Recent Trends in Civil Engineering and Built Environment Vol. 3 No. 1 (2022) 536-545

RTCEBE

Homepage: http://publisher.uthm.edu.my/periodicals/index.php/rtcebe
e-ISSN :2773-5184

Forecasting Flood Using Markov Chain Model

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DOI: https://doi.org/10.30880/rtcebe.2022.03.01.065
Received 4 July 2021; Accepted 13 December 2021; Available online 15 July 2022

Abstract: Johor is currently experiencing rainfall irregularities and frequent flood event, thus, study on forecasting flood event is crucial. It is quite impossible to elude the event, but people can prepare the hit of the event. Hence, Markov Chain Model was applied to forecast floods to minimize and mitigate the flood risks. The long historical rainfall data were collected Ladang Paya Lang station in Johor from Department of Irrigation and Drainage (DID) Malaysia. In identifying the historical of wet event, the rainfall data of 30 years was obtained, then the Standardized Precipitation Index (SPI) was applied for 6-month, 9-month, and 12-month of time scales. The results from the time scales showed the significant upward trend for all stations. Meanwhile, to forecast the flood, the Markov Chain Model was applied as it uses the transition probability matrix to determine the probability of flood occurrence. Initial state and initial month were used for the prediction of 1 to 4 months ahead. The results showed the prediction for 1 month ahead obtained the highest value around 0.843. The highest value obtained for 2 months ahead was 0.743, while 3 months and 4 months ahead were 0.676 and 0.652, respectively. Overall, the results prove that the Markov Chain Model has a potential to forecast wet events.

Keywords: Forecasting Flood, Markov Chain Model, Standardized Precipitation Index

1. Introduction

Precipitation plays important role in supplying water for society, animals, plants, and helps to maintain atmospheric balance. However, the effects of heavy rainfall and human alterations of the natural environment could lead to overflowing of water or briefly, flood. Flood is a common phenomenon that can have much further implications for humans and the atmosphere. It is often thought of as a mixture of heavy rainfall that allows rivers or oceans to spill over their banks and can strike at any time of the year. In any part of the waterway system, a flood is described as overflowing water that threatens the natural or artificial banks. Hence, the waterway stretches over the flood plain where a waterway bank is overtopped and generally becomes a threat to society [1].

Nevertheless, precipitation is not the only factor that contributes to flooding. A poor water management system which often happens in the urban area can be one of the contributors. The inundation occurs as a result of the inefficiency of the drainage system and there are several causes of

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urban flooding [2] For example, the drainage basins in the urban area which mostly made of impermeable material such as concrete causing the flowing of water unable to infiltrate into the ground. Some drains are even clogged with a high amount of waste and debris due to poor maintenance, contributing to flooding after the downpour. The failure of dam structure which is triggered by overtopping or earthquakes also contributes to flooding. Depending on the severity, a flood can cause the destruction of properties, affect health conditions, and even cause fatalities.

Standardized Precipitation Index (SPI) is created based only on precipitation and it can be computed in various and multiple time scales [3]. The SPI identifies the level to which the accumulated precipitation for a certain period differs from the average state. It is typically used for the detection, monitoring and assessment of dry and wet areas and for the identification of their variance in multiple space and time scales. SPI provides various benefits, include, the requirement is only for single input variable which is precipitation, it provides a means for both rainy and dry periods, multiple time scales can be computed, and it is probability-based which can be used to assess risk and decision-making [4]. SPI was widely used at any location to compute and analyze a long-term monthly precipitation database of 30 years or more of data [5].

Although most of the SPI applied to drought, the earliest publication was focused on flood. The SPI's effectiveness in measuring the flood risk suggests that the superficial water should be quantified for 3-6 months of time scale, while for the sub-soil moisture the SPI should have 12-24 months [6]. Research on water bodies, groundwater and lakes confirmed the ability of the SPI to be used in hydrology [7].

Markov Chain is known as the stochastic process by which any data that could determine the further evolution of the process is completely retrieved by the analysis of the present condition [8]. A Markov chain, which is often represented by a transition probability matrix, is a type of Markov process. The transition probability matrix determines the probability of an object passing inside the structure being modelled from one state to another [9]. From the historical rainfall data obtained, the floods can be predicted using the Markov Chain technique. The most obvious advantage that makes the Markov Chain Model more common is possibly the fast parameter estimation and the easy data generation [10].

2. Methodology

2.1 Study area

The study covers the entire state of Johor, which is located in southern Malaysia between latitudes 1°20”N and 2°35”N. From November to February the State is swamped, rainy in the tropics and monsoon rains. The average annual rainfall is 2355 mm with an average temperature of 25.5°C to 27.8°C [11]. In the highest region, with 2500 mm annual precipitation the precipitation rate is usually higher and a large part of the rainfall during the north-eastern monsoon season drops. A series of floods in the history of 100 years, from 1948, 1969, 1979, 1982, 1983, 1987, 1989, 1991, 2004, 2006 and 2007, were recorded. Flood incidents also occur. Heavy precipitation would lead to large sediments along the river shore during the Northeast monsoon season. In the study region there was a lot of flooding [12]. Ladang Payang Lang station was illustrated in Figure 1.

Figure 1: Rainfall station selected for the study

2.2 Procedure of SPI

The SPI computation method has been developed for the analysis of relative departures of precipitation from standard [5]. In several studies it was commonly used [13]. There are different time scales of monthly precipitation combinations. The next is the normalization method whereby a suitable probability density function is first fitted to the aggregate precipitation long-term time scales. The distribution of gamma is applied, and its frequency is defined as follows:

$$G(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_{0}^{c} x^{\alpha-1}e^{\frac{-x}{\beta}}\,dx \quad Eq.1$$

Where β is a scale parameter, α is a shape parameter, *x* is a monthly rainfall data, and $\Gamma(\alpha)$ is a gamma distribution function. The gamma distribution parameters for each station are calculated for the selected time scale (1-, 3-, 12-month, etc.). The α and β parameters are calculated by the formula of maximum likelihood. The gamma distribution is not defined for the value $x = 0$, but the rainfall may be of zero value, so the cumulative probability distribution is derived as follows:

$$H(x) = q + (1-q)G(x) \quad Eq.2$$

Where *q* is a probability of zero (0) precipitation value. In addition to calculating SPI, the estimated probabilities of precipitation were converted to the corresponding standard normal values for the SPI values. [4,14]. The index has a normal distribution, so both dry and wet periods can be calculated. A flood period can be defined on a time scale according to the SPI's value, as the period for which the SPI is always positive and reaches a value of +1 or higher and where the SPI's value is consistently negative and reaches -1,0 or lower, drought begins. [4,5]. An SPI at different time scales is the deviation in total precipitation for the same month and current including previous 2 months. It proves how the precipitation compares with the entire record at a certain station for a particular time [4].

In this study, the 6-month, 9-month, and 12-month of time scales were applied using SPI Generator software as an identification of historical flood events. The application SPI Generator generates SPI data and illustrates how the SPI Dynamically Linked Library (DLL) interacts. This application accepts daily, weekly, and monthly precipitation data and works with a variety of time scales and data sources (i.e. weekly, monthly). It generates SPI data as well as frequency and drought period data if desired. It can run as a Windows Graphical User Interface (GUI), and it can also run from the command line. The SPI Generator application is shown in Figure 2.

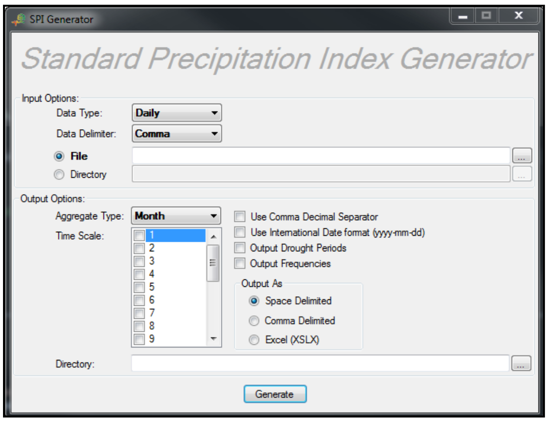

Figure 2: The GUI of SPI software

2.3 Procedure of Markov Chain

In this procedure, transition probability matrix was applied. If the *n* value is independent, then the Markov chain has stationary transition probability, which is called a homogeneous Markov chain. $\{X_n, n \geq 0\}$ is a homogeneous Markov Chain with a discrete infinite state space $E = \{0,1,2, \ldots\}$. The equations are as follows:

$$p_{ij} = P\{X_{n+1} = j | X_n = i\} \qquad i \geq 0, j \geq 0 \quad Eq.3$$

Where:

$P\{x = j|X = i\}$ = one-step transition probability

Regardless of value *n*, a transition probability matrix is defined by:

$$P = [p_{ij}] = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ p_{20} & p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \vdots & \end{bmatrix} \quad Eq.4$$

Where:

$$p_{ij} \geq 0 \quad \sum_{j=1}^{m} p_{ij} = 1 \qquad i = 0,1,2\ldots$$

If the state space *E* is finite and $\{1, 2, ..., m\}$ equivalent, *P* is *m* x *m* dimensional:

$$P = [p_{ij}] = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \quad Eq.5$$

Where:

$$p_{ij} \geq 0 \quad \sum_{j=1}^{m} p_{ij} = 1 \qquad i = 1,2,\ldots,m$$

3. Results and Discussion

3.1 Historical wet events using SPI

Figures 2, 3, and 4 depict the 6-month of time scale for Ladang Paya Lang station where the minimum value of wet event occurred in February 2001 was 1.00. While the maximum value of wet event was 2.96 which occurred in December 2007. It indicated that the rainfall had occurred extremely during that period. The wet event for this station also had occurred 11 times throughout the accumulation period. On the 9-month of time scale, the minimum and maximum value of wet event was 1.00 and 2.44 respectively. It indicated that the extreme rainfall had occurred in March 2008. The rainfall also had occurred moderately in August 2006. From the historical flood event, Johor was struck by storm causes heavy flooding in December 2006. The flood was said unusual as the return period of average rainfall for 2006 was 50 years [15]. Referring to 12-month of time scale, the minimum and maximum value of wet event was 1.00 and 2.73 respectively. It means that the wet event had occurred moderately in January 1995 and extremely in June 2008.

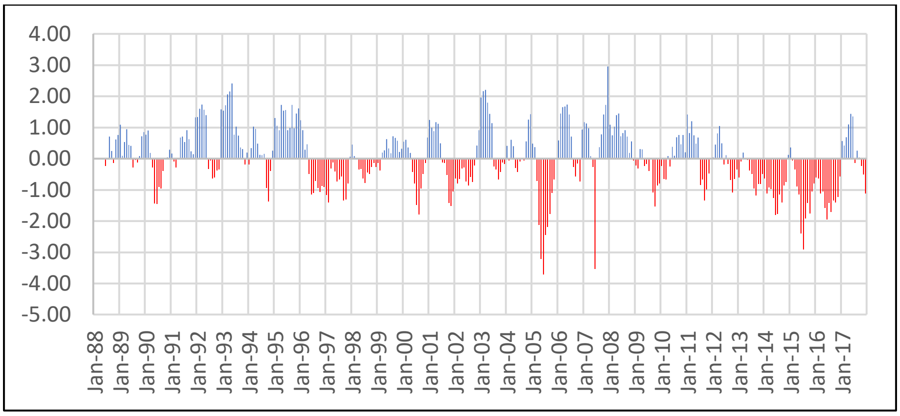

Figure 3: Wet events identified using SPI on 6-month time scale

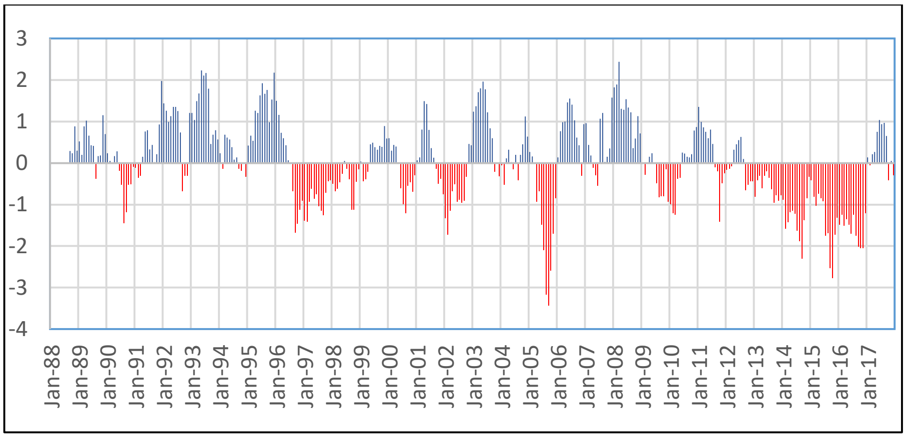

Figure 4: Wet events identified using SPI on 9-month time scale

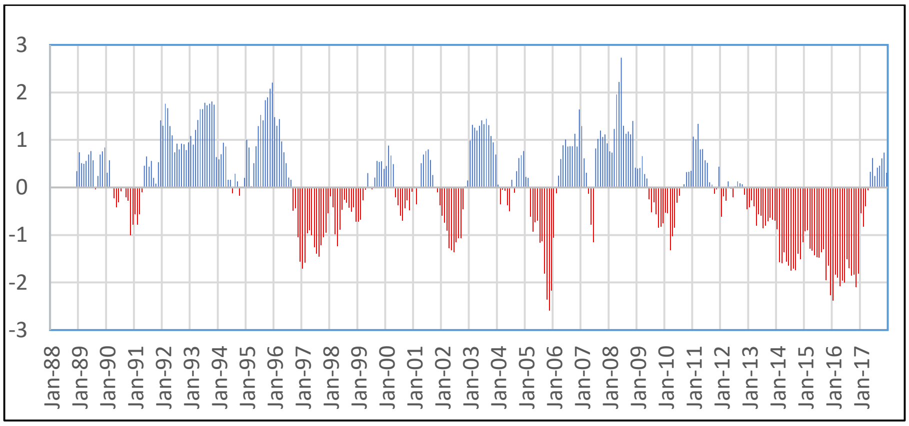

Figure 5: Wet events identified using SPI on 12-month time scale

3.2 Markov Chain Analysis

The 6-month, 9-month, and 12-month time scale of SPI values for Ladang Paya Lang station are tabulated in Table 1. It showed the number of transitions and occurrence of every flood class. For instance, for the 6-month of time scale, the transitions from NF in January to NF in December showed 150 occurrences. While the transitions NF in January to NN, Mod, and Sev showed 27, 0, 1 occurrence, respectively. This means that the sum of occurrences of NF were 178. The transitions of NN in January to NF, NN, Mod, and Sev in December showed 25, 70, 17, and 3 occurrences respectively, and the sum of the occurrences were 115. From Mod in January to NF, NN, Mod, and Sev in December, the transitions showed 3, 15, 11, and 4 respectively with the sum of occurrences equal to 33. While the transitions Sev to NF, NN, Mod, and Sev showed 23 occurrences in total. These probabilities were computed for 9-month and 12-month time scale and results were tabulated in Table 1.

Table 1: The number of transitions ($N_i^{(n)}$) and occurrences (N_i) of every flood class at Ladang Paya Lang station

Initial state	Non-Flood				Near Normal				Moderate Flood				Severe Flood			
6-month time scale (January – December)																
Next month state	NF	NN	Mod	Sev	NF	NN	Mod	Sev	NF	NN	Mod	Sev	NF	NN	Mod	Sev
$N_i^{(n)}$	150	27	0	1	25	70	17	3	3	15	11	4	0	3	5	15
N_i	178				115				33				23			
9-month time scale (January – December)																
$N_i^{(n)}$	142	24	2	0	26	84	11	3	0	14	15	5	0	2	6	15
N_i	168				124				34				23			
12-month time scale (January – December)																
$N_i^{(n)}$	149	19	0	0	19	94	11	1	0	11	22	5	0	1	5	12
N_i	168				125				38				18			

3.3 Flood Prediction

Referring to the results presented in Table 2, the class transfers from January to December for the 6-month time scale was computed. Matrix $P^{(1)}$, $P^{(2)}$, $P^{(3)}$, and $P^{(4)}$ are the values of transitions from the flood class in specific month to other flood class. The sample was estimated using a transition probability matrix by counting the number of times SPI moves from flood class.

$$P^{(1)} = \begin{array}{c} \\ \text{NF} \\ \text{NN} \\ \text{Mod} \\ \text{Sev} \end{array} \begin{array}{c} \begin{array}{cccc} \text{NF} & \text{NN} & \text{Mod} & \text{Sev} \end{array} \\ \begin{bmatrix} 0.843 & 0.152 & 0 & 0.006 \\ 0.217 & 0.609 & 0.148 & 0.026 \\ 0.091 & 0.455 & 0.333 & 0.121 \\ 0 & 0.130 & 0.217 & 0.652 \end{bmatrix} \end{array} \quad P^{(2)} = \begin{array}{c} \\ \text{NF} \\ \text{NN} \\ \text{Mod} \\ \text{Sev} \end{array} \begin{array}{c} \begin{array}{cccc} \text{NF} & \text{NN} & \text{Mod} & \text{Sev} \end{array} \\ \begin{bmatrix} 0.743 & 0.221 & 0.024 & 0.012 \\ 0.329 & 0.474 & 0.145 & 0.052 \\ 0.206 & 0.458 & 0.205 & 0.132 \\ 0.048 & 0.263 & 0.234 & 0.455 \end{bmatrix} \end{array}$$

$$P^{(3)} = \begin{array}{c} \\ \text{NF} \\ \text{NN} \\ \text{Mod} \\ \text{Sev} \end{array} \begin{array}{c} \begin{array}{cccc} \text{NF} & \text{NN} & \text{Mod} & \text{Sev} \end{array} \\ \begin{bmatrix} 0.676 & 0.260 & 0.043 & 0.021 \\ 0.393 & 0.411 & 0.130 & 0.066 \\ 0.291 & 0.420 & 0.165 & 0.124 \\ 0.119 & 0.333 & 0.216 & 0.332 \end{bmatrix} \end{array} \quad P^{(4)} = \begin{array}{c} \\ \text{NF} \\ \text{NN} \\ \text{Mod} \\ \text{Sev} \end{array} \begin{array}{c} \begin{array}{cccc} \text{NF} & \text{NN} & \text{Mod} & \text{Sev} \end{array} \\ \begin{bmatrix} 0.630 & 0.283 & 0.057 & 0.029 \\ 0.433 & 0.377 & 0.118 & 0.072 \\ 0.352 & 0.391 & 0.144 & 0.113 \\ 0.192 & 0.362 & 0.193 & 0.252 \end{bmatrix} \end{array}$$

From the transition probability matrix, the prediction of 1 to 4 months ahead can be computed. For the Ladang Paya Lang station, the prediction of 1 to 4 months ahead was computed with NF as initial state and December as initial month. The results obtained were 0.843 for 1 month ahead, 0.743 for 2 months ahead, 0.676 for 3 months ahead, and 0.630 for 4 months ahead, showed it was present state. Those probabilities were the highest among other states. When the initial state changed to NN, the probabilities of 1 to 4 months ahead were 0.609, 0.474, 0.411, and 0.433, respectively. However, the value at the probability transition from NN to NF was a bit higher compared to probability transition from NN to NN. At the Mod state, all probability transition from Mod to NN were higher than the value from Mod to Mod. The values were 0.455, 0.458, 0.420, and 0.391 for prediction of 1 to 4 months ahead, respectively. The probabilities transition for the Sev to Mod also a bit higher for the prediction of 3 and 4 months ahead compared to transition from Sev to Sev.

Table 2: Probability transition of prediction from 1 to 4 months ahead for Ladang Paya Lang station station at 6-month of time scale

Prediction		Non flood	Near normal	Moderate	Severe
1 month	Non flood	**0.843**	0.152	0.000	0.006
Next 2 mths		**0.743**	0.221	0.024	0.012
Next 3 mths		**0.676**	0.260	0.043	0.021
Next 4 mths		**0.630**	0.283	0.057	0.029
1 month	Near normal	0.217	**0.609**	0.148	0.026
Next 2 mths		0.329	**0.474**	0.145	0.052
Next 3 mths		0.393	**0.411**	0.130	0.066
Next 4 mths		**0.433**	0.377	0.118	0.072
1 month	Moderate	0.091	**0.455**	0.333	0.121
Next 2 mths		0.206	**0.458**	0.205	0.132
Next 3 mths		0.291	**0.420**	0.165	0.124
Next 4 mths		0.352	**0.391**	0.144	0.113
1 month	Severe	0.000	0.130	0.217	**0.652**
Next 2 mths		0.048	0.263	0.234	**0.455**
Next 3 mths		0.119	**0.333**	0.216	0.332
Next 4 mths		0.192	**0.362**	0.193	0.252

The result obtained for the 9-month timescale was tabulated in Table 3. For the probability transition of NF to NF, the values obtained were 0.845, 0.744, 0.676, and 0.628, for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively. The prediction for NN to NN was 0.677, 0.527, 0.451, and 0.416, for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead respectively. The prediction for Mod to Mod was 0.441, 0.473, 0.459, and 0.435 for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively. For Sev to Sev, the prediction was 0.652, 0.466, 0.352, and 0.364 for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively.

Table 3: Probability transition of prediction from 1 to 4 months ahead for Ladang Paya Lang station station at 9-month of time scale

Prediction		Non flood	Near normal	Moderate	Severe
1 month	Non flood	**0.845**	0.143	0.012	0.000
Next 2 mths		**0.744**	0.222	0.028	0.005
Next 3 mths		**0.676**	0.269	0.042	0.013
Next 4 mths		**0.628**	0.297	0.054	0.021
1 month	Near normal	0.210	**0.677**	0.089	0.024
Next 2 mths		0.319	**0.527**	0.108	0.045
Next 3 mths		0.380	**0.451**	0.110	0.058
Next 4 mths		**0.416**	0.410	0.108	0.065
1 month		0.000	0.412	**0.441**	0.147

Table 3: (Continued)

Next 2 mths	Moderate	0.086	**0.473**	0.270	0.171
Next 3 mths		0.172	**0.459**	0.206	0.162
Next 4 mths		0.242	**0.435**	0.176	0.147
1 month	Severe	0.000	0.087	0.261	**0.652**
Next 2 mths		0.018	0.223	0.293	**0.466**
Next 3 mths		0.062	0.315	0.271	**0.352**
Next 4 mths		0.119	**0.364**	0.240	0.277

The probability transition of prediction for the 12-month of timescale was tabulated in Table 4. For the probability transition of NF to NF, the values obtained were 0.887, 0.804, 0.741, and 0.693, for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively. When the prediction changed to near normal, the values for NN to NN was 0.752, 0.609, 0.522, and 0.467, for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead respectively. The prediction for Mod to Mod was 0.579, 0.397, 0.424, and 0.429 for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively. For Sev to Sev, the prediction was 0.667, 0.481, 0.368, and 0.327 for 1 month ahead, 2 months ahead, 3 months ahead, and 4 months ahead, respectively.

Table 4: Probability transition of prediction from 1 to 4 months ahead for Ladang Paya Lang station station at 12-month of time scale

Prediction		Non flood	Near normal	Moderate	Severe
1 month	Non flood	**0.887**	0.113	0.000	0.000
Next 2 mths		**0.804**	0.185	0.010	0.001
Next 3 mths		**0.741**	0.233	0.022	0.003
Next 4 mths		**0.693**	0.266	0.034	0.007
1 month	Near normal	0.152	**0.752**	0.088	0.008
Next 2 mths		0.249	**0.609**	0.119	0.023
Next 3 mths		0.313	**0.522**	0.129	0.036
Next 4 mths		0.357	**0.467**	0.131	0.045
1 month	Moderate	0.000	0.289	**0.579**	0.132
Next 2 mths		0.044	0.393	**0.397**	0.166
Next 3 mths		0.099	**0.424**	0.311	0.166
Next 4 mths		0.152	**0.429**	0.263	0.155
1 month	Severe	0.000	0.056	0.278	**0.667**
Next 2 mths		0.008	0.159	0.351	**0.481**
Next 3 mths		0.032	0.249	0.351	**0.368**
Next 4 mths		0.066	0.313	**0.327**	0.294

4. Conclusion

The overall aim of this study was to forecast flood of selected station in Johor using Markov Chain Model. The first objective of this study was to identify the historical flood using SPI. Based on the results, the SPI can effectively identify the wet event occurred from 1988 to 2017. Referring to the characteristic of SPI, the 6-month, 9-month, and 12-month of time scales, which refers to accumulation period of 6, 9, and 12 months, respectively, indicated for measuring flood risk and sub-soil moisture. The results from SPI also showed the severity of historical flood. The second objective of this study was applying Markov Chain Model to forecast wet event and determining its effectiveness. Markov Chain Model has successfully computed the probability of flood occurrence. From the transition probability matrix, the prediction of 1 to 4 months ahead can be identified. The prediction was limited up to 4 months ahead to maintain its accuracy. The results obtained show that Markov Chain has the potential to predict the flood for 1 to 4 months ahead. By applying the transition probability matrix formula, the evolution of wet events can be comprehended.

Acknowledgement

The author would like to thank supervisor Dr. Siti Nazahiyah Binti Rahmat, for guiding throughout the project and acknowledge the Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn Malaysia for its support.

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