

Evaluation of Extreme Rainfall Occurrences Using Standard Precipitation Index (SPI)

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Abstract— The main objective of this study is to investigate The Standard Precipitation Index (SPI), a commonly used method for determining extreme rainfall occurrences as well as gauging the duration and severity of droughts. To pinpoint exceptional rainfall events in a specific area, a methodology was provided in this paper for calculating the SPI for different periods of time and thresholds. Overall, the study highlights the potential of using the SPI to improve our understanding of extreme rainfall events. The Standard Precipitation Index (SPI) is utilized to analyze the monthly precipitation data for several selected rain gauge stations between the years 1970 and 2014. The goal of this study is to keep an eye on the extremely moist conditions that may eventually result in floods. Precipitation index data from several rain gauge sites in Peninsular Malaysia are used to calculate SPI time series. Additionally, SPI readings for 3 months or less may usually be used for basic drought monitoring, values for 6 months or less may be useful for monitoring agricultural impacts, and values for 12 months or more may be useful for monitoring hydrological impacts. In this study, two states that are affected by monsoon season were selected, which are Johor and Kelantan. Two rain gauges stations were selected from these two states to calculate the SPI results. From this study, statistics of occurrence for dry and wet events in specified areas were determined based on the SPI readings for 3-month, 9-month, 12-month and 24-month.

Keywords— Extreme Rainfall, Standard Precipitation Index (SPI), Peninsular Malaysia.



I. INTRODUCTION

In Malaysia, flooding is one of the yearly natural calamities. Extreme rainfall events can lead to flooding [1], which can have detrimental effects on the environment, people's health, and public safety. Therefore, analyzing the probability distribution with the best fit for the yearly maximum rainfall can give relevant government agencies and authorities the essential concepts they need to reduce flooding issues. Over the previous ten years, rainfall in Malaysia had varied, particularly in Kelantan. Every year during the monsoon season, this leads to major floods in the state of Kelantan. The Southwest Monsoon and the Northeast Monsoon are the two monsoon seasons that often occur in Malaysia. In comparison to the Southwest Monsoon, Kelantan experiences higher rainfall during the Northeast Monsoon. A significant problem in Kelantan during the rainy season is flooding. Every year, flooding in Kelantan

results in considerable human casualties and property damage. Flooding happens when a river's capacity to contain water levels is exceeded, causing water to overflow into low-lying areas and negatively impacting the human populations located outside the buffer zone [2]. On the other hand, in recent news of flood that happens in year 2022, Johor is the most affected by the extreme rainfall, other than the facts that it is going through rapid development that could cause other facts such as development residues.

Kelantan and Johor are two states in Malaysia that experience floods during the monsoon season[3]. Kelantan is particularly vulnerable to severe floods [4] due to its location and topography, which make it susceptible to overflowing rivers. While Johor is not one of the states that are the most severely affected by floods during the monsoon season, its

location and relatively high population make it a good case study for examining the impact of floods in urban areas. Johor is also undergoing rapid development, which can increase its vulnerability to floods due to changes in land use and urbanization. Therefore, studying floods in these two states can provide insight into the impact of extreme weather events on different regions [5].

The purpose of this study is to investigate the probability distribution that best fits the Kelantan and Johor yearly maximum rainfall data from 1970 to 2014. The historical rainfall data was fitted using the Gamma, Weibull, Log Normal, and Normal distributions. Each probability distribution's performance is determined, and the goodness of fit tests will be evaluated.

II. CASE STUDY AREA

Kelantan is located at the northeastern part of Peninsular Malaysia. The location is between latitudes 4°40' and 6°12' North, and longitudes 101°20' and 102°20' East. Kelantan also covers area of 6,602.31 sq miles (17,100 km²) (Kelantan, n.d.) Kelantan is a state in the which has the effect of Northeast Monsoon, from November to March every year [6], and the level of floods that occur is dependent on the intensity and rainfall value that falls at a time during the season [7]. In this monsoon season several flood events have occurred in the state[8], some of which have occurred in the districts of Jeli, Tanah Merah, Pasir Puteh and Pasir Mas [9][10].

Another area that was focused on are in Johor state. The location is in 2°04' 103°38' East of Malaysia. Johor, formerly known as Johore, is a state of Malaysia in the south of the Malay Peninsula. Johor has land borders with the Malaysian states of Pahang to the north and Malacca and Negeri Sembilan to the northwest. Johor covers the land of 19,166 km² in south of Malaysia. Several rainfall stations will be chosen to find a significant differences between the area in Malaysia when Monsoon season came[11].

III. MARGINAL DISTRIBUTION

The use of marginal distributions in the analysis of rainfall data plays a crucial role in understanding and characterizing the behaviour of rainfall variables. Marginal distributions provide insights into the probability distribution of individual variables without considering the influence of other variables [12]. These abstract highlights the significance of utilizing marginal distributions in rainfall data analysis and its applications in various fields. These variables can include factors such as geographical locations, time periods, or specific features related to rainfall measurements. By analyzing these variables individually, researchers can gain valuable insights into the behaviour and characteristics of rainfall in different regions or over specific time intervals.

By counting the occurrences of each unique value for a particular variable and dividing it by the total number of data points, the probability of different values is determined. These probabilities represent the marginal distribution of the variable, providing valuable information on the likelihood of specific

rainfall outcomes. By incorporating marginal distributions into rainfall data analysis, researchers and practitioners can enhance their understanding of rainfall phenomena and its implications for a wide range of applications.

The marginal distribution typically refers to the probability distribution of a single variable in a multivariate dataset. In the context of rainfall data analysis, calculating the marginal distribution involves calculating the Cumulative Distribution Function (CDF) for the rainfall variable.

IV. STANDARD PRECIPITATION INDEX (SPI)

Researchers at Colorado State University designed the SPI in 1993 to be a relatively simple [13], year-round index applicable to the water supply conditions important to Colorado and as a supplement to information provided by the PDSI and a second drought index, the Surface Water Supply Index. The Standard Precipitation Index (SPI) is based on precipitation alone [14]. Its fundamental strength is that it can be calculated for a variety of timescales [15]. This versatility allows the SPI to monitor short-term water supplies, such as soil moisture, important for agricultural production, and longer-term water resources such as groundwater supplies, stream flow, and lake and reservoir levels. The ability to examine different timescales also allows droughts [16] to be readily identified and monitored for the duration of the drought. Colorado has now used the SPI information as part of the Water Availability Task Force since 1994 including 1996, when drought affected portions of the state.

The World Meteorological Organisation (WMO) advises SPI as the primary meteorological drought indicator for nations to monitor and research drought conditions [17]. The SPI is the major meteorological drought index that the WMO advises nations to use, to monitor and analyze drought conditions. The SPI is a straightforward index that can be calculated using only the amount of rain across various time periods [18], such as 3, 9, 12 or 24 months. The SPI normalizes and converts the rainfall data into a command unit. The standard deviations by which the observed rainfall deviates from the long-term average for a random variable with a normal distribution is known as the normalized number. In this investigation, the SPI was calculated using the RStudio application package version.

Calculation of the SPI for a specific time at any location requires a long-term monthly precipitation database with 30 year or more of data [19]. The probability distribution function (PDF) is determined from the long-term record by fitting a function to the data. The cumulative distribution is then transformed using equal probability to a normal distribution with a mean of zero and standard deviation of one, so the values of the SPI are really in standard deviations. A particular precipitation total for a specified period is then identified with a particular SPI value consistent with probability. Positive SPI values indicate greater than median precipitation, while negative values indicate less than median precipitation [20].

V. METHODOLOGY

A. Parameter Estimation

The maximum likelihood estimation is a method that determines the parameter values of a model. The parameter values maximize the likelihood that the process described by the model produced the data that were observed. The maximum likelihood estimate for the continuous probability distribution can be described as:

$$\hat{\theta} \in \{\arg \max L(\theta; x)\} \quad (1)$$

B. Fitting the probability distribution

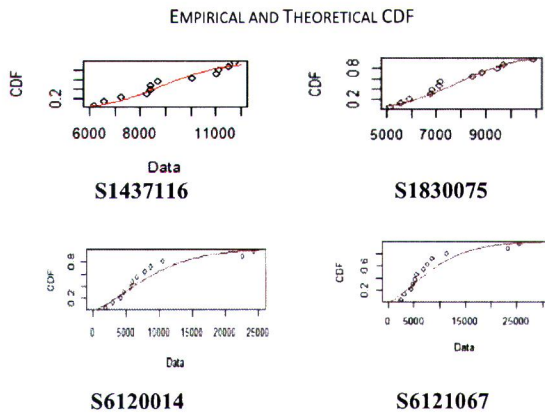
Probability distribution is a concept related to statistics, where the outcome of statistical experiments and their probabilities of occurrence relate to the probability distributions [21]. Five types of probability distributions were used, namely the Gamma, Weibull, Lognormal, Normal and Exponential [22] to examine the rainfall data from Kelantan and Johor state to determine the best fit distribution [7][23]. The probability distribution of the precipitation data is used to create the cumulative distribution function (CDF). The CDF gives data on the likelihood of seeing a certain amount of precipitation or less. It provides a hint as to how extreme or normal certain precipitation values are across the dataset. Below is included the CDF graph that represents data distribution for each station in each distribution.

The Gamma distribution is a widely used continuous probability distribution which is related to the beta distribution. The probability density function (PDF) and cumulative distribution function (CDF) of the Gamma distribution can be computed using the two formulas below:

$$f(x) = \frac{\left(\frac{x-\mu}{\beta}\right)^{\gamma-1} \exp\left(-\frac{x-\mu}{\beta}\right)}{\beta \Gamma(\gamma)}$$

$$F(x) = \frac{\Gamma_x(\gamma)}{\Gamma(\gamma)} \quad (1)$$

where γ is the shape parameter, μ is the location parameter, β is the scale parameter and Γ is the gamma function.



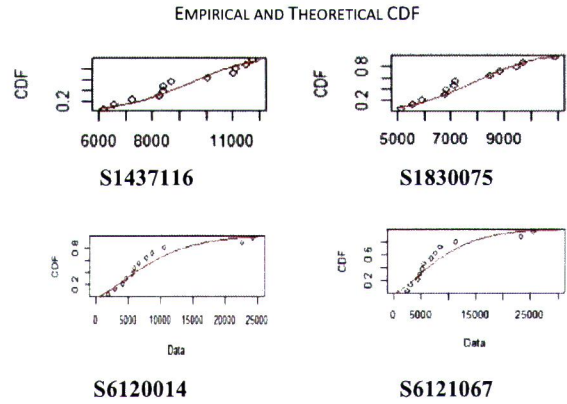
The Weibull distribution is known as continuous probability distribution that can fit an extensive range of distribution shapes [24]. Like the normal distribution, the Weibull distribution is unimodal and describes probabilities associated with continuous data. One of the reason Weibull distribution were used is because of its flexibility [25] because it capable of replicating several distributions, including normal and exponential distributions. Weibull's distribution reliability is measured with the help of parameters. The formula general Weibull Distribution for three-parameter pdf is given as

$$f(x) = \frac{\gamma}{\alpha} \left(\frac{x-\mu}{\alpha}\right)^{\gamma-1} \exp\left(-\left(\frac{x-\mu}{\alpha}\right)^\gamma\right) \quad x \geq \mu; \gamma, \alpha > 0 \quad (2)$$

Where,
 γ is the shape parameter, also called the Weibull slope or the threshold parameter.
 α is the scale parameter, also called the characteristic life parameter.
 μ is the location parameter, also called the waiting time parameter or sometimes the shift parameter.

The standard Weibull distribution is derived, when $\mu=0$ and $\alpha=1$, the formula is reduced, and it becomes:

$$f(x) = \gamma x^{\gamma-1} \exp(-x)^\gamma, \quad x \geq 0; \gamma > 0 \quad (3)$$



The Lognormal distribution is a probability distribution that is derived from the natural logarithm of a random variable. It is commonly used to model variables that are positive and have a skewed distribution. In the analysis of precipitation for rainfall data, the lognormal distribution is often used because rainfall amounts tend to have a skewed distribution with a long tail on the higher values. By using the logarithmic transformation, the skewed distribution can be transformed into a symmetrical distribution, making it easier to analyze using statistical techniques that assume normality.

One of the main advantages of using the lognormal distribution for precipitation analysis is that it allows for a more accurate representation of extreme rainfall events, which are critical in many applications. Since extreme rainfall amounts are often of particular interest in areas such as flood risk

assessment, water resource management, and infrastructure design, the lognormal distribution can provide valuable insights into the behaviour of these events. The probability density function (PDF) of the lognormal distribution is given by the following formula:

$$\phi(x) = \begin{cases} \frac{\exp\left(-\frac{1}{2}\left(\frac{\log x - m}{s}\right)^2\right)}{xs\sqrt{2\pi}} & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (4)$$

Where:

- x is the random variable (rainfall amount in this case).
- μ is the mean of the logarithm of the variable.
- σ is the standard deviation of the logarithm of the variable.
- $\ln(x)$ represents the natural logarithm of x.
- π is a mathematical constant (approximately 3.14159).

The formula calculates the probability density of the lognormally distributed variable x taking on a specific value. By integrating this function over a range of values, the probability of x falling within that range can be calculated. It's important to note that the lognormal distribution has a support of $x > 0$, as the logarithm of zero or negative values is undefined.

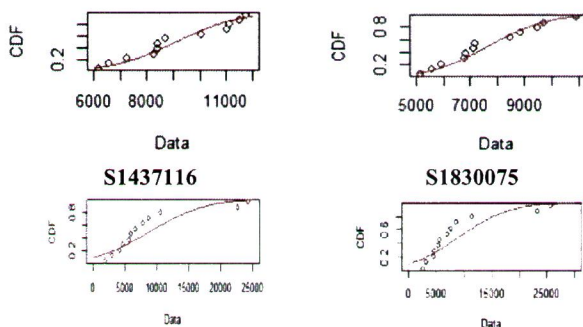
The Normal distribution is widely used in statistics and probability theory due to its mathematical properties and its ability to model a wide range of phenomena. The normal distribution, also known as the Gaussian distribution, is a continuous probability distribution that is symmetric and bell-shaped. The normal distribution is characterized by two parameters: the mean (μ) and the standard deviation (σ). The formula for the probability density function (PDF) of the normal distribution is:

$$y = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2\sigma^2}} \quad (5)$$

Where,

- x is the random variable.
- μ is the mean of the distribution, representing the center of the distribution.
- σ is the standard deviation, which determines the spread or variability of the distribution.
- π is a mathematical constant (approximately 3.14159).

EMPIRICAL AND THEORETICAL CDF



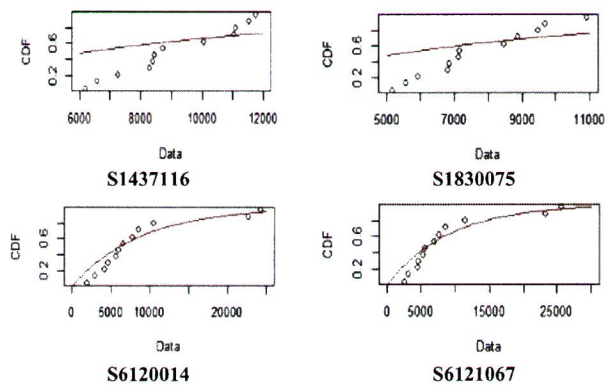
The exponential distribution is a continuous probability distribution that models the time between events in a Poisson process. It is often used to describe the time until the occurrence of a specific event in various fields, such as reliability engineering, queuing theory, and survival analysis. The exponential distribution is characterized by a single parameter, often denoted as λ (lambda), which represents the rate parameter. The formula for the probability density function (PDF) of the exponential distribution is:

$$f(x) = \begin{cases} 0, & x < 0 \\ \lambda e^{-\lambda x}, & x \geq 0 \end{cases} \quad (6)$$

Where,

- x is the random variable representing the time until the event occurs.
- λ is the rate parameter, which determines the average number of events per unit of time.

EMPIRICAL AND THEORETICAL CDF



Once the CDF is calculated, it is transformed to a standard normal distribution. This transformation helps in making the SPI values comparable across different locations and time periods, as it standardizes the distribution to have a mean of 0 and a standard deviation of 1. The SPI values are then calculated based on the transformed distribution. Positive SPI values indicate wetter-than-average conditions, while negative SPI values indicate drier-than-average conditions.

C. Goodness of fit Tests

After calculating the five probability distributions for these computations, the goodness of fit for each distribution is evaluated by comparing the observed rainfall data with the fitted distributions. The statistical measures that were chosen are Kolmogorov-Smirnov test to select the best-fitted distribution for each station based on the goodness-of-fit analysis.

The Kolmogorov-Smirnov (KS) test is a statistical test used to determine whether a sample comes from a specific distribution or if it differs significantly from that distribution. It is a non-parametric test, meaning that it makes no assumptions about the underlying distribution of the data being tested. The

KS test is often used to compare a sample distribution to a known theoretical distribution or to compare two sample distributions.

Each station was suited with a specific distribution based on the calculated test results. Weibull distributions were most likely fitted for all, given they do not display a p-value of 0. This is demonstrated. Weibull distribution may have been chosen because the data set was suitable for a group of data that would typically be fitted by a two-parameter Weibull distribution with a zero value. Flexible charting of visual data is needed since the amount of rainfall in the selected region can vary from a minimum rainfall value of 0 for days to a maximum value of monthly rainfall data during the monsoon season.

Based on other research by recent paper in 2017 [26]. The results shows that rainfall data for stations that is in Malaysia were fit with Gamma distribution. The formula below was used in the finding:

The long-term precipitation data of the station is fitted to a Gamma distribution, which is then transformed into a normal distribution so that mean SPI for the station and desired period is zero. This is done through a process of maximum likelihood estimation of the gamma distribution parameters, α and β are obtained:

$$\hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \text{ and } \beta = \frac{x}{\hat{\alpha}}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (7)$$

n is the number of precipitation observations and \bar{x} refers to the sample mean of the data. The cumulative Gamma distribution $F(y)$ resulting from the parameters has been estimated from precipitation events for the given month and time scale for different selected stations. The multiple of time scales is a main advantage of SPI that enables temporal flexibility in the evaluation precipitation conditions.

To overcome this issue, a different statistical measure such as Anderson-Darling were used to test and verify the best fitted distributions for the rainfall data. The prediction using the second statistical measure is as shown in Fig. 2.

TABLE I
GOODNESS-OF-FIT RESULTS USING ANDERSON-DARLING TEST

Station	Weibull Distribution		
	AD Statistic	Significance level	Likely follows
1437116	0.3364	50.00%-99.50%	Yes
1830075	0.6903	95.00%-99.50%	Yes
6120014	29.2173	0	No
6121067	25.7489	0	No

VI. RESULTS AND DISCUSSION

The methodology chosen above was applied to the rainfall series collected from the 4 rainfall stations in Kelantan and Johor state. The study period was from 1970-2014 which is a total of 45 years [27]. The one probability distributions mentioned above were fitted to the annual maximum rainfall series of the 4 rainfall stations. This wide range of probability distributions can be used to explore and examine the best fit distribution for the annual maximum rainfall series [28]. The prediction of the distributions of the selected station rainfall data as shown in Table 1 was carried out using the methods and the computer program described above.

The Kolmogorov-Smirnov Test produces a statistic (the KS statistic) that measures the maximum difference between the cumulative distribution function (CDF) of the empirical data and the CDF of the fitted distribution. Which distribution provides the best match can be identified by comparing the KS statistics for different distributions. The distribution with the smallest KS statistic is often considered the best-fit distribution.

TABLE II
GOODNESS-OF-FIT RESULTS USING KOLMOGOROV-SMIRNOV TEST

Station	Gamma Distribution	
	KS Statistic	KS p-value
1437116	0.0278	0.9854
1830075	0.0537	0.4177
6120014	0.9741	0
6121067	0.9796	0
Station	Weibull Distribution	
	KS Statistic	KS p-value
1437116	0.0296	0.9720
1830075	0.0574	0.3360
6120014	0.0759	0.0889
6121067	0.0981	0.0110
Station	Normal Distribution	
	KS Statistic	KS p-value
1437116	0.1222	0.0006
1830075	0.0796	0.0651
6120014	0.1907	0
6121067	0.2074	0
Station	Exponential Distribution	
	KS Statistic	KS p-value
1437116	0.1833	0
1830075	0.2407	0
6120014	0.0722	0.1196
6121067	0.0704	0.1379

The Kolmogorov-Smirnov Test p-value is a probability value that assesses the evidence against the null hypothesis (H_0) in the Kolmogorov-Smirnov test. It indicates the likelihood of observing a KS statistic as extreme as the one calculated from the sample data, if the sample distribution comes from the specified theoretical distribution (or is the same as the second sample distribution, in the case of a two-sample KS test).

A small p-value suggests that the sample distribution significantly deviates from the specified distribution, leading to a rejection of the null hypothesis. A larger p-value indicates less evidence against the null hypothesis. For the longest time scales for these entire periods, for both stations were start of time series with smaller values of SPI and higher SPI values were present at the end.

The SPI values are categorized as shown in Table 1. The specific interpretation of the p-value depends on the chosen significance level (alpha). If the p-value is less than or equal to alpha, the null hypothesis is typically rejected.

TABLE III
WEATHER CLASSIFICATION BASED ON SPI VALUES.

SPI Value	Weather Category
$SPI \geq 2$	Extreme wet
$1.5 < SPI < 2$	Severe wet
$1 < SPI < 1.5$	Moderate wet
$-1 < SPI < 1$	Near Normal
$-1.5 < SPI < -1$	Moderate dry
$-2 < SPI \leq -1.5$	Severe dry
$SPI \leq -2$	Extreme dry

After calculating the departure from the mean for each month by subtracting the long-term mean from the observed rainfall value for that month and divide the departure from the mean by the long-term standard deviation to obtain the standard normal deviate (Z-score) for each month. Cumulative distribution function (CDF) of the selected fitted distribution for the Z-score of each month were then calculated to get the SPI result for each month by transforming the CDF value to a standard normal deviate (Z-score).

Fig. 3 Comparison of 3-month SPI values for selected rain-gauge stations

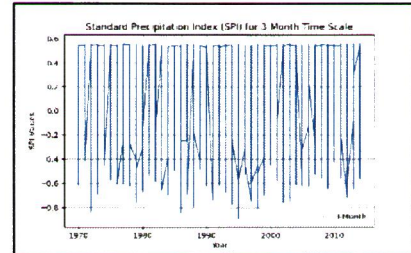
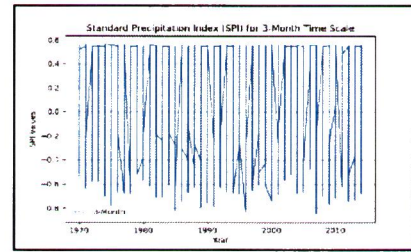
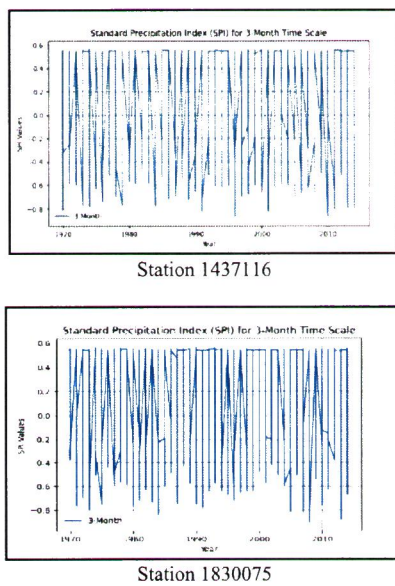


Fig. 4 Comparison of 9-month SPI values for selected rain-gauge stations

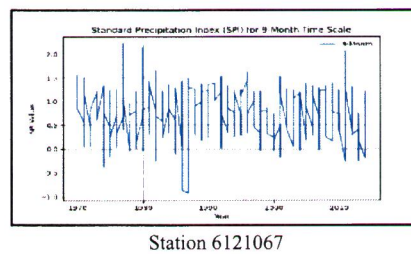
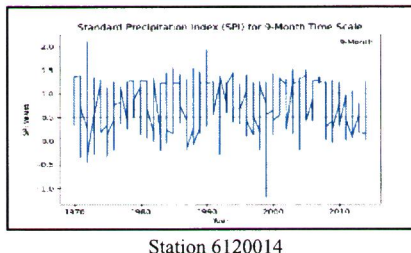
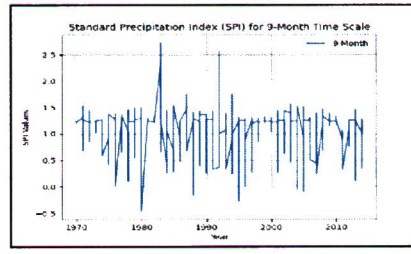
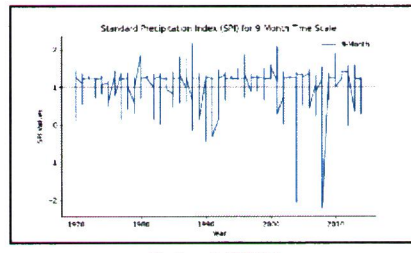
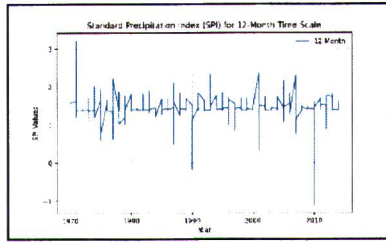
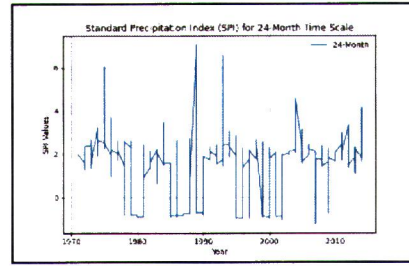


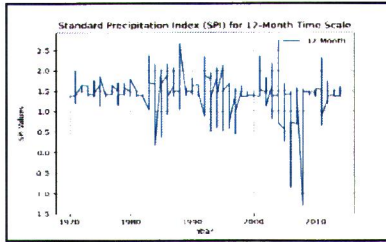
Fig. 5 Comparison of 12-month SPI values for selected rain-gauge stations



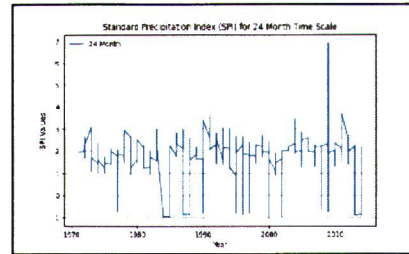
Station 1437116



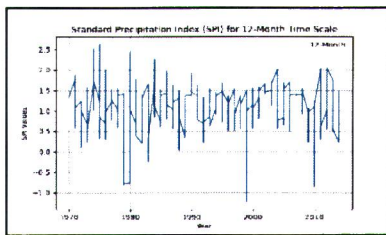
Station 6120014



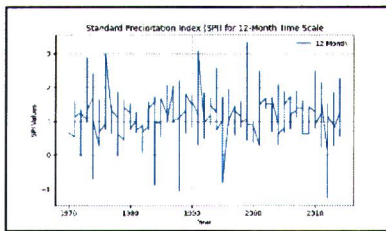
Station 1830075



Station 6121067

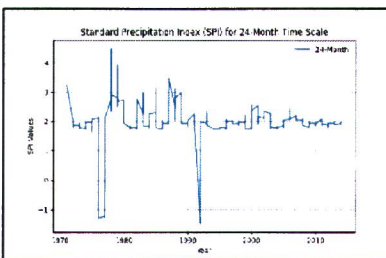


Station 6120014

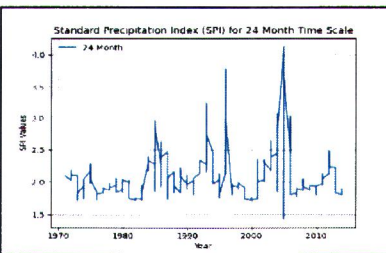


Station 6121067

Fig. 6 Comparison of 24-month SPI values for selected rain-gauge stations



Station 1437116



Station 1830075

There is a distinct difference that can be seen between graph of SPI values for 3-month and 24-month for selected rain-gauge stations. The distribution pattern that would result in a suspected dry occurrences value cannot be determined from the first graph's 3-month results. The difference becomes more apparent when it continues to estimate the value using the 6-month, 9-month, and 12-month SPI calculations, and further predictions can be drawn from the graph pattern. As previously stated, SPI measurements for 3 months or less may be helpful for basic drought monitoring, values for 6 months or less may be helpful for monitoring impacts on agriculture, and values for 12 months or more may be helpful for monitoring impacts on hydrology.

The 24-month statistics indicate that Station 1437116 likely had a past drought since it has more dry occurrences over time compared to other stations, which are more likely to have repeated flooding over the course of several years. For Stations 1830075, 6120014, and 6121067, the region selected had more wet occurrences throughout time, and it may be inferred that this is an area that could be vulnerable to significant flooding for a long time if it experiences ongoing rainfall seasons.

VII. CONCLUSION

The aim of this study is to investigate The Standard Precipitation Index (SPI), a commonly used method for determining extreme rainfall occurrences as well as gauging the duration and severity of droughts for rainfall data in selected stations [29]. Overall, the study highlights the potential of using the SPI to improve our understanding of extreme rainfall events. In this study, two states that affected by monsoon season were focused on, which is Johor and Kelantan. Two rain gauges stations selected from each state to calculate SPI [30]. SPI readings for 3 months or less may be useful for basic drought monitoring, values for 6 months or less may be useful for monitoring agricultural impacts, and values for 12 months or more may be useful for monitoring hydrological impacts. SPIs for long accumulation periods (SPI-12 to SPI-48) are indicators for reduced reservoir and groundwater recharge [31].

From the first glance at the graph, Kelantan and Johor experienced an even normal weather most of the times except a few extreme values during the monsoon season based on 3-month SPI values. When the standard precipitation index was computed for additional 6, 9, and 12 months, these several extreme values start to show an impact in the graph. According to the findings, the researched area could undergo extreme weather conditions or potential flooding over the course of several years, which could have an impact on the region's agriculture and people.

In conclusion, this study should encourage more research into effective prediction methods. Overall, the SPI provides a standardized framework for assessing rainfall anomalies and their impact on water resources, agriculture, and ecosystems, allowing decision-makers to better understand and respond to the variability and extremes in precipitation.

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