. The null hypothesis states that no trend exists. This test does not conform to any particular distribution and is particularly useful if datasets have missing values [8].

B. Model Choices and Parameter Estimates

The basic principle in selecting the best model is to obtain the simplest model possible that explains as much of the variation in the data as possible [3]. Two models are considered namely a stationary Model 1 (classical GEV), and non-stationary Model 2 (with time as covariates). The models are as follow:

Model 1: μ, σ and ξ are constants,

Model 2: $\mu(t) = \beta_0 + \beta_1(t)$, σ and ξ are constants,

where t refers to units of the selection period (monthly).

Model 1 assumes that the three parameters are time-independent. However, if trends are detected in the data, the non-stationary case where the parameters are no longer constants but time-dependent, will be considered. In this case, time is expressed as a covariate where the location parameter μ is modelled as a linear trend (Model 2). Model 2 is a four-parameter model, with the shape parameter ξ remains constant since it is difficult to estimate with precision and unrealistic to model it as a smooth function of time.

To estimate the parameters, the *L*-moments methods (LMOM) and maximum likelihood estimators (MLE) are used. The LMOM are based on linear combinations of data arranged in ascending order. They are more reliable than the MLE as they are less sensitive to outliers [16] while the advantage of MLE is its adaptability to changes in model structure. However, the LMOM methods can only be applied to estimate stationary parameters in Model 1 while MLE is used to estimate the parameters in Model 2 since it is time-dependent.

C. Likelihood Ratio (LR) Test and Model Diagnostics

The Likelihood Ratio (LR) test is used to compare the fit of two models where the null model, L_0 is a special case of the other (alternative model, L_1). The best model is determined by deriving the probability or *p*-value of the difference in γ, the LR test statistic, defined as: $\gamma = -2\ln\left(\frac{L_0}{L_1}\right)$, where γ has a chi-square distribution with one degree of freedom (since Model 1 has three parameters model, while Model 2 and Model 3 have four parameters).

The null model (Model 1) is preferred if, $\gamma < \chi^2_{1,0.95} = 3.8415$. Otherwise, the alternative model (Model 2) is preferred. The LR test requires nested models, which means that comparison can only be made between one complex model and one simpler model.

Model diagnostics such as probability plots, quantile plots, return level plots and density plots are also looked into. Probability plots and quantile plots contain the same information but on different scales. The best fitted model has points on the probability plot that lie on the unit diagonal but these graphical tests are only used as complements to statistical tests.

However for non-stationary cases (Model 2), some modification is needed due to the lack of homogeneity in the distribution assumptions for each observation [3]. It is only possible to apply to a standardized version of the data, conditional on the fitted parameter values. Thus, the diagnostic plots for Model 2 are applied to residuals (residual probability plot and residual quantile plot-Gumbel scale).

D. Return Level Estimate

The estimation of return level, z_p is the level of events (maximum temperature) which is expected to be exceeded once, on average, in a given number of months. Since the return level is associated with the $1/p$-month return period, it is defined as the level which is expected to be exceeded on average once every $1/p$-months. For more precisely, it is the level exceeded by the monthly maxima in any month with probability, p. Estimation of the return level, z_p is obtained from the stationary models by inverting the cumulative function for GEV distribution:

$$z_p = \begin{cases} \mu - \frac{\sigma}{\xi}\left[1 - y_p^{-\xi}\right], & \text{for } \xi \neq 0 \\ \mu - \sigma \log y_p, & \text{for } \xi = 0 \end{cases}$$

where $G(z_p) = 1 - p$, $y_p = -\log(1-p)$, and $0 < p < 1$. Long return periods, corresponding to small values of p, which are greater interest. In this study, we focus on providing return level estimates for monthly maximum temperatures.

Confidence intervals may be estimated based on the profile likelihood method by finding the intersection between the respective profile likelihood values and the average of the distance between the maximum of the profile log-likelihood and the α quantile of a χ^2_1 distribution.

III. Result and Discussions

In this paper, we have used the average daily temperatures for 32 years covered from 1 January 1981 to 13 October 2012 for twenty-two stations. The monthly block maximum is selected as a selection period to study the extreme temperature in Malaysia by using Generalized Extreme Value distribution.

A. Descriptive Statistics

Table I shows the descriptive statistics for monthly selection period.

TABLE I
DESCRIPTIVE STATISTICS FOR THE MONTHLY PERIODS

Station	*N*	*Min*	*Max*	*SD*
B-Lepas	382	81	87.4	1.24
Bintulu	382	80	91.4	1.41
Butterworth	111	75.5	87.3	1.56
KLIA	76	81.7	86.3	0.94
K-Bharu	382	79.3	88.1	1.65
K-Kinabalu	382	79.6	88.6	1.36
Kuantan	382	77.3	93.0	1.98
Kuching	380	76.6	88.6	1.61
Kudat	124	81.6	91.9	1.43
Labuan	308	81.0	88.9	1.25
Langkawi	112	78.8	90.1	1.37
Malacca	382	80.5	87.6	1.30
Mersing	100	80.6	85.3	1.11
Miri	382	79.4	87.8	1.40
SAAS	78	75.7	91.9	1.83
Sandakan	382	81.3	90.3	1.42
SAS	100	81.0	87.4	1.33
Senai	153	73.4	87.0	1.35
Sibu	382	79.8	91.6	1.65
Sitiawan	382	80.2	87.3	1.25
Subang	382	80.3	89.6	1.69
Tawau	308	79.9	86.2	1.04

N = sample size, SD = standard deviation

Based on Figs. 1 (a) and 1 (b), it shows how the monthly maximum average daily temperatures have varied throughout the considered period for each station. A number of stations such as Bayan Lepas, KLIA, Kota Bharu, Kudat, Malacca and Subang appear to exhibit some kind of non-stationarity.

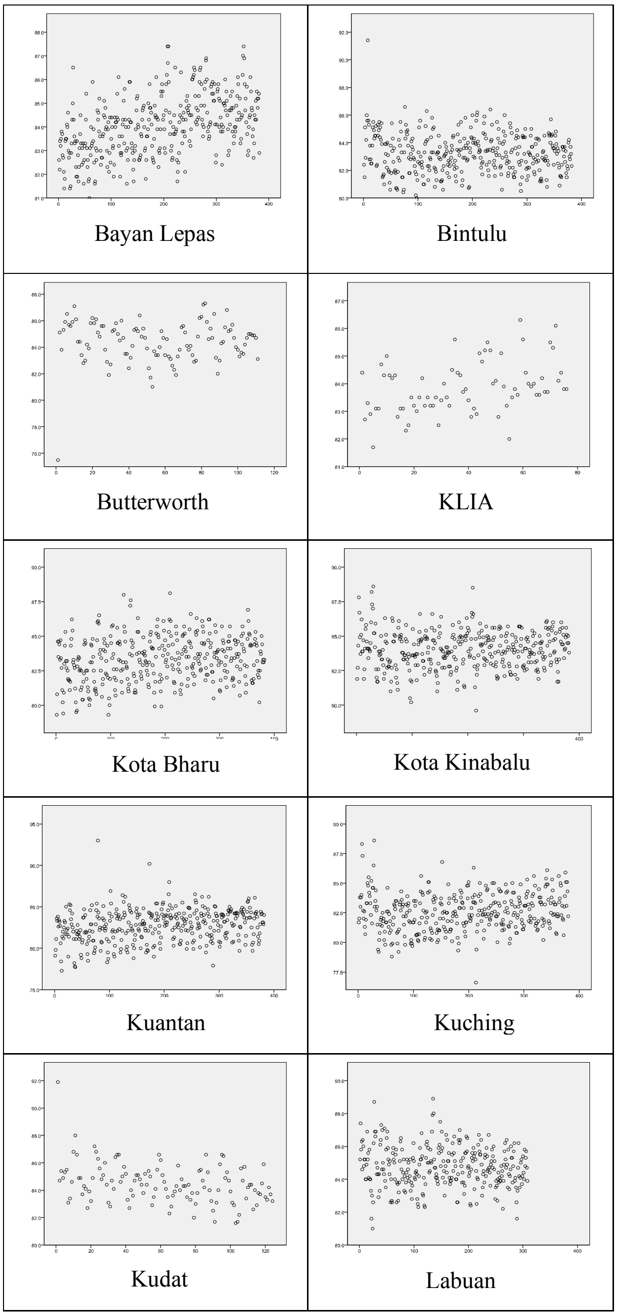
B. Testing for Trend

The Mann-Kendall (MK) trend test is performed to detect the presence of monotonic trend in the data for each station, under the null hypothesis of an absence of trends.

The resulting normalized test statistics and *p*-values for the stations with trend are shown in Table II which led to the fact that half of the stations show the existence of trends. The remaining 11 stations did not have a trend that was statistically significant.

TABLE II
MANN-KENDALL (MK) TREND TEST

Station	*Normalised Test Statistic*	*p-value*	*Trend at 95% Level of Significant*
B-Lepas	9.1701	0.0000	Increasing
KLIA	3.3591	0.0004	Increasing
K-Bharu	3.4101	0.0003	Increasing
Kuantan	4.5873	0.0000	Increasing
Kuching	3.0525	0.0011	Increasing
Malacca	6.8614	0.0000	Increasing
Sitiawan	2.9680	0.0015	Increasing
Subang	12.3904	0.0000	Increasing
Kudat	-3.5914	0.0002	Decreasing
SAAS	-1.8916	0.0293	Decreasing
Tawau	-3.1386	0.0008	Decreasing



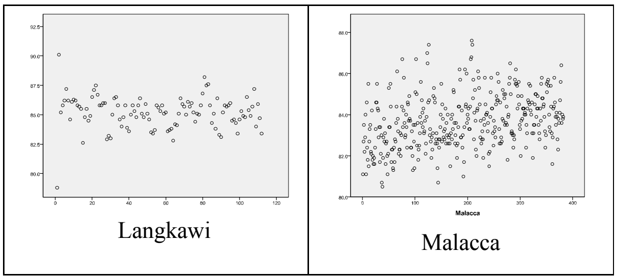


Fig. 1 (a) Monthly Maxima Average Daily Temperature

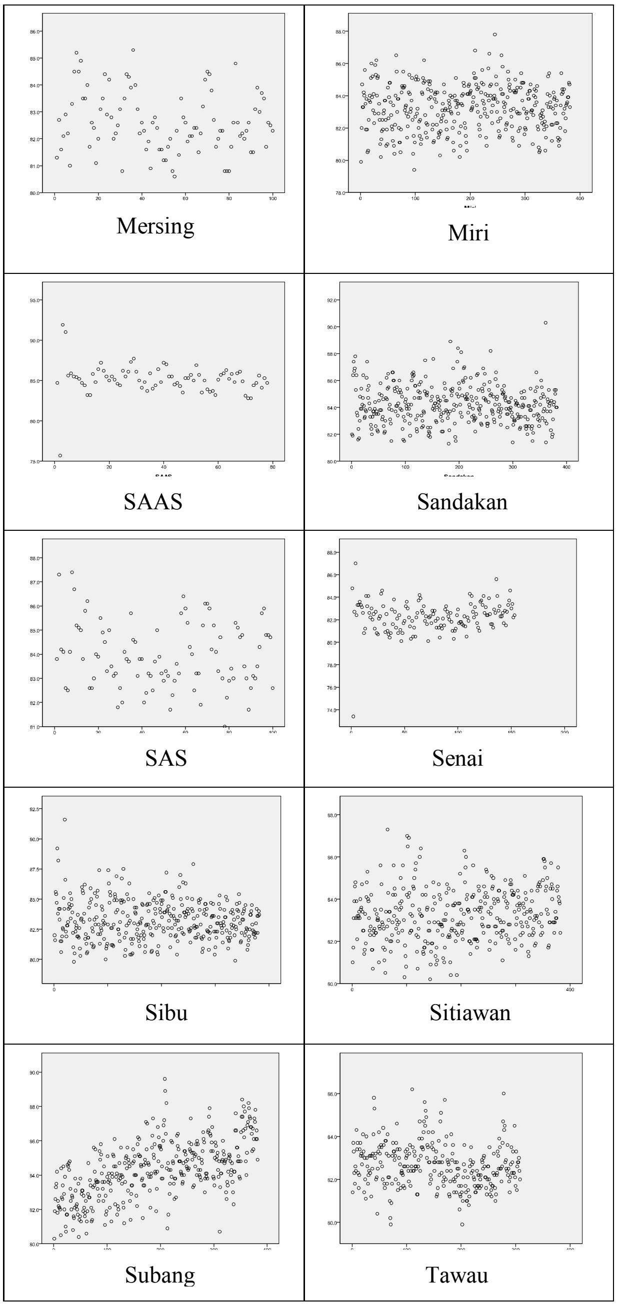


Fig. 1 (b) Monthly Maxima Average Daily Temperature

C. Parameter Estimates

Based on the above result, we ought to model for both stationary and non-stationary of the data set for the stations listed in the Table II. Parameter estimates for Model 1 and Model 2 are shown in Tables III and IV, respectively.

The negative values of ξ, indicates the bounded (or short tailed distribution) of the GEV distribution. The maximized log likelihood under the different models is listed to enable the Likelihood Ratio (LR) test statistic to be computed.

TABLE III
PARAMETER ESTIMATION FOR MODEL 1

Station	*μ (se)*	*σ (se)*	*ξ (se)*	*-log L*
B-Lepas	83.6(0.068)	1.21(0.048)	-0.230(0.033)	622.387
Bintulu	82.6(0.071)	1.29(0.049)	-0.105(0.020)	669.642
Butterworth	84.0(0.171)	1.69(0.118)	-0.487(0.042)	199.887
KLIA	83.5(0.109)	0.86(0.076)	-0.172(0.075)	101.048
K-Bharu	82.7(0.091)	1.63(0.063)	-0.257(0.026)	732.441
K-Kinabalu	83.5(0.074)	1.35(0.050)	-0.220(0.021)	663.560
Kuantan	81.9(0.107)	1.95(0.071)	-0.149(0.014)	813.443
Kuching	82.0(0.086)	1.57(0.058)	-0.194(0.020)	721.744
Kudat	83.9(0.120)	1.23(0.083)	-0.070(0.040)	214.586
Labuan	84.3(0.076)	1.23(0.051)	-0.218(0.026)	507.585
Langkawi	84.7(0.158)	1.50(0.089)	-0.253(0.024)	200.416
Malacca	83.2(0.069)	1.23(0.049)	-0.192(0.032)	639.153
Mersing	82.1(0.113)	0.99(0.081)	-0.141(0.083)	149.148
Miri	82.7(0.077)	1.39(0.052)	-0.241(0.021)	671.881
SAAS	84.3(0.258)	2.09(0.133)	-0.229(0.027)	165.996
Sandakan	83.6 (0.072)	1.27(0.050)	-0.121(0.029)	666.436
SAS	83.4 (0.137)	1.21(0.098)	-0.164(0.075)	168.175
Senai	81.8(0.138)	1.61(0.079)	-0.293(0.018)	275.521
Sibu	82.5(0.081)	1.45(0.057)	-0.093(0.027)	720.729
Sitiawan	82.8(0.067)	1.19(0.046)	-0.197(0.029)	625.395
Subang	83.7(0.092)	1.65(0.064)	-0.236(0.026)	741.014
Tawau	82.2(0.060)	0.96(0.040)	-0.155(0.030)	442.889

TABLE IV
PARAMETER ESTIMATION FOR MODEL 2

Station	β_0 *(se)*	β_1 *(se)*	*σ (se)*	*ξ (se)*	*-log L*
B-Lepas	82.646	0.005	1.05	-0.199	576.298
	(0.110)	(<0.001)	(0.041)	(0.031)	
KLIA	82.910	0.016	0.79	-0.175	95.053
	(0.191)	(0.004)	(0.071)	(0.082)	
K-Bharu	82.110	0.003	1.57	-0.228	724.713
	(0.171)	(0.001)	(0.062)	(0.029)	
Kuantan	81.025	0.005	1.87	-0.130	800.955
	(0.201)	(0.001)	(0.069)	(0.015)	
Kuching	81.523	0.002	1.54	-0.174	717.839
	(0.175)	(0.001)	(0.056)	(0.020)	
Malacca	82.391	0.004	1.11	-0.132	612.531
	(0.118)	(0.001)	(0.044)	(0.033)	
Sitiawan	82.401	0.002	1.16	-0.175	620.457
	(0.131)	(0.001)	(0.045)	(0.029)	
Subang	82.045	0.009	1.32	-0.199	658.551
	(0.139)	(0.001)	(0.049)	(0.019)	
Kudat	84.641	-0.012	1.17	-0.074	207.666
	(0.225)	(0.003)	(0.079)	(0.044)	
SAAS	85.405	-0.023	2.19	-0.305	164.323
	(0.697)	(0.016)	(0.155)	(0.049)	
Tawau	82.453	-0.001	0.96	-0.161	440.538
	(0.117)	(0.001)	(0.040)	(0.028)	

Since the MK trend test shows non-stationarity in the data sets for Bayan Lepas, KLIA, Kota Bharu, Kuantan, Kuching, Malacca, Sitiawan, Subang, Kudat, SAAS and Tawau, it is plausible to investigate if the monthly extremes change linearly across the observation period of the stations. Parameter β_1 in Model 2 corresponds to the monthly rate of change in monthly maximum temperature.

The result for Likelihood Ratio test is shown in Table V. As we compare the results of Model 1 versus Model 2, it can be seen that Model 2 is preferred for those stations except SAAS station.

TABLE V
LIKELIHOOD RATIO TEST

Station	*Test Statistics*	*p -value*
B-Lepas	92.178	0.000
KLIA	11.999	0.001
K-Bharu	15.458	0.001
Kuantan	24.970	0.000
Kuching	7.810	0.005
Malacca	53.245	0.000
Sitiawan	9.875	0.002
Subang	164.926	0.000
Kudat	13.839	0.000
SAAS	3.346	0.067
Tawau	4.7018	0.030

D. Model Diagnostics

Figs. 2 and 3 show the model diagnostics for four stations. Inspection of the probability and quantile plots in Fig. 2 shows points that are scattered along the linear line; thus there is no doubt on the validity of the fitted model. The negative estimates of the ξ cause the return level curve to asymptote to a finite level. The estimated curve for the return level plot is close to being linear since the values of ξ is close to zero.

The residual probability and residual quantile plots (Gumbel scale) are obtained for Model 2 as shown in Fig. 3. Based on all plots, we conclude that all models are well- fitted.

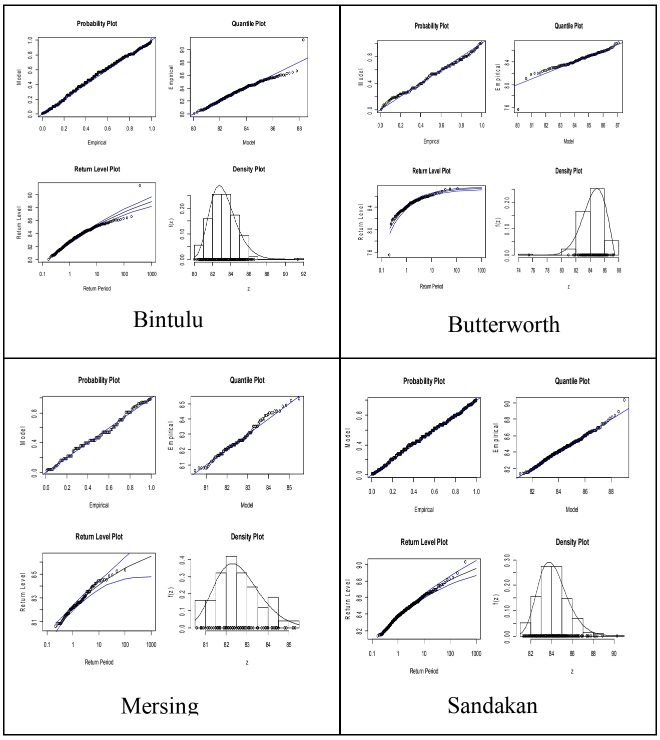


Fig. 2 Model Diagnostics for Model 1

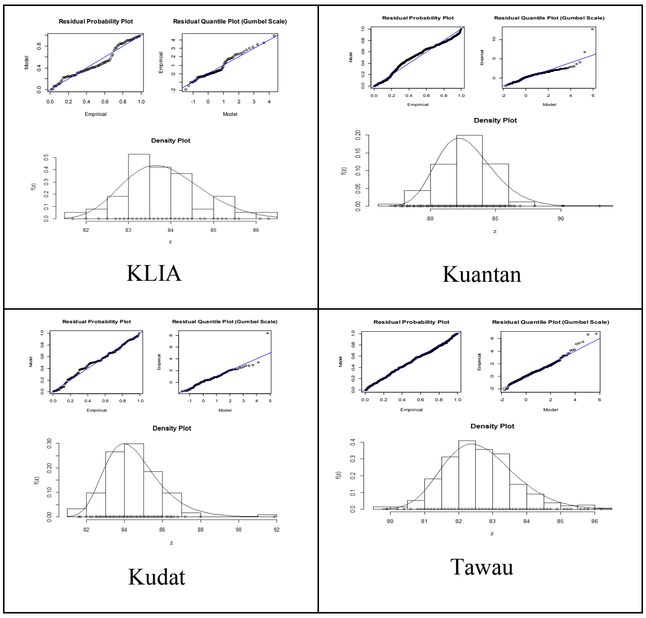


Fig. 3 Model Diagnostics for Model 2

E. Return Level Estimate

Estimated return levels and 95% confidence interval (inside bracket) for every station are shown in Table VI for several return periods. The values of the 95% confidence interval estimated from profile likelihood. For the stations which favour the non-stationary models, the trends are removed and the return levels obtained are then transformed according to the model.

The estimation of the T -month return levels for T = 120, 600 and 900 return periods are estimated as shown in Table VI. From this table, it is revealed that temperature for all stations are increasing over the 900-months except Kudat and Tawau. Based on the 95% confidence intervals, we can expect a maximum temperature event will reappear for Butterworth, KLIA, Mersing and SAS stations within the next 120 months. It is almost certain the monthly maximum will not exceed the current maximum within 900 months for Bintulu, Kudat, Senai and Sibu stations. As for the remaining stations, we expect that the maximum temperature will reappear within 600 months except Kuantan and Miri which will reappear within 900 months.

TABLE VI
RETURN LEVEL ESTIMATES

Station	Return Period, T (Months)		
	120	600	900
B-Lepas	86.49	89.451	91.066
	(86.221,86.914)	(89.073,90.090)	(90.661,91.761)
Bintulu	87.46	88.62	88.88
	(87.066,88.016)	(88.097,89.478)	(88.325,89.826)
Butterwoth	87.13	87.31	87.34
	(86.970,87.432)	(87.165,87.668)	(87.194,87.706)
KLIA	87.38	95.54	100.44
	(86.900,88.447)	(94.859,97.154)	(99.708,102.196
K-Bharu	87.05	89.21	90.25
	(86.720,87.582)	(88.768,89.983)	(89.783,91.088)
K-Kinabalu	87.47	88.11	88.24
	(87.226,87.856)	(87.804,88.642)	(87.916,88.808)
Kuantan	88.21	92.07	93.89
	(87.745,88.841)	(91.500,92.981)	(93.294,94.880)
Kuching	86.78	88.68	89.472
	(86.435,87.279)	(88.234,89.383)	(89.005,90.234)
Kudat	87.91	83.40	80.09
	(87.208,89.309)	(82.402,85.564)	(79.012,82.472)
Labuan	87.93	88.51	88.63
	(87.657,88.345)	(88.178,89.113)	(88.278,89.278)
Langkawi	88.91	89.50	89.61
	(88.548,89.461)	(89.140,90.181)	(89.254,90.319)
Malacca	86.81	89.58	90.97
	(86.414,87.403)	(88.993,90.525)	(90.328,92.008)
Mersing	85.58	86.31	86.47
	(84.923,87.046)	(85.320,88.636)	(85.392,89.024)
Miri	86.62	87.19	87.30
	(86.401,86.966)	(86.940,87.667)	(87.043,87.811)
SAAS	90.37	91.31	91.50
	(89.794,91.579)	(90.617,92.728)	(90.775,92.966)
Sandakan	88.23	89.28	89.51
	(87.804,88.893)	(88.660,90.327)	(88.841,90.668)
SAS	87.42	88.20	88.37
	(86.738,88.947)	(87.221,90.554)	(87.309,90.936)
Senai	85.94	86.45	86.54
	(85.697,86.277)	(86.219,86.839)	(86.316,86.947)
Sibu	88.12	89.51	89.82
	(87.588,88.935)	(88.738,90.836)	(88.990,91.300)
Sitiawan	86.39	88.07	88.82
	(86.077,86.875)	(87.629,88.801)	(88.348,89.619)
Subang	87.18	92.20	95.05
	(86.931,87.570)	(91.899,92.746)	(94.729,95.629)
Tawau	85.47	85.62	85.46
	(85.173,85.914)	(85.213,86.295)	(85.018,86.192)

IV. SUMMARY AND CONCLUSION

In this study, we have modelled the average daily maximum temperatures recorded at twenty-two meteorological stations in Malaysia. The modelling of maximum temperature was applied to the monthly block maxima. The Mann-Kendall (MK) test shows the existence of trend for some stations. We thus model the annual maximum temperatures by applying stationary and non-stationary GEV distribution to the different stations. The parameters are estimated using the LMOM and MLE methods.

The non-stationary model is recommended to describe extreme temperature series for Bayan Lepas, KLIA, Kota Bharu, Kuantan, Kuching, Malacca, Sitiawan, Subang, Kudat and Tawau stations. The return level is obtained to predict the temperature for the long run in the future. In general, the return level is increasing for the next 900-months and the maximum temperature will start to reappear in the different T-month for different stations.

Based on the study, we have shown how extreme value theory serves as a useful analysis tool in describing extreme events. In this paper, we only considered two models and the standard likelihood ratio test was used to compare the models. Further analysis will be carried out to find the best-fitting model which may be based on other model selection methods. We hope our study of extreme temperatures using the GEV distribution can be very useful in understanding extreme temperature events in Malaysia.

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