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TABLE OF CONTENT

PART 1: MATHEMATICS

	Page
STATISTICAL ANALYSIS ON THE EFFECTIVENESS OF SHORT-TERM PROGRAMS DURING COVID-19 PANDEMIC: IN THE CASE OF PROGRAM BIJAK SIFIR 2020 *Nazihah Safie, Syerrina Zakaria, Siti Madhihah Abdul Malik, Nur Baini Ismail, Azwani Alias Ruwaidiah Idris*	**1**
RADIATIVE CASSON FLUID OVER A SLIPPERY VERTICAL RIGA PLATE WITH VISCOUS DISSIPATION AND BUOYANCY EFFECTS *Siti Khuzaimah Soid, Khadijah Abdul Hamid, Ma Nuramalina Nasero, NurNajah Nabila Abdul Aziz*	**10**
GAUSSIAN INTEGER SOLUTIONS OF THE DIOPHANTINE EQUATION $x^4+y^4=z^3$ FOR $x \neq y$ *Shahrina Ismail, Kamel Ariffin Mohd Atan and Diego Sejas Viscarra*	**19**
A SEMI ANALYTICAL ITERATIVE METHOD FOR SOLVING THE EMDEN-FOWLER EQUATIONS *Mat Salim Selamat, Mohd Najir Tokachil, Noor Aqila Burhanddin, Ika Suzieana Murad and Nur Farhana Razali*	**28**
ROTATING FLOW OF A NANOFLUID PAST A NONLINEARLY SHRINKING SURFACE WITH FLUID SUCTION *Siti Nur Alwani Salleh, Norfifah Bachok and Nor Athirah Mohd Zin*	**36**
MODELING THE EFFECTIVENESS OF TEACHING BASIC NUMBERS THROUGH MINI TENNIS TRAINING USING MARKOV CHAIN *Rahela Abdul Rahim, Rahizam Abdul Rahim and Syahrul Ridhwan Morazuk*	**46**
PERFORMANCE OF MORTALITY RATES USING DEEP LEARNING APPROACH *Mohamad Hasif Azim and Saiful Izzuan Hussain*	**53**
UNSTEADY MHD CASSON FLUID FLOW IN A VERTICAL CYLINDER WITH POROSITY AND SLIP VELOCITY EFFECTS *Wan Faezah Wan Azmi, Ahmad Qushairi Mohamad, Lim Yeou Jiann and Sharidan Shafie*	**60**
DISJUNCTIVE PROGRAMMING - TABU SEARCH FOR JOB SHOP SCHEDULING PROBLEM *S. Z. Nordin, K.L. Wong, H.S. Pheng, H. F. S. Saipol and N.A.A. Husain*	**68**
FUZZY AHP AND ITS APPLICATION TO SUSTAINABLE ENERGY PLANNING DECISION PROBLEM *Liana Najib and Lazim Abdullah*	**78**
A CONSISTENCY TEST OF FUZZY ANALYTIC HIERARCHY PROCESS *Liana Najib and Lazim Abdullah*	**89**
FREE CONVECTION FLOW OF BRINKMAN TYPE FLUID THROUGH AN COSINE OSCILLATING PLATE *Siti Noramirah Ibrahim, Ahmad Qushairi Mohamad, Lim Yeou Jiann, Sharidan Shafie and Muhammad Najib Zakaria*	**98**

RADIATION EFFECT ON MHD FERROFLUID FLOW WITH RAMPED WALL TEMPERATURE AND ARBITRARY WALL SHEAR STRESS **106**
Nor Athirah Mohd Zin, Aaiza Gul, Siti Nur Alwani Salleh, Imran Ullah, Sharena Mohamad Isa, Lim Yeou Jiann and Sharidan Shafie

PART 2: STATISTICS

A REVIEW ON INDIVIDUAL RESERVING FOR NON-LIFE INSURANCE **117**
Kelly Chuah Khai Shin and Ang Siew Ling

STATISTICAL LEARNING OF AIR PASSENGER TRAFFIC AT THE MURTALA MUHAMMED INTERNATIONAL AIRPORT, NIGERIA **123**
Christopher Godwin Udomboso and Gabriel Olugbenga Ojo

ANALYSIS ON SMOKING CESSATION RATE AMONG PATIENTS IN HOSPITAL SULTAN ISMAIL, JOHOR **137**
Siti Mariam Norrulashikin, Ruzaini Zulhusni Puslan, Nur Arina Bazilah Kamisan and Siti Rohani Mohd Nor

EFFECT OF PARAMETERS ON THE COST OF MEMORY TYPE CHART **146**
Sakthiseswari Ganasan, You Huay Woon and Zainol Mustafa

EVALUATION OF PREDICTORS FOR THE DEVELOPMENT AND PROGRESSION OF DIABETIC RETINOPATHY AMONG DIABETES MELLITUS TYPE 2 PATIENTS **152**
Syafawati Ab Saad, Maz Jamilah Masnan, Karniza Khalid and Safwati Ibrahim

REGIONAL FREQUENCY ANALYSIS OF EXTREME PRECIPITATION IN PENINSULAR MALAYSIA **160**
Iszuanie Syafidza Che Ilias, Wan Zawiah Wan Zin and Abdul Aziz Jemain

EXPONENTIAL MODEL FOR SIMULATION DATA VIA MULTIPLE IMPUTATION IN THE PRESENT OF PARTLY INTERVAL-CENSORED DATA **173**
Salman Umer and Faiz Elfaki

THE FUTURE OF MALAYSIA'S AGRICULTURE SECTOR BY 2030 **181**
Thanusha Palmira Thangarajah and Suzilah Ismail

MODELLING MALAYSIAN GOLD PRICES USING BOX-JENKINS APPROACH **186**
Isnewati Ab Malek, Dewi Nur Farhani Radin Nor Azam, Dinie Syazwani Badrul Aidi and Nur Syafiqah Sharim

WATER DEMAND PREDICTION USING MACHINE LEARNING: A REVIEW **192**
Norashikin Nasaruddin, Shahida Farhan Zakaria, Afida Ahmad, Ahmad Zia Ul-Saufie and Norazian Mohamaed Noor

DETECTION OF DIFFERENTIAL ITEM FUNCTIONING FOR THE NINE-QUESTIONS DEPRESSION RATING SCALE FOR THAI NORTH DIALECT **201**
Suttipong Kawilapat, Benchlak Maneeton, Narong Maneeton, Sukon Prasitwattanaseree, Thoranin Kongsuk, Suwanna Arunpongpaisal, Jintana Leejongpermpool, Supattra Sukhawaha and Patrinee Traisathit

ACCELERATED FAILURE TIME (AFT) MODEL FOR SIMULATION PARTLY INTERVAL-CENSORED DATA **210**
Ibrahim El Feky and Faiz Elfaki

MODELING OF INFLUENCE FACTORS PERCENTAGE OF GOVERNMENTS' RICE RECIPIENT FAMILIES BASED ON THE BEST FOURIER SERIES ESTIMATOR **217**
Chaerobby Fakhri Fauzaan Purwoko, Ayuning Dwis Cahyasari, Netha Aliffia and M. Fariz Fadillah Mardianto

CLUSTERING OF DISTRICTS AND CITIES IN INDONESIA BASED ON POVERTY INDICATORS USING THE K-MEANS METHOD **225**
Khoirun Niswatin, Christopher Andreas, Putri Fardha Asa OktaviaHans and M. Fariz Fadilah Mardianto

ANALYSIS OF THE EFFECT OF HOAX NEWS DEVELOPMENT IN INDONESIA USING STRUCTURAL EQUATION MODELING-PARTIAL LEAST SQUARE **233**
Christopher Andreas, Sakinah Priandi, Antonio Nikolas Manuel Bonar Simamora and M. Fariz Fadillah Mardianto

A COMPARATIVE STUDY OF MOVING AVERAGE AND ARIMA MODEL IN FORECASTING GOLD PRICE **241**
Arif Luqman Bin Khairil Annuar, Hang See Pheng, Siti Rohani Binti Mohd Nor and Thoo Ai Chin

CONFIDENCE INTERVAL ESTIMATION USING BOOTSTRAPPING METHODS AND MAXIMUM LIKELIHOOD ESTIMATE **249**
Siti Fairus Mokhtar, Zahayu Md Yusof and Hasimah Sapiri

DISTANCE-BASED FEATURE SELECTION FOR LOW-LEVEL DATA FUSION OF SENSOR DATA **256**
M. J. Masnan, N. I. Maha3, A. Y. M. Shakaf, A. Zakaria, N. A. Rahim and N. Subari

BANKRUPTCY MODEL OF UK PUBLIC SALES AND MAINTENANCE MOTOR VEHICLES FIRMS **264**
Asmahani Nayan, Amirah Hazwani Abd Rahim, Siti Shuhada Ishak, Mohd Rijal Ilias and Abd Razak Ahmad

INVESTIGATING THE EFFECT OF DIFFERENT SAMPLING METHODS ON IMBALANCED DATASETS USING BANKRUPTCY PREDICTION MODEL **271**
Amirah Hazwani Abdul Rahim, Nurazlina Abdul Rashid, Abd-Razak Ahmad and Norin Rahayu Shamsuddin

INVESTMENT IN MALAYSIA: FORECASTING STOCK MARKET USING TIME SERIES ANALYSIS **278**
Nuzlinda Abdul Rahman, Chen Yi Kit, Kevin Pang, Fauhatuz Zahroh Shaik Abdullah and Nur Sofiah Izani

PART 3: COMPUTER SCIENCE & INFORMATION TECHNOLOGY

ANALYSIS OF THE PASSENGERS' LOYALTY AND SATISFACTION OF AIRASIA PASSENGERS USING CLASSIFICATION **291**
Ee Jian Pei, Chong Pui Lin and Nabilah Filzah Mohd Radzuan

HARMONY SEARCH HYPER-HEURISTIC WITH DIFFERENT PITCH ADJUSTMENT OPERATOR FOR SCHEDULING PROBLEMS **299**
Khairul Anwar, Mohammed A.Awadallah and Mohammed Azmi Al-Betar

A 1D EYE TISSUE MODEL TO MIMIC RETINAL BLOOD PERFUSION DURING RETINAL IMAGING PHOTOPLETHYSMOGRAPHY (IPPG) ASSESSMENT: A DIFFUSION APPROXIMATION – FINITE ELEMENT METHOD (FEM) APPROACH **307**
Harnani Hassan, Sukreen Hana Herman, Zulfakri Mohamad, Sijung Hu and Vincent M. Dwyer

INFORMATION SECURITY CULTURE: A QUALITATIVE APPROACH ON MANAGEMENT SUPPORT **325**
Qamarul Nazrin Harun, Mohamad Noorman Masrek, Muhamad Ismail Pahmi and Mohamad Mustaqim Junoh

APPLY MACHINE LEARNING TO PREDICT CARDIOVASCULAR RISK IN RURAL CLINICS FROM MEXICO **335**
Misael Zambrano-de la Torre, Maximiliano Guzmán-Fernández, Claudia Sifuentes-Gallardo, Hamurabi Gamboa-Rosales, Huizilopoztli Luna-García, Ernesto Sandoval-García, Ramiro Esquivel-Felix and Héctor Durán-Muñoz

ASSESSING THE RELATIONSHIP BETWEEN STUDENTS' LEARNING STYLES AND MATHEMATICS CRITICAL THINKING ABILITY IN A 'CLUSTER SCHOOL' **343**
Salimah Ahmad, Asyura Abd Nassir, Nor Habibah Tarmuji, Khairul Firhan Yusob and Nor Azizah Yacob

STUDENTS' LEISURE WEEKEND ACTIVITIES DURING MOVEMENT CONTROL ORDER: UiTM PAHANG SHARING EXPERIENCE **351**
Syafiza Saila Samsudin, Noor Izyan Mohamad Adnan, Nik Muhammad Farhan Hakim Nik Badrul Alam, Siti Rosiah Mohamed and Nazihah Ismail

DYNAMICS SIMULATION APPROACH IN MODEL DEVELOPMENT OF UNSOLD NEW RESIDENTIAL HOUSING IN JOHOR **363**
Lok Lee Wen and Hasimah Sapiri

WORD PROBLEM SOLVING SKILLS AS DETERMINANT OF MATHEMATICS PERFORMANCE FOR NON-MATH MAJOR STUDENTS **371**
Shahida Farhan Zakaria, Norashikin Nasaruddin, Mas Aida Abd Rahim, Fazillah Bosli and Kor Liew Kee

ANALYSIS REVIEW ON CHALLENGES AND SOLUTIONS TO COMPUTER PROGRAMMING TEACHING AND LEARNING **378**
Noor Hasnita Abdul Talib and Jasmin Ilyani Ahmad

PART 4: OTHERS

ANALYSIS OF CLAIM RATIO, RISK-BASED CAPITAL AND VALUE-ADDED INTELLECTUAL CAPITAL: A COMPARISON BETWEEN FAMILY AND GENERAL TAKAFUL OPERATORS IN MALAYSIA **387**
Nur Amalina Syafiqa Kamaruddin, Norizarina Ishak, Siti Raihana Hamzah, Nurfadhlina Abdul Halim and Ahmad Fadhly Nurullah Rasade

THE IMPACT OF GEOMAGNETIC STORMS ON THE OCCURRENCES OF EARTHQUAKES FROM 1994 TO 2017 USING THE GENERALIZED LINEAR MIXED MODELS **396**
N. A. Mohamed, N. H. Ismail, N. S. Majid and N. Ahmad

BIBLIOMETRIC ANALYSIS ON BITCOIN 2015-2020 **405**
Nurazlina Abdul Rashid, Fazillah Bosli, Amirah Hazwani Abdul Rahim, Kartini Kasim and Fathiyah Ahmad@Ahmad Jali

GENDER DIFFERENCE IN EATING AND DIETARY HABITS AMONG UNIVERSITY STUDENTS **413**
Fazillah Bosli, Siti Fairus Mokhtar, Noor Hafizah Zainal Aznam, Juaini Jamaludin and Wan Siti Esah Che Hussain

MATHEMATICS ANXIETY: A BIBLIOMETRIX ANALYSIS **420**
Kartini Kasim, Hamidah Muhd Irpan, Noorazilah Ibrahim, Nurazlina Abdul Rashid and Anis Mardiana Ahmad

PREDICTION OF BIOCHEMICAL OXYGEN DEMAND IN MEXICAN SURFACE WATERS USING MACHINE LEARNING **428**
Maximiliano Guzmán-Fernández, Misael Zambrano-de la Torre, Claudia Sifuentes-Gallardo, Oscar Cruz-Dominguez, Carlos Bautista-Capetillo, Juan Badillo-de Loera, Efrén González Ramírez and Héctor Durán-Muñoz

REGIONAL FREQUENCY ANALYSIS OF EXTREME PRECIPITATION IN PENINSULAR MALAYSIA

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Peninsular Malaysia's climate is directly affected by wind from the mainland, being hot and humid throughout the year, it is categorized as equatorial due to its location near to the equator. This study employed the cluster analysis and regional frequency analysis based on L-moments to investigate the areas represented by data obtained from 32 measuring stations and TRMM. The study of the region, which is homogeneous in terms of L-moment ratios, defined the definition of homogeneous regions and identified the regional distribution and the identification of the best distribution based on L-Moment Ratio Diagram (LMRD) and goodness-of-fit criterion. The results show that, for observation data, GLO was the most appropriate probability distribution for Region I, GNO for Region II, GEV for Region III, and GPA for Region IV. Meanwhile, for satellite data, the distribution functions were GPA for Region I, GEV for Region II, GLO for Region III, and the selected distribution for Region IV was GEV. The regional estimation based on Monte Carlo simulation, producing reliable rainfall quantiles were performed and the estimation of the quantiles, GNO, GEV, and GPA distributions gave approximately similar quantile estimates until 50 years return period. Results suggested that the estimation of extreme precipitation at ungauged sites with no flow data has become a real problem for scientists and hydrologists.
***Keywords*:** Ward's method, homogeneous Region, L-moments, regional frequency analysis

1. Introduction

Planning and designing water resources projects and extreme rainfall management depend on the hydrology estimation of extreme events practical application. The design of hydraulic structures as flood protection, storm sewer networks, and engineering in many applications requires the frequency precipitation quantiles knowledge. When there is no local data available at a site of interest or when the data is insufficient for a credible calculation of rainfall quantiles during the critical return period, Regional Frequency Analysis (RFA) is used. The specification of the homogeneous region, the derivation of appropriate probability density functions (or frequency curves) of the observed data, and the building of a regional frequency model are the three key components of the analysis (i.e., a relationship between precipitation of different return periods, precipitation characteristics, and climatic data). The research covers identifying homogenous regions based on site attributes cluster analysis, identifying appropriate regional frequency distributions, and developing a regional frequency model for Peninsular Malaysia. To account for records of short time series at an individual site, a regional method to frequency analysis substitutes space for time by employing estimates from numerous sites in the region. The research covers identifying homogenous regions based on site attributes cluster analysis, identifying appropriate regional frequency distributions, and developing a regional frequency model for Peninsular Malaysia. To account for records of short time series at an individual site, a regional method to frequency analysis substitutes space for time by employing estimates from numerous sites in the region. Dalrymple (1960) proposed the regional frequency analysis to estimate quantiles of the underlying variable at each site in the homogenous region of consideration, "trading space for time" by using data from nearby or similar sites. The quantiles calculated using the regional sample are more precise (J. Hosking & Wallis, 1997).

Regional frequency analysis has become a commonly used hydrological instrument (Adamowski, 2000; Gottschalk & Krasovskaia, 2002; Kjeldsen & Rosbjerg, 2002; Pilon &

Adamowski, 1992). It is also common in climatological studies (Fowler & Kilsby, 2003; Guttman et al., 1993; Naghavi & Yu, 1995; Smithers & Schulze, 2001). As noted above, it uses information from several measurement sites to estimate probability distributions at any given location. Other studies used the marginal distribution of severity and duration of drought by implementing regionalization to site frequency, with few exceptions by Mirakbari et al. (2010); Sadri & Burn (2014); Zhang et al. (2015), which used the L-moments in the regional frequency approach to identify marginal distributions. When data from regions is insufficient, the regional frequency analysis is more successful than the site frequency analysis in examining marginal distributions. It provides information from neighbouring homogenous sites to help the site's data deficiency (J. R. M. Hosking & Wallis, 1997; Jingyi & Hall, 2004). When data from regions is insufficient, the regional frequency analysis is more successful than the site frequency analysis in examining marginal distributions. It provides information from neighbouring homogenous sites to help the site's data deficiency (J. R. M. Hosking & Wallis, 1997; Jingyi & Hall, 2004). Besides, by identifying regions with similar drought behaviors (Goyal & Sharma, 2016), the regional analysis helps describe and comprehend spatial precipitation coverage effectively. East Asia is predicted to be one of the most vulnerable areas under global warming to the potential rise in weather and climate extremes (IPCC 2012). Several studies have recently been done at severe summer climates in East Asia using observations and different climate models (Boo et al., 2006; Griffiths et al., 2005; Ho et al., 2011; Im et al., 2008; Kusunoki & Arakawa, n.d.; Oh et al., 2013; Suh et al., 2012). Ahmad et al. (2017) conducted research on 10 days low flow series on 9 sites of Indus basin with the regional frequency analysis. Meanwhile Kar et al. (2017) investigated the use of L-moments approach for hourly regional rainfall frequency estimation in Jeju Island, Korea. Mortuza et al. used regional frequency analysis in the evaluation of bivariate drought characteristics in Bangladesh in 2018 to assess both past and prospective drought duration and severity. Thus in 2019, Parchure identified homogeneous rainfall regions using a combination of cluster analysis and the L-moments approach for Mumbai City, India. The economic impacts of extreme climatic events including sea-level rise and storm surge risk and the benefits of the adaptation strategies in the Pearl River Delta, a lowing-lying area located in southern China was also conducted using the regional frequency analysis (He et al,2019). These scholars indicated that hot and wet extremes across East Asia have generally increased in magnitude and frequency over recent years. Under global warming, those extremes are expected to increase in the future. The benefits of regional over singular-location estimation are more significant on the distribution tails, which are concerned by many potential implementations, including the preparation of weather-related emergency purposes and the performance and construction of water reservoirs.

The L-moment method is the standard approach for defining such homogeneous regions since it uses an algorithm, which is statistically efficient and straightforward to implement (J. Hosking & Wallis, 1997). This study used the regional frequency analysis method with the L-moment approach to develop regional growth curves and improve estimates on the design values of extreme precipitation events in Peninsular Malaysia. This research study aims to develop a method for estimating the 00-h, 03-h, 06-h, 09-h, 12-h, 15-h, 18-h, and 21h maximum consecutive rainfall series in various regions using a weather model and evaluate the reliability and accuracy of the goodness-of-fit tests for rainfall and their uncertainty analysis. This information perceived from the study may provide beneficial probability distribution upshots for extreme rainfall events.

2. Data and Study Area

The study area considered was West Malaysia, also known as Peninsular Malaysia, which incorporates 131794 km2. Malaysia is a country near the equator; thus, it experiences hot and humid weather with daily temperature ranges from 25.5°C to 35°C. It is in the northern latitude between 1° and 6°N and the eastern longitude from 100° to 103° E. The three-hourly precipitation totals measured at 32 stations operated by the Department of Irrigation and Drainage Malaysia and satellite data from the Tropical Rainfall Measuring Mission (TRMM) were used (Table 1). The data set was the observations spanned the period from 1998 to 2014; there were no missing values in the dataset. Samples of three hourly maximum annual precipitation amounts were drawn from each station's records and examined as extreme precipitation events. Table 1 provides the basic information of each station, such as station name, station abbreviation, state, position based on latitude, longitude, altitude, and the mean annual precipitation.

3. Methods

3.1 Ward's Clustering Process

Cluster analysis is a fundamental multivariate statistical analysis method to divide a data set into groups and efficiently used for regional frequency analysis to form regions. Cluster analysis is often referred to as classification analysis or numerical taxonomy. In cluster analysis, no prior group or cluster membership knowledge exists for any of the objects. Cluster analysis requires problem formulation, distance calculation selection, clustering method selection, number of clusters determination, profile cluster understanding, and lastly, validity evaluation of clustering. Clustering processes can be hierarchical, non-hierarchical, or a two-step method in cluster analysis. In cluster analysis, the creation of a tree-like structure characterizes a hierarchical technique.

A hierarchical clustering method minimizing the Euclidean distance in site characteristics space within each cluster is Ward's method for determining homogeneous regions in regional frequency analysis (Rostami, 2013). This method is often known as the "low variance form" of Ward's hierarchical cluster system. This method is distinct from other approaches since it uses a variance approach methodology to measure the differences between clusters. Ward's clustering method is very efficient for clusters as membership is evaluated by calculating the total sum of squared deviations from a cluster mean. The fusion requirement is that the error sum of squares should be increased to the smallest possible. In this study, the site characteristics used were latitude, longitude, elevation, and mean annual precipitation. All the data were transformed to get the rescaled data range from 0 to 1 before applying the hierarchical method of clustering Ward. The Euclidean distance or scale of the variables used in the study is very sensitive to most clustering algorithms (J. Hosking & Wallis, 1997). Therefore, to ensure that the ranges are comparable, the variables with large absolute values are normalized. The variables are rescaled such that their values would lie between 0 and 1 to prevent site-characteristics dominance (Malekinezhad & Zare-Garizi, 2014):

$$X_{ij}^{N} = \frac{X_{ij} - X_{i,min}}{X_{i,max} - X_{i,min}} \tag{1}$$

where X_{ij} is the i^{th} attribute of j^{th} station, $X_{i,min}$ is the minimum i^{th} attribute in all stations, $X_{i,max}$ is the maximum i^{th} attribute in all stations, and X_{ij}^{N} is the normalized i^{th} attribute in all stations.

Distance is a calculation of how far apart two objects are. The distance measures are small for cases that are alike. The standard version to form the distance measure uses squared Euclidean distance in Ward's clustering method (Lee et al., 2014). The formula of squared Euclidean distance is as follows:

$$\sum_{j=1}^{k} (a_j - b_j)^2 \tag{2}$$

where k denotes the number of variables, and a and b are two different clusters.

3.2 Index Flood Procedure

The regional frequency analysis of extreme precipitation implemented is built on L-moments and is correlated with the "Flood index" system(Dalrymple, 1960) applied to hydrological data. The approach utilised is a scale invariance method, which means that the frequency distributions of the sites within a homogeneous region are identical except for a scale factor that is unique to each site. The population average at the location is the scale factor (J. Hosking et al., 1997). Consequently, quantiles of frequency F at the site i of a homogeneous region of N sites can be determined as follows: $Q_i(F) = \mu_i q(F)$ where μ_i is the scale factor or the mean at the site i. The regional quantities $q(F)$ form the "regional growth curve" defined by regional distribution of the reduced variable $y_{ij} = x_{ij}\sqrt{x_i}$ where x_{ij} represents the annual maximum daily rainfall, $\bar{x}$ is their mean at each site and $j = 1, 2, \ldots, n_i, n_i$, is the population of site i. The regional distribution parameters derive from all the at-site statistics of the homogeneous region. The study used the L-moment test to estimate these numbers.

Table 1: Location of the stations used in the study.

No.	Stations	Stations ID	Latitude	Longitude	Altitude(m)	MAP
1	Air Itam	5302002	5.4063	100.2821	23	67.46
2	Hospital Baling	5609072	5.6755	100.9768	71	91.62
3	JKR Benta	4019001	4.0118	101.9686	89	75.85
4	Besut	5424001	5.8290	102.5524	8	114.58
5	Klinik Bkt Bendera	5402001	5.4189	100.2732	22	96.49
6	Bkt Bentong	4219001	3.3926	101.8417	78	77.65
7	Bt 8 Jln Setul	2819002	2.2547	102.1709	65	71.30
8	Komp. Peng Chaah	2230001	2.2483	103.0408	30	55.25
9	Bkt Durian, Chalok	5328002	5.3903	102.8236	17	101.45
10	Chengkau	2521050	2.5581	102.1251	44	83.99
11	Chinchin	2224038	3.1309	101.7108	41	69.42
12	SM. Sul. Omar Dungun	4734079	4.7548	103.4182	13	106.34
13	Ladang Edinburgh	3116006	3.1544	101.7151	63	91.62
14	Emp. Genting Klang	3217002	3.2051	101.7152	105	86.51
15	Stor JPS Johor Bahru	1437116	1.4927	103.7414	37	87.10
16	Kalong Tengah	3416002	3.4444	101.6570	48	80.24
17	Stor JPS K. Terengganu	5331048	5.3296	103.1370	13	93.58
18	Kampung Laloh	5322044	2.1887	103.1945	54	77.51
19	Ngolang	6402008	6.4414	100.1986	8	57.61
20	Padang Besar	6603002	6.6569	100.3097	63	61.44
21	Padang Katong	6401002	6.4458	100.1875	12	60.84
22	Padang Sanai	6306031	6.3430	100.6903	48	65.52
23	Pekan Merlimau	2124037	2.1486	102.4305	10	79.81
24	Politeknik PD	2418034	2.4278	101.8708	82	95.70
25	Parit Madirono	1732001	1.7139	103.2791	3	91.99
26	Stor JPS Raub	3818054	3.7935	101.8575	144	65.19
27	Emp. Semenyih	3018101	3.0786	101.8806	88	81.59
28	Simpang Mawai	1839196	1.9167	103.9653	9	89.18
29	Kampung Tandak	5920012	5.9656	102.0166	10	87.57
30	Tanjong Malim	3615003	3.6833	101.5236	42	81.18
31	Ulu Kinta	4611001	4.6806	101.1694	75	75.12
32	Upper Chiku	4721001	4.7653	102.1736	152	79.15

3.2 L-moments Theoretical Background

In 1997, Hosking and Wallis characterized L-moments as a linear function of probability-weighted moments (PWMs), robust to outliers and essentially unbiased for small samples. Greenwood et al. (1979) formally described the PWMs of order *r* as:

$$\beta_r = \int x(F)F^R df \tag{3}$$

where $F = F(x)$ is a cumulative distribution function, $x(f)$ is an inverse distribution function, and r = 0, 1, 2, ... is a non-negative integer. The first four L-moments, expressed as linear combinations of PWMs, are:

$$\begin{aligned}
\beta_0 &= n^{-1}\sum_{j=1}^{n} x_{j:n} \\
\beta_1 &= n^{-1}\sum_{j=1}^{n} \frac{j-1}{n-1} x_{j:n} \\
\beta_2 &= n^{-1}\sum_{j=1}^{n} \frac{(j-1)(j-2)}{(n-1)(n-2)} x_{j:n} \\
\beta_3 &= n^{-1}\sum_{j=1}^{n} \frac{(j-1)(j-2)(j-3)}{(n-1)(n-2)(n-3)} x_{j:n}
\end{aligned} \tag{4}$$

L-moments can be estimated using the PWM:

$$\begin{aligned}
l_1 &= \beta_0 \\
l_2 &= 2\beta_1 - \beta_0 \\
l_3 &= 6\beta_2 - 6\beta_1 + \beta_0 \\
l_4 &= 20\beta_3 - 30\beta_2 + 12\beta_1 - \beta_0
\end{aligned} \tag{5}$$

3.3 Regional Frequency Analysis using L-moment

In 1993, Hosking and Wallis identified the following four steps to explain the RFA procedure: data screening, designing the homogeneous region, selecting an appropriate probability distribution, and estimating the proper probability distribution. Data anomalies usually must go through data screening before applying any statistical analysis. In this research, we checked for the stationarity and independence test for the data sets. Sites discordant with the population have been defined using a discordance measure based on L-moments (Hosking & Wallis, 1993) and investigated for errors or sources of possible non-reliability in measurements. To determine an unusual site for each region in this study, the discordancy measure, D_i, which based on the L-moments, was proposed. D_i is defined as:

$$D_i = \frac{1}{3}(u_i - \bar{u})^T s^{-1}(u_i - \bar{u}) \tag{6}$$

where u_i is the vector of L-moments, Lcv, Lcs, and Lck, for a site i:

$$S = (N_s - 1)^{-1}(u_i - \bar{u})(u_i - \bar{u})^T \tag{7}$$

$$\bar{u} = N_s^{-1}\sum_{i=1}^{N_s}(u_i) \tag{8}$$

S is the sample covariance matrix, $\bar{u}$ represents the unweighted regional average of L-moments ratio for each region, and N_s refers to the sum number of sites. Therefore, if D_i exceeds 3 for each station, the site is considered as a discordant station.

3.3.1 Homogeneous Region Test

The next step in designing the RFA is the allocation of the sites to regions. The study employed the statistical homogeneity test in which the weighted average L-moment statistics are the representative parameters of a region. It aims to validate the homogeneity of a region (a group of stations) concerning the L-moment ratios.

Thus, the regional L-moments and the L-moment ratios for a region of N site having each n_i length recording calculated as follows:

$$\bar{t_r} = \frac{\sum_{i=1}^{N} n_i t_r^{(i)}}{\sum_{i=1}^{N} n_i} \tag{9}$$

$$\bar{l_r} = \frac{\sum_{i=1}^{N} n_i l_r^{(i)}}{\sum_{i=1}^{N} n_i} \tag{10}$$

where: $t_r^{(i)}$, $l_r^{(i)}$ are values of t_r and l_r at the site i.

The heterogeneity test H_V as computed as:

$$H_V = \frac{V_{obs} - \mu_v}{v} \tag{11}$$

where V_{obs} is the observed value of either V_1, V_2 or V_3; the mean and standard deviation of V obtained through simulations are μ_v and σ_v. Variable H allows the dispersion of results to be measured relative to those of the simulations. According to Hosking & Wallis (1997), a region is acceptably homogeneous if $H < 1$, possibly heterogeneous if $1 \leq H < 2$, and certainly heterogeneous if $H \geq 2$. V_{obs} is calculated from the regional data and is based on the corresponding *V*-statistics.

3.3.3 Goodness-of-fit Measurement

Hosking and Wallis (1997) suggested two approaches for selecting the distribution that best matched the data: the L-moment ratio diagram and the *Z*-test. The L-moment ratio diagram uses unbiased estimators (J. Hosking et al., 1997; Vogel & Fennessey, 1993). The L-moment ratio diagram plots the distribution function's measured values L-C_s and the observed values L-C_k. The curves represent the candidate distribution's hypothetical relations between the L-C_s and L-C_k. The L-moment ratio diagram discriminates between the candidate probability distributions in describing the regional details (J. R. M. Hosking, 1990; J. R. M. Hosking et al., 1997). The diagram used for regional knowledge as a part of the probability distribution method (ÖnÖz et al., 1995; PEEL et al., 2001; Schaefer, 1990; Vogel, Thomas, et al., 1993; Vogel & Fennessey, 1993; Vogel et al., 1996). J. Hosking & Wallis, 1997 proposed a test to see how well the L-C_s and L-C_k of the fitted probability distribution compared with the observed information to the regional average L-C_s and L-C_k.

The measure of fitness for each selected probability distribution is determined as follows:

$$Z^{DIST} = \frac{(\tau_4^{DIST} - \tau_4^R)}{\sigma_4} \tag{12}$$

where τ_4^{DIST} represents the L-C_k value of the fitted distribution, τ_4^R represents the weighted regional average L-C_k, and σ_4 represents the standard deviation of τ_4^R obtained from the simulation of the Kappa probability distribution. If the computed value of Z^{DIST} is equal to zero, so the probability distribution is the most suitable fit. If the computed value of Z-statistic is less than 1.64 at a 90% confidence level (i.e., $|Z^{DIST}| \leq 1.64$), it indicates that the distribution qualifies the goodness of fit criteria. If there is more than one distribution that qualifies the criteria, the most suitable distribution has the minimum $|Z^{DIST}|$ value.

3.3.4 Estimation of Regional Rainfall Quantiles

The regional quantile estimates $\hat{q}(F)$ with varying non-exceedance probability F for the GNO, GEV, GPA, GLO, and PE3 distributions based on L-moment. For fitted regional frequency distributions, the quantile function is usually written as $\hat{q}(\cdot)$. By combining the estimates of μ_i and $(\cdot)$, the quantile estimate at location i is created. The quantile estimate with non-exceedance probability F has the following mathematical form:

$$\hat{Q}(F) = l_1^i \hat{q}(F) \tag{13}$$

For each site, $\hat{Q}_i(F)$ for various periods, extreme precipitations quantile estimates obtained by simply multiplying regional quantile estimates, $\hat{q}(F)$ to the average sample $(l_1^{(i)})$ of each site in the respective area.

4. Result

The first step in the RFA method in terms of discordance measures classified the stations whose statistical parameters differ markedly in the whole stations as per the description provided in the methodology section. Table 2 shows the 32 stations' discordant measurement values ranging from 0.11 to 4.25 and from 0.15 to 3.43 for the observation data and TRMM3B42. In the case in which there are stations with discordant measurement, Hosking and Wallis (1997) suggested the regional adjustment to achieve the "acceptably homogeneous" classification for all regions. The modification options are as follows: (i) split an area into two or more new regions, (ii) migrate one or more sites from one area to another, or (iii) delete one or more sites from the data collection by using the method calculated with the required number of groups (clusters) (Malekinezhad et al., 2014). All the discordance values for each area in each area are less than 3, indicating that the analysis did not include any outlier, as shown in Figure 1. Table 3 outlines the cluster-based measures of heterogeneity.

L-moment diagrams aid in the identification of sites with similar flood frequency behaviour and the definition of the statistical distribution most likely to appropriately reflect this behaviour. The L-moment ratio diagrams for homogeneous regions in Peninsular Malaysia are shown in Figures 2 and 3. (I, II, III, and IV).

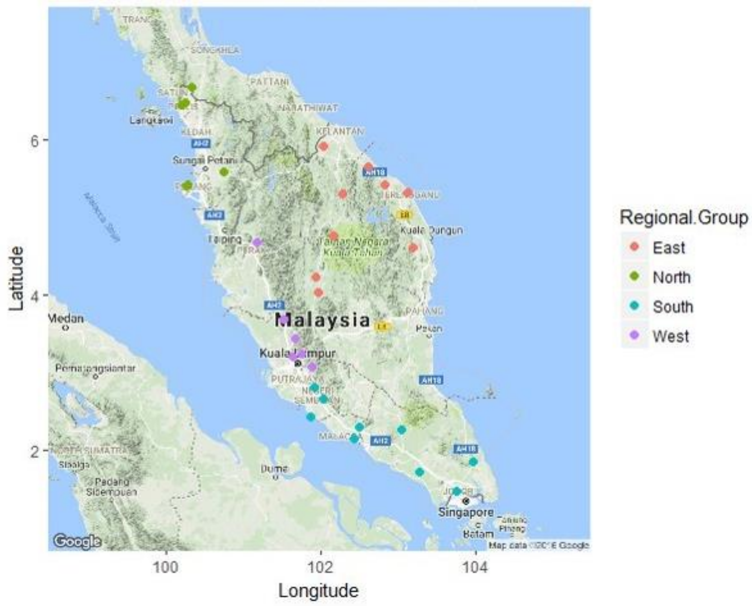

Figure 1. Homogeneous regions based on cluster analysis.

The sample points should be distributed above and below the theoretical line of an acceptable distribution; thus, the sample L-moments are unbiased. The following L-moment diagrams show that region I and Region II distributions of observation data are GLO, GEV, GNO, and PE3. On the other hand, the distributions for region I and Region II of TRMM 3B42 are PE3 and GPA, GLO, GEV, GNO, PE3, and GPA. Meanwhile, for Region III, the distributions are GLO and GEV for the observation data, GLO, GEV, GNO, and PE3 for TRMM 3B42. As for Region IV, the distributions for both the observation data and TRMM 3B42 are GEV, GNO, PE3, and GPA.

Since the field was homogenous, the Z^{DIST} statistics determined regional distribution between the GLO, GEV, GNO, PE3, and GPA distributions using 1000 simulations of the Kappa distribution. Table 4 shows each distribution value for the latter and the potential L-kurtosis values for each distribution.

Table 2: Discordancy Measures of each site for observation and TRMM3B42

Stations				**Observation**					**TRMM 3B42**		
	n	l_1	τ	τ_3	τ_4	D_i	l_1	τ	τ_3	τ_4	D_i
Air Itam	15	67.4600	0.1242	-0.0132	0.1266	0.31	26.1257	0.2321	0.2108	0.0965	1.24
Hospital Baling	15	91.6200	0.1087	-0.1306	0.0644	0.81	27.2063	0.2023	0.2393	0.1105	0.40
JKR Benta	15	75.8533	0.3389	0.5183	0.5396	**3.86 ***	28.825	0.1459	0.1231	-0.0478	1.62
Besut	15	114.580	0.2205	0.3509	0.0886	1.13	34.7251	0.1502	0.0231	0.1184	0.42
Klinik Bkt Bendera	15	96.4933	0.2007	0.4150	0.4384	0.99	23.002	0.2103	0.3040	0.0846	1.10
Bkt Bentong	15	77.6533	0.1603	0.0682	0.1603	0.17	27.8987	0.1071	0.0262	0.0197	1.53
Bt 8 Jln Setul	15	71.3000	0.1187	-0.0488	-0.0703	0.92	31.8265	0.2086	-0.0022	0.1550	1.28
Komp. Peng Chaah	15	55.2467	0.1191	0.2847	0.2349	0.78	16.8521	0.2226	0.2545	0.3730	**3.32 ***
Bkt Durian, Chalok	15	101.4533	0.232	0.2724	0.2854	0.64	36.6806	0.1717	-0.103	-0.016	1.52
Chengkau	15	83.9867	0.1295	0.2428	0.4240	1.47	25.6587	0.2418	0.2338	0.1682	1.33
Chinchin	15	69.4200	0.1267	0.3586	0.1826	1.09	20.2422	0.2346	0.0529	0.1022	1.76
SM. Sul. Omar Dungun	15	106.340	0.1705	0.1044	0.0430	0.45	25.4319	0.1553	0.1037	0.0793	0.15
Ladang Edinburgh	15	91.6200	0.1087	-0.1306	0.0644	0.81	26.3200	0.1842	0.2910	0.2626	1.12
Emp. Genting Klang	15	86.5133	0.1264	-0.0167	-0.0865	1.02	25.5545	0.1389	0.1626	0.1604	0.75
Stor JPS Johor Bahru	15	87.1000	0.1634	0.2665	0.2191	0.11	14.8132	0.1746	-0.0356	0.0142	0.87
Kalong Tengah	15	80.2400	0.1557	0.3663	0.2431	0.59	25.5545	0.1389	0.1626	0.1604	0.75
Stor JPS K. Terengganu	15	93.5800	0.1493	0.0680	0.2738	0.45	29.1358	0.1618	0.2569	0.1684	0.53
Kampung Laloh	15	77.5133	0.1066	-0.0427	0.0472	0.46	34.6099	0.1849	0.1364	0.0580	0.28
Ngolang	15	57.6133	0.2382	0.2174	0.0486	1.69	25.5235	0.1795	0.3599	0.1541	0.99
Padang Besar	15	61.4400	0.1814	0.2157	0.1139	0.24	28.1332	0.1636	0.1853	0.0472	0.48
Padang Katong	15	60.8400	0.1599	0.1976	0.0338	0.49	24.2658	0.2004	0.3519	0.1955	0.84
Padang Sanai	15	65.5267	0.1806	-0.2120	0.3501	**4.25 ****	26.4143	0.196	0.3115	0.1118	0.73
Pekan Merlimau	15	79.8133	0.1631	0.2582	0.2717	0.16	17.0031	0.1832	0.019	0.2029	1.12
Politeknik PD	15	95.7000	0.2051	0.5510	0.4990	1.93	20.1638	0.2019	0.0922	0.1969	0.73
Parit Madirono	15	91.9933	0.2642	0.3722	0.2072	1.42	13.4684	0.1458	0.0114	0.1079	0.48
Stor JPS Raub	15	65.1867	0.1416	0.2668	0.1288	0.38	28.0152	0.149	0.1684	0.1058	0.33
Emp. Semenyih	15	81.5867	0.1354	0.2098	0.2219	0.21	26.0919	0.1751	0.28	0.2123	0.67
Simpang Mawai	15	89.1800	0.1603	0.3903	0.2355	0.68	15.8041	0.1823	0.012	-0.0085	1.02
Kampung Tandak	15	87.5667	0.0629	-0.1014	0.2543	1.97	34.2786	0.1136	-0.2353	0.1026	**3.43 ***
Tanjong Malim	15	81.1800	0.1265	0.1147	-0.0475	0.83	21.7665	0.1728	0.0613	0.0493	0.26

Ulu Kinta	15	75.1200	0.1222	0.0368	0.2336	0.45	25.6702	0.1424	0.2124	0.0936	0.71
Upper Chiku	15	79.1533	0.0657	0.0494	-0.0243	1.24	30.8349	0.1551	0.1683	0.1170	0.21

Table 5(a) to 5(d) show the extreme precipitation regional quantile estimates (growth curve estimates, $\hat{q}(F)$) for return periods of 2, 5, 10, 20, 50, 100, 500, and 1000 years of Region I, II, III, and IV, respectively. Figures 4(a) to 4(d) display the graphical representation of growth curve estimates by calculating return periods based on non-exceedance probabilities along the horizontal axis and geographic frequency distribution quantities (growth curves) on the vertical axis.

Table 5(a) and Figure 4(a) indicate that growth curves for different distributions for return period up to 50 years reflect almost a close behaviour for each data. However, for the higher return periods, the quantile estimates of GLO are higher than other candidate distributions of Region I for observation data. For region I of satellite data, the quantile estimates of GNO have higher return periods than other distributions. Based on Table 5(b) and Figure 4(b), for Region II, the quantile estimates for lower return periods that are almost in the close agreement are GPE and GNO for observation and TRMM 3B42; however, for higher return periods, the quantile estimates for GLO are high. Meanwhile, according to Table 5(c) and Figure 4(c) for Region III, the quantile estimates for both observation and TRMM 3B42 are GLO. For Region IV, Table 5(d) and Figure 4(d) show that the quantile estimates for lower return periods are GEV and GNO for the observation. At the same time, the GLO gives a high return period. Concerning the TRMM 3B42, the candidate of quantiles estimates is GLO distribution.

Table 3. Heterogeneity measures based on cluster method.

Homogeneous Measurement	Rain Gauge I	II	III	IV	TRMM 3B42 I	II	III	IV
H_1	0.76	0.99	2.98	0.80	-1.20	1.19	0.05	-0.97
H_2	2.29	2.08	1.33	0.42	-1.42	-0.05	1.38	-0.78
H_3	2.18	2.75	1.06	0.39	-2.00	-1.19	0.74	-0.44

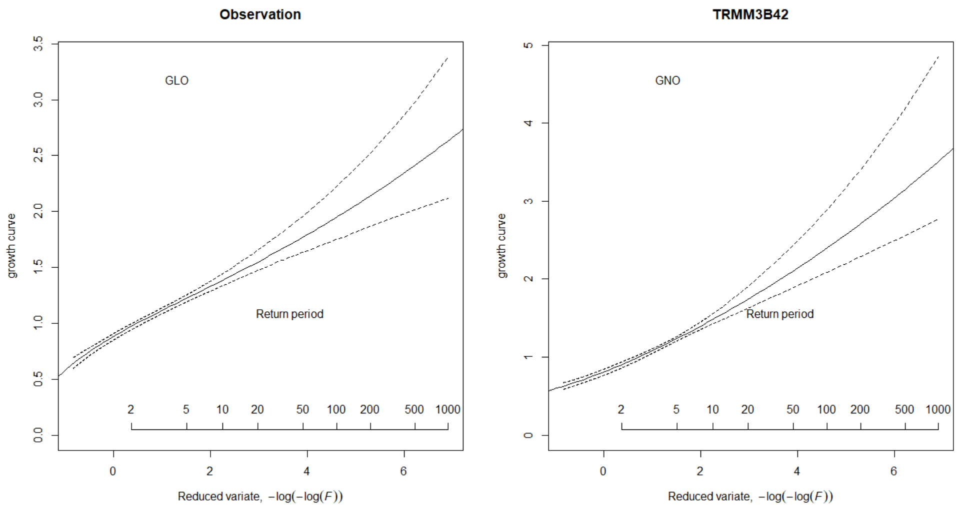

Figure 4(a): Region I Quantile Function with 90% error bounds for Observation and TRMM 3B42

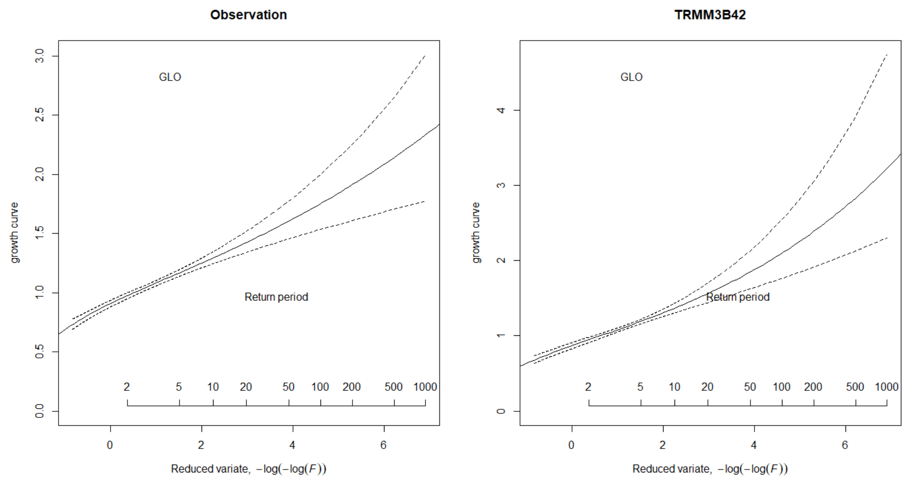

Figure 4(b): Region II Quantile Function with 90% error bounds for Observation and TRMM 3B42

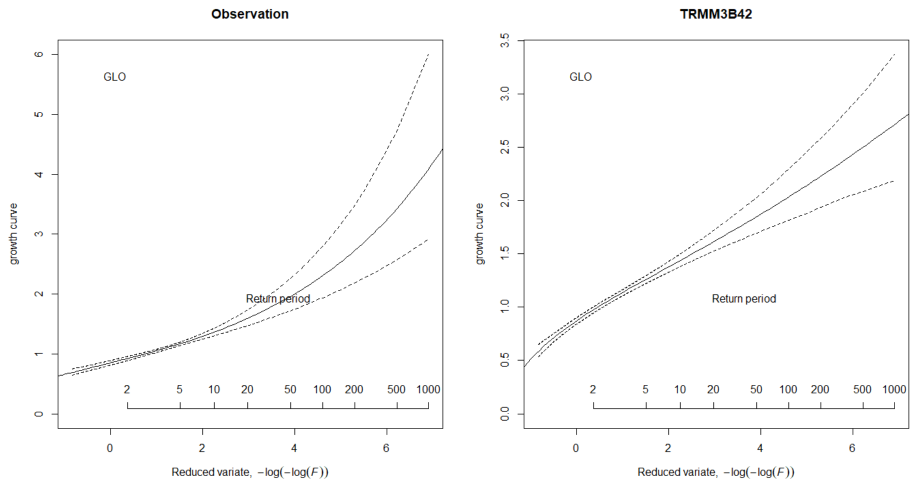

Figure 4(c): Region III Quantile Function with 90% error bounds for Observation and TRMM 3B42

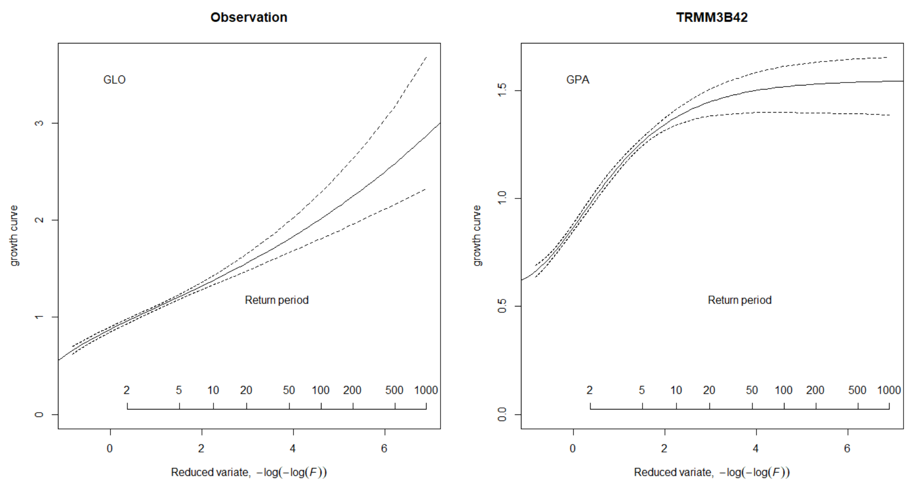

Figure 4(d): Region IV Quantile Function with 90% error bounds for Observation and TRMM 3B42

5. Conclusion

In this study, by using the site characteristics and Ward's method, the hierarchical clustering method, based on minimizing the Euclidean distance in site characteristics space within each cluster, Peninsular Malaysia is divided into four acceptably homogeneous regions. The L-moment-based regional frequency analysis identifies that the regions under study are acceptably homogeneous. The finding on the regional distribution is a significant phase in the regional study. The Z^{DIST} statistics criteria are used to identify the most suitable regional distribution. The set of popular distributions in hydrological studies, namely GLO, GEV, GNO, PE3, and GPA distributions, four distributions, GNO, GLO, GEV, and GPA, are suitable candidates for the regional distribution. For the GNO, GLO, GEV, and GPA distributions, regional quantile estimates with non-exceedance probability F were derived. Equation xi can be used to calculate the quantile estimates for each site in the region. This study investigates whether the quantile estimates from the GNO, GEV, and GPA distributions are roughly identical until the 50-year return period, i.e., F = 0.99. For scientists and hydrologists, estimating high precipitation at ungauged sites with no flow data has become a serious challenge. By linking the parameters of the regional distribution to the available site features, reliable connections for observation data and satellite data can be constructed. The current research presents the b Forecasts of the quantile precipitation will assist managers in tackling the extreme rainfall-like situation and, by better preparation considering such predictions, to reduce possible losses.

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