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Drought Forecasting using SPI and EDI under RCP-8.5 Climate Change Scenarios for Langat River Basin, Malaysia

Yuk Feng Huang[a], Jong Tat Ang[a]*, Yong Jie Tiong[a*], Majid Mirzaei [a*], Mohd Zaki Mat Amin [b]

[a]*Department of Civil Engineering, Lee Kong Chian Faculty of Engineering & Science, Universiti Tunku Abdul Rahman, UTAR Sungai Long Campus, Jalan Sungai Long, Bandar Sungai Long, 43000 Cheras, Kajang, Selangor, Malaysia*
[b]*Water Resources and Climate Change Research Centre, National Hydraulic Research Institute Malaysia (NAHRIM), Jalan Putra Permai, 43300 Seri Kembangan, Selangor, Malaysia*

Abstract

In Malaysia, droughts often lead to water deficit and overcoming a lack of fresh water has become one of the important challenges in the country. Climate change have brought about a big environmental impact globally, such as the rise in sea levels, unavailability of fresh portal water and more extreme drought and flood events occurring and Malaysia is no different and not spared all this calamities. The Langat River Basin is located in a fast growing region in Peninsular Malaysia, the Greater Kuala Lumpur Valley and hence the implementation of the drought index in this basin is vital important and necessary. Normally drought characteristics can be determined or identified using the drought indices. The two drought indices were used in this study, namely the SPI (Standardized Precipitation Index) and the EDI (Effective Drought Index) to assess the severity, duration and extend of drought event. The CanESM2 outputs under Representative Concentration Pathway (RCP) 8.5 emission scenario of IPCC Fifth Assessment Report (AR5) were utilized to produce regionalized precipitation and temperature data. The GCM outputs were statistically downscaled using the Statistical Downscaling Model (SDSM) version 4.2.9. Next, the SPI for time scale period of 1-month, 6-months and 12-months (SPI-1, SPI-6 and SPI-12) and EDI were calculated for both the observed and statistically downscaled climate data to investigate and analyze the severity and extent of drought. Both indices were compared to get a more operational index between SPI-1, SPI-6, SPI-12 and EDI outlook for representing Malaysia drought events.

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* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: author@institute.xxx

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1. Introduction

Droughts have become a frequent occurrence in many parts of the earth surface and are a calamity of big magnitude that needs global intervention. The reasons of drought occurrence are a deficiency of rainfall and prolonged periods of warmer temperatures. Recurring and permanent droughts will inevitably lead to desertification of sizeable areas of our planet. Since there is no single definition for droughts, a wide range of drought identification and assessment indexes had been introduced to monitor drought: the Standardized Precipitation Index (SPI) [1], Standardized Precipitation Evapotranspiration Index (SPEI) [2] and Effective Drought Index (EDI) are the commonly used for gauging droughts. This study focuses on the Langat River Basin, a fast growing urbanized region in Malaysia. In this study, the SPI and EDI will be analysed and used to identify the severity of potential future drought events. The main objective of this study is as follows: (i) to develop a future rainfall scenario for the 21st century, (ii) to investigate and analyse the severity and extent of drought events, and (iii) to develop a framework for operational drought indices outlook for the Langat River Basin.

2. Methodology

Rainfall observations from a specific station were used to establish SPI and EDI time series baseline and identify drought during 1976 to 2011. This observed rainfall is further used along with other large scale data such as NCEP and GCM data to downscale future rainfall event. Future rainfall generated based on the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) scenario are then examined for future drought events using the SPI and EDI. The methods and data used here are described below.

2.1. Location of study and precipitation

The Langat River Basin in the state of Selangor, Malaysia has a total catchment area of about 1815 km^2, formed by 15 sub-basins which lie within latitudes 2˚40’15” N to 3˚16’15” N and longitudes 101˚19’20” E to 102˚1’10” E. This basin is a fast growing region in this country in terms of rapid urbanization, new build-up areas, modern road network, industrialization and agricultural expansion. Unavoidably, the basin is subject to dire consequences of land use and land cover changes, pollution stress, forest fragmentation, depletion of ecosystem. These posed numerous challenges to sustainable development. Under such circumstances, the implementation of a best suited drought index on future climate outlook was deemed necessary. The rainfall data from station 3818110 at Sekolah Kebangsaan Kampung Sungai Lui (3°10'25"N, 101°52'20"E, 91.0m above sea level), was use to represent Langat River Basin. One of the reasons of this selection was due to its close proximity to the Langat reservoir. The 36 years (1976-2011) data available had been subjected to homogeneity tests before perusal.

2.2. General Circulation Model and downscaled data

The Canadian Earth System Model, CanESM2 Model from Canadian Centre for Climate Modeling and Analysis (CCCma) was chosen as a sole GCM output used for generating future rainfall in Langat River Basin. This model employed T63 triangular truncation with spatial resolution of 128x64 and 35 vertical layers [3]. In this study, Representative Concentration Pathway - 8.5 W/ m2 (RCP 8.5) scenario was employed rather than the ‘peak-and-decline’ scenario (RCP 2.6) or ‘stabilization’ scenario (RCP 4.5 and RCP 6.0). This decision was made because of the assumption that the GHG emissions will continue to rise according to current trends. Our goal was to project future drought based on the continuity of the present level of CO2 emissions which more likely to happen as no significant strategies of GHG reduction has come into play yet. Besides the GCM data, the NCEP/NCAR Reanalysis data was another set of large scale data used in the downscaling model to establish the statistical relationship with observed station data. This Global Reanalysis Model has a resolution of about 210 km horizontally and 28 levels vertically [4].

The Statistical Downscaling Model (SDSM) version 4.2.9 developed by [5] was adopted as the only downscaling model. The SDSM calculates statistical relationship of large-scale data (predictors) and regional data (predictands) based on multiple linear regression techniques. The procedures of rainfall downscaling are summarized as: (i) Screen variables-a crucial step to establish a creditable regression model and involved the selection of most suitable NCEP predictors, (ii) Calibration- a conditional process in establishing monthly regression function between selected predictors and 20 years of observed data, (iii) Validation- a process to justify the validity of downscaled for further usage, and (iv) Scenario generation-involving generation of future rainfall from 2016 to 2100.

2.3. Computation of Standard Precipitation Index (SPI)

The method of SPI computation herein follows the exact way proposed by [1]. For the prediction of future drought events, two parts of SPI computation were carried out. For the first part, SPI was computed based on the observed rainfall from 1976-2011 (36 years of data). The Gamma probability distribution function was chosen to describe the rainfall in Peninsular Malaysia. This probability distribution function is similar to the method first proposed by [1] in their research for computation of SPI and its suitability is further proven by Sharma and Singh (2010)[3] for description of rainfall in monsoon seasons. After that, the function was further normalized and standardized to obtain the SPI value. In other words, the SPI value is a z-score of the distribution function which represents a deviation event from the mean of historical rainfall data.

The second part is the computation of futuristic SPI, which is almost the same as part one but using generated rainfall from previous section at year 2016 to 2100. The difference is the SPI value at this part was computed based on the rainfall distribution established in part one (year 1976 to 2011). In other words, the future rainfalls were used to compare with the mean and standard deviation of historical rainfall to generate SPI value. This decision was made with the consideration of a more comprehensive way to present how far the deviated rainfall event will go based on the current scenario. As mentioned above, the downscaled rainfall from GCM only consists 365 days per year, the 29th February of leap year will then be assumed to have the same rainfall as on the 28th February in the drought index computation.

One of the advantages of SPI is the flexibility in choosing its time scale. This research focus only on SPI-1, SPI-6 and SPI-12, which are 1-month, 6-month and 12-month time scale respectively. This decision was made with the reason that SPI-1, SPI-6 and SPI-12 is suitable to describe meteorological, agricultural and hydrological drought respectively and fit to the purpose of this study. The calculation of SPI values here follows the method by [6] and demonstrated in the following steps:

First, the cumulative gamma distribution is defined as:

$$\mathrm{G}(x_{\mathrm{k}}) = \int_0^{\chi_k} g(x_k)dx_k = \frac{1}{\beta^{\alpha}\Gamma(a)}\int_0^{x_k} x_k^{\alpha^{-1}} e^{-x_k/\beta} dx_k \qquad (1)$$

Where α is shape factor, β is scale factor, and x_k is the amount of precipitation over k consecutive months (selected time scale) in millimeter. The function Γ (α) is the gamma function and the parameters α and β to be estimated using the approximation by [7].

When x_k = 0, the cumulative gamma distribution is undefined and, the cumulative probability may be written as below to encounter this situation.

$$\mathrm{H}(x_{\mathrm{k}}) = q + (1-q)G(x_{\mathrm{k}}) \qquad (2)$$

Where, q is probability of zero rainfall.

The cumulative probability, $H(x_k)$, is then standardized to obtain the value of SPI. Lastly, the approximate conversion provided by [8] will be used in this study to calculate SPI values.

$$Z = \mathrm{SPI} = -\left(\mathrm{t} - \frac{\mathrm{c}_0 + \mathrm{c}_1 t + \mathrm{c}_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{\ln\left(\frac{1}{H(x_k)^2}\right)} for 0 < H(x_k) < 0.5 \quad (3)$$

And,

$$Z = \mathrm{SPI} = \left(\mathrm{t} - \frac{\mathrm{c}_0 + \mathrm{c}_1 t + \mathrm{c}_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{\ln\left(\frac{1}{(1 - H(x_k))^2}\right)} for 0.5 > H(x_k) < 1.0 \quad (4)$$

Where c_0 = 2.515517, c1 = 0.802853, c2 = 0.010328, d1 = 1.432788, d2 = 0.189269, d3 = 0.001308.The negative values indicate the rainfall is less than median of historical precipitation.

The drought classification of SPI values are classified by certain ranges. It represents mild drought when the SPI values fall in between 0 to -0.99, moderate drought when -1.00 to -1.49 and severe drought when the SPI values between -1.5 to -1.99. When the SPI values fall below -2.00, it indicates an extreme drought event.

2.4. Computation of Effective Drought Index(EDI)

EDI was developed to monitor drought condition on daily time step [9] [10]. Subsequently, it was extended for monthly drought monitoring [11]. In this study, daily time step EDI was chosen. The computation of EDI involves the following equations:

$$EP = \sum_{n=1}^{i}\left[\left(\sum_{m=1}^{n} P_m\right) / n\right] \quad (5)$$

$$\mathrm{DEP} = \mathrm{EP} - \mathrm{MEP} \quad (6)$$

$$\mathrm{SEP} = \mathrm{DEP_i} / \mathrm{Std}(\mathrm{DEP_i}) \quad (7)$$

$$\mathrm{EDI} = \mathrm{DEP_j} / \mathrm{Std}(\mathrm{DEP_j}) \quad (8)$$

The effective precipitation (EP) represents the total amount of daily precipitation relative to a time dependent reduction function, where P_m is the precipitation of m days ago, N is the duration of preceding period, and *i* is the duration of summation. At first, *i* is set to be 365 days, as it could be representative of available water resources or water stored for a long duration. Several equations to calculate the EP had been proposed but the equation above is the most suitable to show the depletion of water resources [12]. The mean effective precipitation (MEP) represents the mean of the EP values over the study period. Thus, DEP is the deviation of the actual precipitation from its mean. The next step was to compute the standardized value of DEP (SEP), where Std(DEP) is the standard deviation of each day's DEP. In order to take into account of dry period longer than 365 days, *j* value is considered as 356 plus the consecutive negative value of SEP. Finally, EDI is computed from DEP of *j* period instead of *i*=365.

As mentioned in the SPI computation, EDI computation in this study involves two parts as well. The historical EDI is computed based on the rainfall records from year 1976 to year 2011. The futuristic EDI was computed based on the mean and standard deviation generated from historical EDI and rainfall downscaled from CanESM2 using SDSM (year 2016 to 2100).

3. Results and discussion

3.1. Statistical rainfall downscaling

The list of selected predictor variables, their correlation coefficient and significance level for stations 3818102 is given in Table 1.

Table 1. Screening results.

Predictand	Predictors	Description of Predictor	Partial r	P-value
Precipitation (3118102)	P1_zgl (lag 5)	1000hPa Relative vorticity of wind	0.031	0.0911
	P8zhgl (lag 1)	850hPa Divergence of true wind	-0.042	0.0197
	S850gl	850hPa Specific humidity	0.037	0.0465
	Mslpgl	Mean sea level pressure	-0.002	0.5610

For the selection of predictors, the significant level is set to be 10%, which means the P-value more than 0.1 should be rejected. From Table 2, however, the mean sea level pressure with a large P-value is still included as predictor because the local precipitation is largely dependent on this variable and thus should not be excluded.

The results of calibration and validation are shown in Table 3. The explained variance and standard error of calibration were based on the average values of each month while the explained variance of validation part was computed from monthly average of model generated rainfall and observed rainfall.

Table 2. Result of calibration and validation.

Predictand	Calibration		Validation
	Explained Variance, %	Standard Error	Explained Variance, %
Precipitation (3118102)	24.0	0.473	78.3

In general, the relationship of selected predictors and predictand (rainfall) is considered low. Thus, the calibration result of the model does not give a high explained variance as well. For the purpose of this study, a good validated monthly rainfall would be enough. Thus, 78% of correlation is accepted. On the other hand, a higher correlation in validation of daily rainfall does not indicate a high accuracy of future rainfall prediction. Futuristic rainfall is highly dependence on the accuracy of the General Circulation Model used.

3.2. Drought indices comparison

On average, the indices perform differently with a same series of rainfall. However, a trend still can be observed. Graphically, SPI-12, SEP and EDI agree with each other to some extend while SPI-1 deviate from this three indices most. Coefficient of correlation among indices from Table 3 suggest SEP and EDI have a correlation as high as 0.995. The second highest correlation is between SEP and SPI-12 while EDI and SPI-12 have a correlation of 0.893. Highest correlation between SEP and EDI can be explained with the same distribution chosen in index computation, while the high correlation between SEP and SPI-12 is due to both of these indices basically consider 12 months precipitation. Correlation between EDI and SPI-12 does not expect to have highest correlation as EDI consider the drought longer than 12 months and probability distribution chosen to describe rainfall by these two indices is not the same.

Table 3. Coefficient of correlation among drought indices.

Drought Index	SEP	EDI	SPI-1	SPI-6	SPI-12
SPI-1	0.171	0.171	1.000	0.391	0.219
SPI-6	0.533	0.530	0.391	1.000	0.656
SPI-12	0.903	0.893	0.219	0.656	1.000
SEP	1.000	0.995	0.171	0.533	0.903
EDI	0.995	1.0	0.171	0.530	0.893

It could be observed that EDI identify a longer period of drought than SPI-12. In other words, SPI-12 might underestimate the drought period as it only considers 12 months rainfall before the concerned month. A longer period of rainfall deficit than 12 months will not be taken into account by SPI-12 unless a longer time scale SPI is used. EDI, on the other hands, considers the dryness more than 12 months until the rainfall deficit recovers to normal. Thus, a false recover signal will not be given by EDI unless the rainfall shortage is truly over.

SPI computation involves analysis of the monthly rainfall deviation from its recorded rainfall series of that particular month. For example, the SPI value at February 2016 is computed by analyzing its rainfall deviation from February rainfall series of 1976 to 2011. On the other hand, EDI considers the average daily rainfall throughout the year in index computation (analyzes how much daily rainfall of day concerned deviated from average daily rainfall of year 1976 to 2011 regardless the month and date). This could explain the scenario why SPI-12 of November is generally lower than other months even though the rainfall over 12 consecutive months at November is generally higher than others.

The correlation between SPI-1 and EDI is the lowest among others. The correlations between SPI-1 with other indices are generally low as well (less than 0.5). This suggests that SPI-1 identify drought differently with others. Since only one month of rainfall is considered into computation, SPI-1 is more likely to detect drought of shorter period and these droughts may not be detected with longer time scale drought indices such as SPI-12 and EDI. This could be the scenario of a relatively low amount of rainfall in dry season follows or followed by a high rainfall event in rainy season. In this situation, longer-time-scale index cannot detect such drought occurrence. Therefore, a high fluctuation of SPI-1 can be observed in Figure 1.

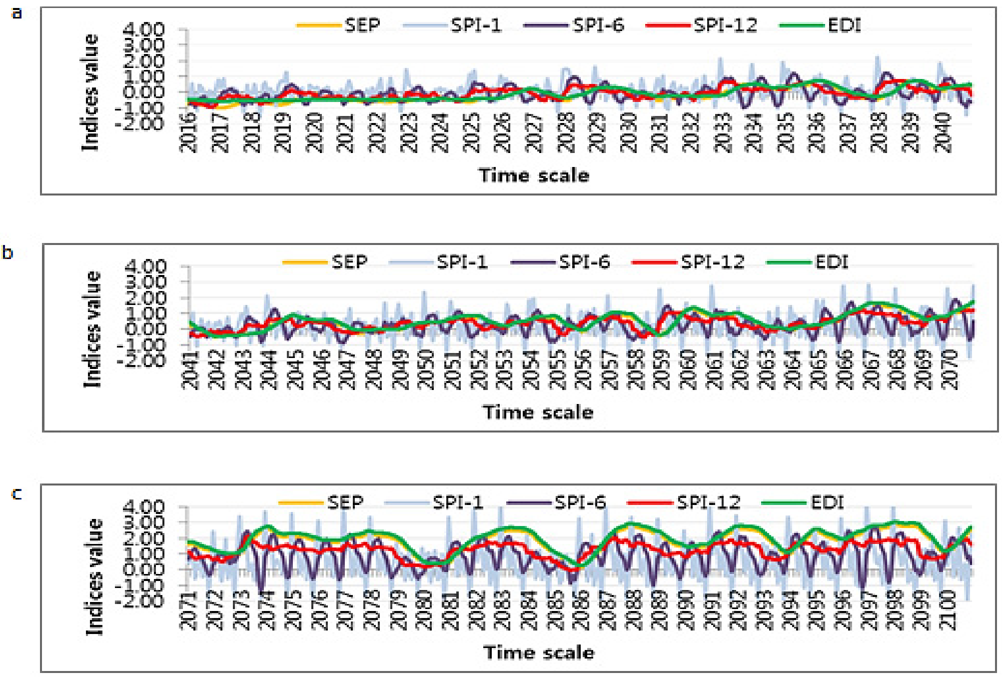

Figure 1.Comparison of SEP, EDI, SPI-1, SPI-6, and SPI-12 under RCP8.5 at station 3118102 from year (a) 2016-2040; (b) 2041-2070; (c)2071-2100.

The longest drought duration is successfully identified by EDI with the period of 127 months starting from January 2016, as shown in Table 4. This again proves EDI as a good indicator for hydrological drought. EDI suggests that the shortage rainfall will only recover and return back to normal on July 2026. This information is deemed to be important for the Langat reservoir located near to the station. SPI-6 have identified the longest total period of droughts happens between the 2016 to 2100, which is 370 months out of 1140 months (33%). Since SPI-6 is an indicator for agricultural drought, this could be an alert to the agricultural activities within Langat River Basin. However, within 370 months, only two months of them consist SPI less than -1.0. Thus, no frequent severe agricultural drought is expected to happen within the period of study.

Table 4.Summary statistics of indices.

Drought Index	SPI-1	SPI-6	SPI-12	SEP	EDI
Highest drought index	4.271	2.705	2.111	2.827	3.021
Lowest drought index	-0.914	-1.384	-0.908	-0.999	-0.560
Total amount of drought months (month)	363	370	245	271	259
Longest continuous drought months (month) and period	4 (Jul – Oct of year 2022, -23, -30, -33, -34, -36, -42, -46, -73, -74, -76, -88, -96, -97 & -98)	17 (Aug 17 – Dec 18 & Jul 23 – Nov 24)	67 (Jul 19 – Jan 25)	120 (Jan 16 – Nov 25)	127 (Jan 16 – June 26)

4. Conclusions

Drought is obviously one of the more damaging yet hardly determined natural disasters among others. Drought monitoring using drought indices often serves as an important base. Drought indices computed from forecasted rainfall gives a better outlook of potential risk that may be inflicted upon the region. In this study, a means is provided to compare among drought indices of different time scales for further study into respective drought types.

The usage of SDSM in future rainfall downscaling is deemed to be sufficient for drought index computation although the rainfall generation might not be highly accurate. The comparison between SPI-1, SPI-6, SPI-12, SEP, and EDI suggests that all these indices are correlated to certain extent especially SPI-12, SEP and EDI. For hydrological drought, EDI performs better in the sense of less likelihood of the index to produce false signal of drought recovery. Even though the SPI-1 does not seem to agree with other indices, it serves to identify the local meteorological drought which is not detected well by other indices of longer time scales. Thus, the preference for each method and drought indices for drought monitoring depends on the particular application.

In this study, clime change and alteration of rainfall patterns have been detected by all drought indices especially SPI-1. Generally, the rainfall amount increases in future. This conclusion is drawn from high averages indices value (higher than zero).A higher rainfall in future December and a lower rainfall amount in October would be expected in Langat River Basin according to the research. All in all, the drought indices in this study are able to monitor the evolution of a drought event. With the combination of future rainfall downscaled by SDMS, a framework of future drought event outlook could be generated. This information could help the state authority in aspects of drought management.

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