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STANDARDIZED PRECIPITATION INDEX (SPI) AND STANDARDIZED PRECIPITATION EVAPOTRANSPIRATION INDEX (SPEI) DROUGHT CHARACTERISTIC AND TREND ANALYSIS USING THE SECOND GENERATION CANADIAN EARTH SYSTEM MODEL (CanESM2) OUTPUTS UNDER REPRESENTATIVE CONCENTRATION PATHWAY (RCP) 8.5

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Abstract: In the era of changing climate, drought assessment and monitoring are vital at the Langat River Basin, a fast-growing region in Peninsular Malaysia with two dams located in the basin. Drought indices Standardized Precipitation Index (SPI) that is solely based on rainfall, and Standardized Precipitation Evapotranspiration Index (SPEI) that considers both rainfall and potential evapotranspiration (PET), were adopted to assess the frequency and severity of droughts in this study. The General Circulation Model (GCM) outputs from the second generation Canadian Earth System Model (CanESM2) under the Representative Concentration Pathway (RCP) 8.5 were statistically downscaled using the Statistical Downscaling Model (SDSM) version 4.2.9 to produce the required regionalized rainfall and temperature data. Both indices with respective time scales of 1-, 3- and 6-month were calculated using observed and the projected climate data. Downscaling results showed that temperature of the basin will increase drastically in 2021-2050. Therefore, PET should not be excluded in drought assessments. It was found that SPI tends to underestimate drought events, and its correlation with SPEI decreases over time. Hence, SPEI, that considers the effect of PET, is more suitable for describing drought events. In general, projected high rainfall reduces the frequency and severity of drought in the Langat River Basin.

Keywords: Drought Characteristic and Trend, SPI, SPEI, RCP 8.5, CanESM2, SDSM

1. INTRODUCTION

Water is a vital resource for human's health, society and the environment. It is not only the key resource for human beings, but it also has a significant influence on the ecosystem. However, because of its high temporal and spatial distribution variability, this often results in water deficiency in different places and at different times. Environmental issues such as global warming and climate change further amplify the variability and severity of these water resources. Thus, water planning and management is a challenging yet rewarding mandatory task in many regions. Drought is one of the main challenges in the planning and management of water resources. It is a crucially damaging yet least understood natural disaster. Drought events evolve slowly as below-average rainfall over a long span and their impacts could last over a long period. Because of this slow onset characteristic, its onset and offset are hard to be determined. The significant spatial and temporal variability of precipitation also increases the difficulty of drought identification. A drought is loosely defined as a prolonged and abnormal moisture deficiency phenomenon at a given place and is particularly associated with certain periods of significantly lower rainfall, soil moisture, surface water storage, streamflow, and ground water level.

Recurring and permanent droughts will inevitably lead to desertification of sizeable areas on our planet. Since there is no set definition for droughts, a wide range of drought identification and assessment indices had been introduced to monitor and gauging droughts, including the well-known Standardized Precipitation Index (SPI) (Edwards & McKee, 1997), Effective Drought Index (EDI) (Byun & Wilhite, 1999), Palmer Drought Severity Index (PDSI) (Palmer, 1965), Reconnaissance Drought Index (RDI) (Tsakiris & Vangelis, 2005) and Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). These have been widely used for drought monitoring and forecasting studies and have proven effective for describing the frequency and severity of droughts (Venkataraman et al., 2016; Huang et al., 2016; Sierra & Kaya, 2016; Ruqayah & Miklas, 2017; Soh et al., 2018).

According to The Intergovernmental Panel on Climate Change (IPCC), current researches show that anthropogenic emissions of greenhouse gases (GHG) are at its highest in record, highly affecting both society and environment (IPCC, 2014a). One of the impacts to the environment is that of the changing in climate. The projected change of climate system done by IPCC (2014b) predicted that the global surface temperature at the end of 21st century would likely exceed 1.5 ˚C relative to the 1850-1900 average temperature and has a high probability to exceed 4.0 ˚C as well, in one of their projection scenarios. Evidences are showing that with climate change comes changing rainfall pattern and snow/ice melts, which resulted from a changing hydrological system and affecting water sources in term of quality and quantity. All these outcomes affirm that the projection of future climate can no longer be based solely on the statistical analysis of historical records alone, but instead the climate change factors should be included in the prediction of futuristic weather. Climate change assessment generally deals with global Green House Gas (GHG) emissions. In the IPCC Third Assessment Report (TAR), the Special Report on Emissions Scenarios (SRES) was introduced as a report that describes the GHG emission scenarios. It was later superseded by the Representative Concentration Pathways (RCPs), which are the four GHG concentration trajectories employed by the IPCC Fifth Assessment Report (AR5) namely RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. Corresponding to the current CO_2 concentration of about 400 ppm (IPCC, 2014b), the RCP 8.5 scenario where the world's GHG emissions continue to increase resulting in CO_2 concentration exceeding 900 part per million (ppm) by 2100 is the prime focus for this study.

General Circulation Models (GCMs), or sometimes referred as Global Climate Models, are important tools to describe and simulate the components of the climate system and their interaction with each other. More than that, these models are able to estimate the response of climate system under changing GHG emissions in the future, which can be used for future drought risk assessment (Burke at al., 2006). However, the coarse spatial resolution of GCMs about 250km is impractical for direct usage in the regional study of hydrology. Thus, a process of downscaling is necessary to generate higher resolution localized data from the coarse global climate projection. In the past few decades, many downscaling methods have been proposed and tested. They can be identified into the dynamical downscaling and the statistical downscaling categories (Mearns et al., 1999). The first approach is a model-based methodology where the output from the GCM is used to drive a regional climate model (RCM) in higher spatial resolution. The statistical downscaling on the other hand assumes that the local climate is a function of two factors: the large-scale climate state and regional physiographic features. Compared to dynamical downscaling, statistical downscaling directly relates the GCM output to impact-relevant variable without the necessity of simulation by climate models. This allows the users to have flexibility in monitoring the parameters and creating appropriate functions based on their professional analysis.

Malaysia, as every other country, is inevitably undergoing the process of climate change. In addition, future increment of average annual air temperature for the country was reported to be 0.5°C-1.0°C up to 2030, and further to 0.9°C -1.6°C up to 2050 (MESTECC, 2018). Hence, the main objective of this study is to develop drought indices using rainfall and temperature statistically downscaled from the second generation Canadian Earth System Model (CanESM2) under the Representative Concentration Pathway (RCP) 8.5 using the Statistical Downscaling Model (SDSM) version 4.2.9, followed by analysing the frequency and severity of future drought events under climate change in 2021-2050 for the Langat River Basin, a fast-growing urbanized region in Selangor, Malaysia. According to the study done by Amirabadizadeh et al. (2015), the basin was identified to start experiencing increasing trends of both rainfall and temperature since year 2000. The basin is also projected to have increasing rainfall and temperature in the future (Amirabadizadeh et al., 2017). Hence, SPEI was selected in this study to consider both hydrological (rainfall) and ecological (potential evapotranspiration, PET) variables, and represents different types of drought with its multi-scalar characteristic (Fung et al., 2018). The SPEI was constructed using observed

(1976-2011) data and projected downscaled (2021-2050) rainfall and temperature. As for the benchmark index, the well-known index SPI was included for comparison purposes. Incidentally, the SPI is the only drought index currently being used by the authorities in Malaysia to monitor drought (MetMalaysia, 2014).

2. METHODOLOGY

The observed rainfall was used to establish baseline SPIs, while baseline SPEIs were established using both observed rainfall and temperature data, to identify drought events from 1976 to 2011 (36 years) for the study area. These observed rainfall and temperature data were also used in conjunction with other large-scale data such as the National Centers for Environmental Prediction - National Center for Atmospheric Research (NCEP-NCAR) and General Circulation Model (GCM) data in downscaling RCP 8.5 future rainfall for examining future drought events using SPI and SPEI.

2.1. Study area

The Langat River Basin in the state of Selangor, Malaysia has a total catchment area of about 1,815 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 and 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, 91.0 m above sea level) and the temperature record from station 48648 at Petaling Jaya (3°06'00"N, 101°39'00"E, 45.7 m above sea level), were used to represent the Langat River Basin. These stations were selected due to the proximity to the Langat Reservoir and the Semenyih Reservoir. The 36 years of rainfall data was tested for homogeneity prior to study adoption.

2.2. General Circulation Model and downscaled data

The second generation Canadian Earth System Model, CanESM2 Model from Canadian Centre for Climate Modelling and Analysis (CCCMA) was chosen as a sole GCM output used for generating future rainfall in Langat River Basin. This model employed T63 triangular truncations with spatial resolution of 128 x 64 and 35 vertical layers (Arora & Boer, 2014). In this study, Representative Concentration Pathway 8.5 W/ m^2 was chosen rather than the ‘peak-and-decline’ scenario (RCP 2.6) or ‘stabilization’ scenario (RCP 4.5 and RCP 6.0). The decision was made due to the assumption that the GHG emissions will continue to rise according to current trends. The goal of study was to project future drought based on the continuity of the present level of CO_2 emissions, which is very likely to happen as no significant strategies of GHG reduction are in place. In addition to the GCM data, the National Centers for Environmental Prediction - National Center for Atmospheric Research (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 (Kalnay et al., 1996). Given the advantage that statistical downscaling directly relates the GCM output to impact-relevant variable and allows the users to have flexible monitoring on the parameters and creating appropriate functions based on professional analysis, the Statistical Downscaling Model (SDSM) version 4.2.9 developed by Wilby and Dawson (2013) was the downscaling model for this study. In addition, it showed high capability in capturing wet-spells and dry spells length in one of the studies carried out in Langat River Basin (Amirabadizadeh et al., 2016).

2.3. Computation of Standard Precipitation Index (SPI)

For the prediction of future drought events, two parts of the SPI computation were carried out. For the first part, SPI was computed according to the observed rainfall from 1976-2011 (36 years of data). The Gamma distribution function was chosen to describe the rainfall in Peninsular Malaysia. This probability distribution function is similar to the method first proposed by McKee et al. (1993) in their research for the computation of SPI and its suitability was reaffirmed by Sharma and Singh (2010) for the description of rainfall during 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 the futuristic SPI, which has the same procedures as part one but carried out using the generated rainfall from 2021 to 2050. Another difference is the SPI value at this part was computed according to 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 comprehensive way to present the deviated rainfall event according to the current scenario. It is noteworthy that the downscaled rainfall from GCM only consists of 365 days per year, the 29th February of leap year was assumed to have the same rainfall as on the 28th February in the drought index computation of this study.

One of the advantages of the SPI is the flexibility in choosing its time scale. This research focuses on SPI-1, SPI-3 and SPI-6, which are the 1-, 3- and 6-month time scale values, to represent meteorological, agricultural and hydrological droughts (WMO, 2012). The current drought monitoring practice in Malaysia is also adopting these time scales (MetMalaysia, 2014). The calculation of the SPI values follows the method proposed by Asadi et al. (2014). The drought classification of SPI values is classified by certain ranges. Mild drought occurs when the SPI values fall between 0 to -0.99, moderate drought when -1.00 to -1.49 and severe drought between -1.5 to -1.99. When the SPI values fall below -2.00, it indicates an extreme drought event.

2.4. Computation of Standard Precipitation Evapotranspiration Index (SPEI)

Like the SPI computation, the SPEI baseline was generated first. The downscaled climate data was fed into the established baseline to generate the future SPEI. The three parameters log logistic distribution function was chosen to describe the 'climatic water balance', which is the initial value in SPEI computation, rather than the rainfall in SPI and this 'climatic water balance' is defined as the monthly difference between precipitation and the potential evapotranspiration (PET). This probability distribution function is like the method first proposed by Vicente-Serrano et al. (2010) in their research for the computation of SPEI. After that, the function was normalized and standardized to obtain the SPEI value. It is a standardized variable and thus readily to be compared with SPI and other SPEI values across time and space. The computation of future SPEI was same as SPI's. The downscaled climate data from year 2021 to 2050 was fed into established SPEI baseline to generate future values. The detailed calculation of SPEI values can be found in Vicente-Serrano et al. (2010). Like SPI, SPEI-1, SPEI-3 and SPEI-6 were computed to represents time scales of 1-, 3- and 6-month.

2.5. Drought characteristics and trends

To investigate the changes in drought between 1976-2011 and 2021-2050, drought characteristics of the two periods have been quantified into drought frequency, mean drought duration and mean drought severity in this study. The drought frequency is the number of drought events that had occurred at the station; mean drought duration is the average time span of every drought event throughout a period, and mean drought severity is the average drought indices values. The detailed procedures to obtain the aforementioned drought characteristics can be found in Guo et al. (2018). Trend analyses were also carried out in our study to investigate the changes in trend throughout the two periods and the changes of trend between the two periods. With reference to Teegavarapu (2019), the Mann-Kendall/Seasonal Mann-Kendall trend tests are nonparametric tests that are commonly used for assessment of trends in hydrological time-series. They indicate the existence of an upward or downward monotonic trend in the data. According to Huang et al. (2014), there is no seasonal variation in monthly and seasonal rainfall series of Langat River Basin. Hence, Mann-Kendall trend test was chosen over Seasonal Mann-Kendall trend test. Thereafter, Theil Sen's Slope was adopted to measure the magnitude of the trend detected by Mann-Kendall test.

3. RESULTS AND DISCUSSION

3.1. Statistical rainfall and temperature downscaling

The list of selected predictor variables, their correlation coefficient and the significance level for both station 3818102 and station 48648 are given in Table 1. 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. The predictor selection for station 3818102 was done by adopting the results from Huang et al. (2016) and predictors namely 1000hPa relative vorticity of wind, 850hPa divergence of true wind, 850hPa specific humidity and mean sea level pressure were selected to downscale rainfall data. As for station 48648, the results from Table 1 show that all the predictors selected fulfilled the requirement of *p*-value less than 0.1. Hence, 1000hPa zonal wind component, 850hPa zonal wind component, 850hPa divergence of true wind, total precipitation and air temperature at 2m were selected as the predictor variables for temperature downscaling purpose.

Table 1. Screening results

Predictand	Predictors	Description of Predictor	Partial r	P-value
Precipitation (3118102)	p1_zgl (lag 5)	1000hPa Relative vorticity of wind	0.033	0.0712
	p8zhgl (lag 1)	850hPa Divergence of true wind	-0.045	0.0138
	s850gl	850hPa Specific humidity	0.042	0.0201
	mslpgl	Mean sea level pressure	0.019	0.2842
Mean Temperature (48648)	p1_ugl	1000hPa Zonal wind component	-0.203	< 0.001
	p8_ugl (lag 2)	850hPa Zonal wind component	0.157	< 0.001
	p8zhgl	850hPa Divergence of true wind	0.101	< 0.001
	prcpgl (lag -1)	Total precipitation	-0.213	< 0.001
	tempgl	Air temperature at 2m	0.419	< 0.001

The results of validation are shown in Table 2. The well-known methods to measure estimation accuracy namely the coefficient of correlation (CORR), root mean square error (RMSE) and mean absolute percentage error (MAPE) procedures were computed from monthly average of generated data and observed data from the model. In general, the relationship of selected predictors and predictand at the rainfall station is weaker compared to the results at the temperature station. Furthermore, with smaller scale of variations in the temperature series, the learning process for multiple linear regression in SDSM is easier. Thus, the validation results showed higher accuracy in temperature downscaling compared to rainfall downscaling.

Table 2. Result of Downscaling Validation

Predictand	CORR	RMSE	MAPE
Precipitation (3118102)	0.871	1.42	33.12%
Temperature (48648)	0.976	0.16	0.50%

For the purpose of this study, the use of the monthly average to represent the data was deemed to be adequate as the outputs of downscaling would be used in monthly accumulation instead of daily time block when computing drought indices. Therefore, the validation results were accepted. On the other hand, a higher correlation in validation of daily data does not necessary indicate a high accuracy of future prediction as it is highly dependent on the General Circulation Model used as well.

3.2. Projected climate change

The projected climate data from SDSM downscaling, which ranges from 2021 to 2050 was referred to as the futuristic period while the climate data from 1976 to 2011 was referred to as the baseline period. The average monthly rainfall and mean temperature of each time periods were computed and compared.

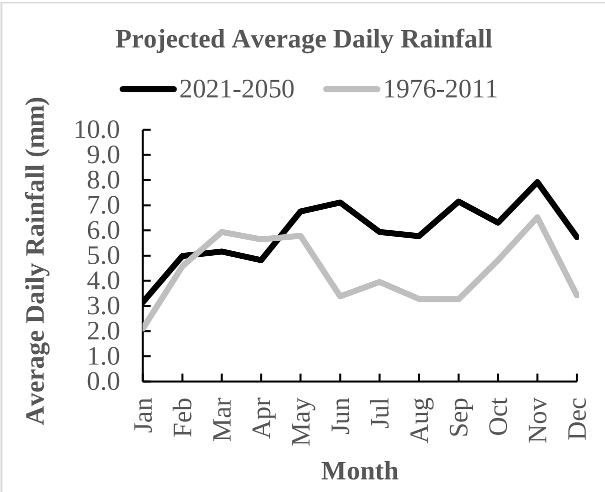

Figure 1. Projected average daily rainfall

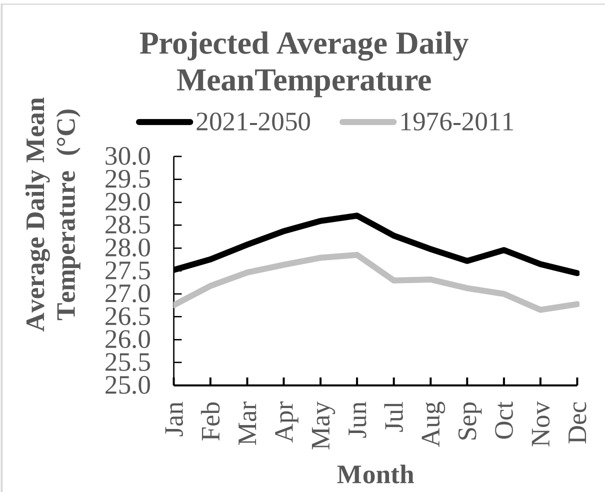

Figure 2. Projected average daily mean temperature

According to Figure 1, the projected futuristic average daily rainfall deviates from the baseline period. The projected average daily rainfall of most of the months have increased in 2021-2050, except for March and April. The largest rainfall increase was shown in September, with the difference of 119% from baseline period. As for March and April, the average daily rainfall decreased by 13% and 15%, respectively. Overall, the deviation in the first half of the years are small but from June onwards, there are significant increases of average daily rainfall for 2021-2050.

The projected average daily mean temperature is shown in Figure 2. The projected temperatures have a consistent trend, which showed that all the months will experience escalations in 2021-2050. The highest escalation was projected to happen in November 2021-2050 with the increment of 1.00°C, an increase of approximately 3.74 % when compared to the records from 1976-2011.

3.3. Baseline drought indices

Theoretically, the period of data used could affect the outputs of drought indices due to the variation in distribution represented by this selected sample. Daily rainfall and daily mean temperature record of 36 years (from year 1976 to year 2011) were used in the establishment of baseline indices. The constructed baseline SPIs and SPEIs are shown in Figure 3 (Parts A and B), respectively. Based on the figures**,** they showed that the recorded severe drought events in 1977, 1987, and 1997 (Pandey et al., 2007) were successfully reflected by both indices. This affirms the performance creditability of the three indices in describing drought.

3.4. Projected drought indices

Drought indices for three different time scales were computed according to the projected climate under RCP 8.5 scenario and are shown in Figure 4, Figure 5 and Figure 6. Rainfall and PET are two prime factors affecting the drought events. From these three figures, it can be seen that the fluctuation of each SPI aligns well with their respective cumulative rainfall amount, so as the computation of SPI relies solely on rainfall. The interpretations of SPEIs must refer to the PET in addition to rainfall and hence, high PET value generally resulted in large differences between SPEI and SPI.

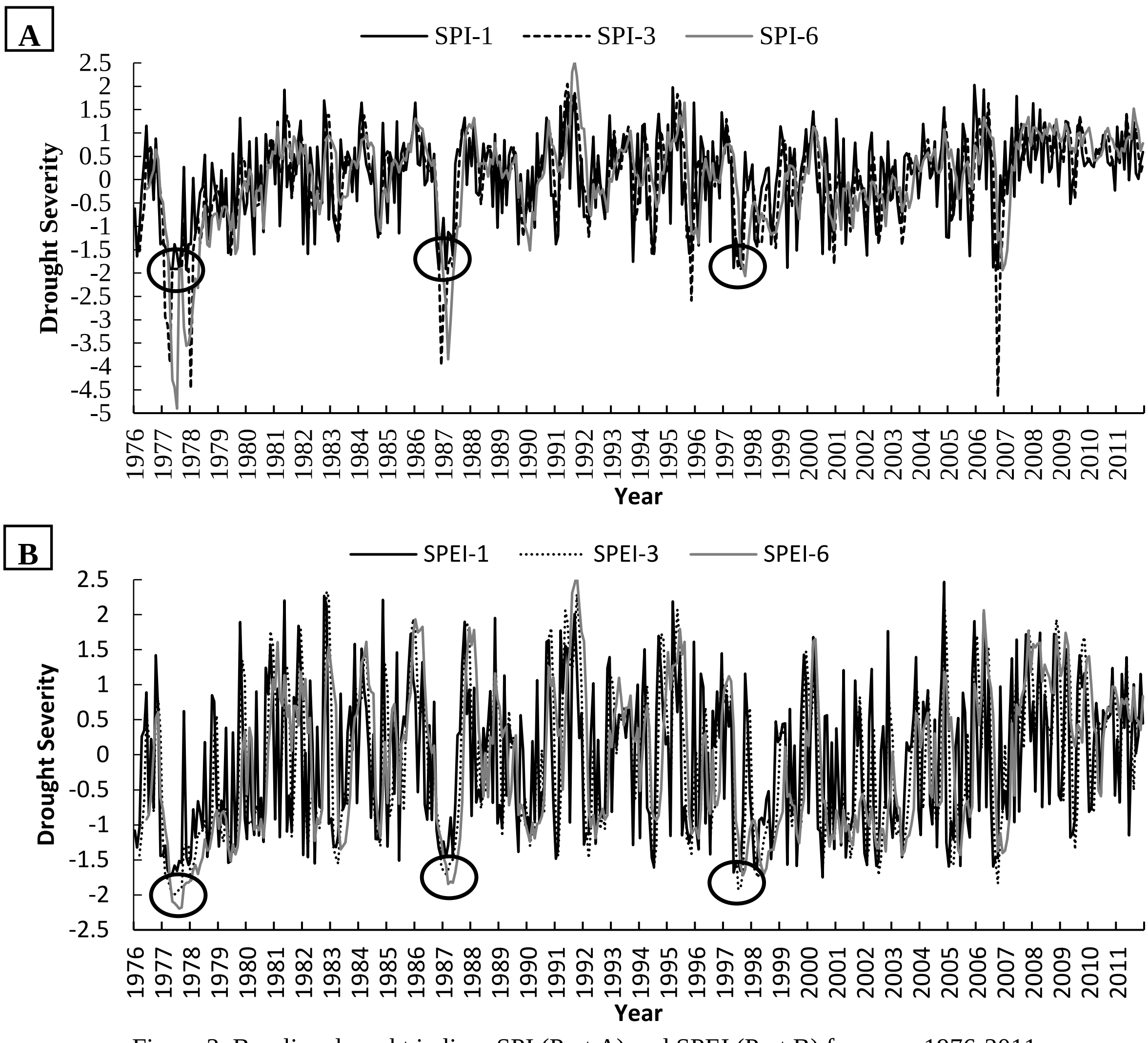

Figure 3. Baseline drought indices SPI (Part A) and SPEI (Part B) for years 1976-2011

Table 3 also shows that the difference (mean absolute difference, MAD) between SPI and SPEI has increased and coefficient of correlation has decreased in 2021-2050 when compared to 1976-2011. According to WMO (2012), SPI is not suitable for climate change analysis because temperature is not an input parameter in the evaluation of SPI. However, the projected temperatures in 2021-2050 will increase up to 1.00 ˚C (Section 3.2). Hence, SPEI that takes both simultaneously, rainfall and PET into consideration will differ from SPI and the differences will increase in 2021-2050, where climate change is projected. Thus, SPEI is better in describing droughts under climate change in the future and especially when the PET is high.

Table 3. Correlation and Measure of Difference between SPI and SPEI under different time scales and period

Period	CORR			MAD		
	1-Month	3-Month	6-Month	1-Month	3-Month	6-Month
1976-2011	0.87	0.86	0.81	0.42	0.43	0.51
2021-2050	0.80	0.63	0.62	0.59	0.54	0.50

Apart from the above, the figures also showed that the differences increased when time scales of the drought indices increased. According to WMO (2012), the increases of time scales in SPI/SPEI can be used to define different type of droughts. For time scale of 1-, 3- and 6-month, they can be used to define meteorological, agricultural and hydrological droughts respectively. This proposed classification is justified by the average required response time for soil moisture conditions, groundwater, streamflow and reservoir storage to reflect the effect from precipitation anomalies. Hence, for longer time scales, the departures between SPI and SPEI increased due to SPEI's higher capacity to define agricultural and hydrological droughts by considering PET.

From the results presented above, SPI can be used to define droughts when climate change doesn't come into action. However, when climate change occurs or when users' objectives are to define non-meteorological droughts, SPEI seems to be a better option. These provide an insight on the selection of proper parameters that should be considered in drought identification and drought indices classification during different conditions.

3.5. Drought characteristics and trends

The Mann-Kendall trend test and Sen's Slope test were carried out for the periods 1976-2011 and 2021-2050 for both indices. The tests were carried out with null hypothesis of no trend in the series, while the alternative hypothesis assumed otherwise. The significance level was set to be 1% to reject the null hypothesis. Based on the trend analysis in Table 4, it can be seen that for both indices in 1976-2011 and 2021-2050, the drought severity gave positive trend. In addition, the summarised drought characteristics also showed potentially less drought occurrence and severity in 2021-2050 (Table 5). For the baseline period 1976-2011, the results are compatible with the finding of increasing rainfall trend in the basin (Palizdan et al., 2013, 2015, 2016), which will cause the tendency of drought index to be positive. As for period 2021-2050, the results reflect an overall increasing rainfall in the projected future climate (Section 3.2). These reveal that the likelihood of a drought event in the Langat River Basin is decreasing

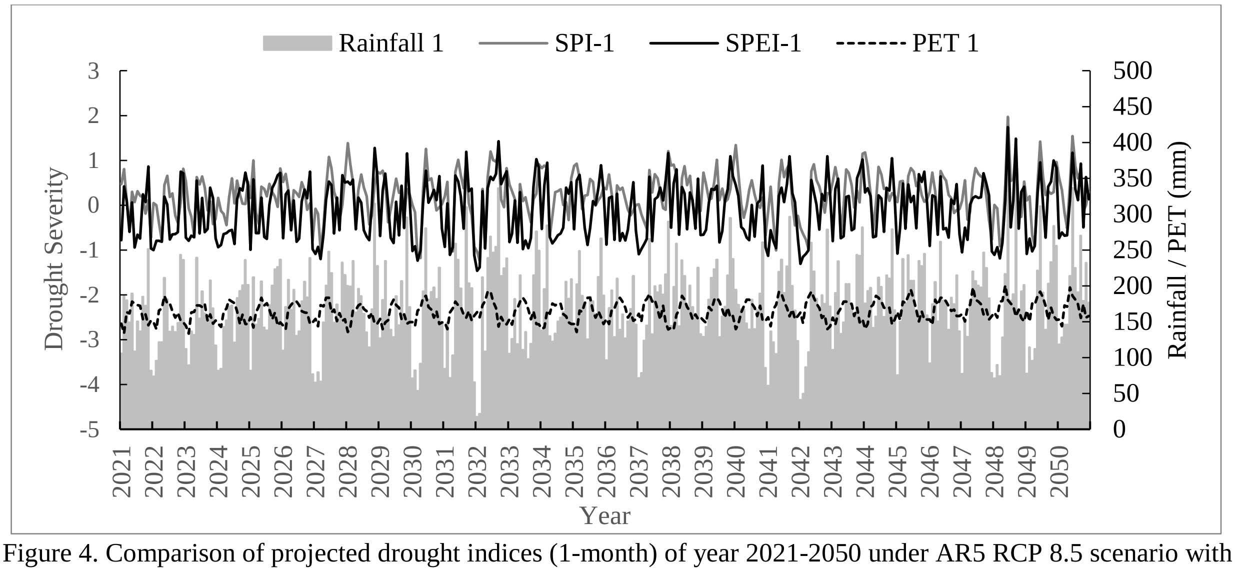

Figure 4. Comparison of projected drought indices (1-month) of year 2021-2050 under AR5 RCP 8.5 scenario with projected rainfall and PET

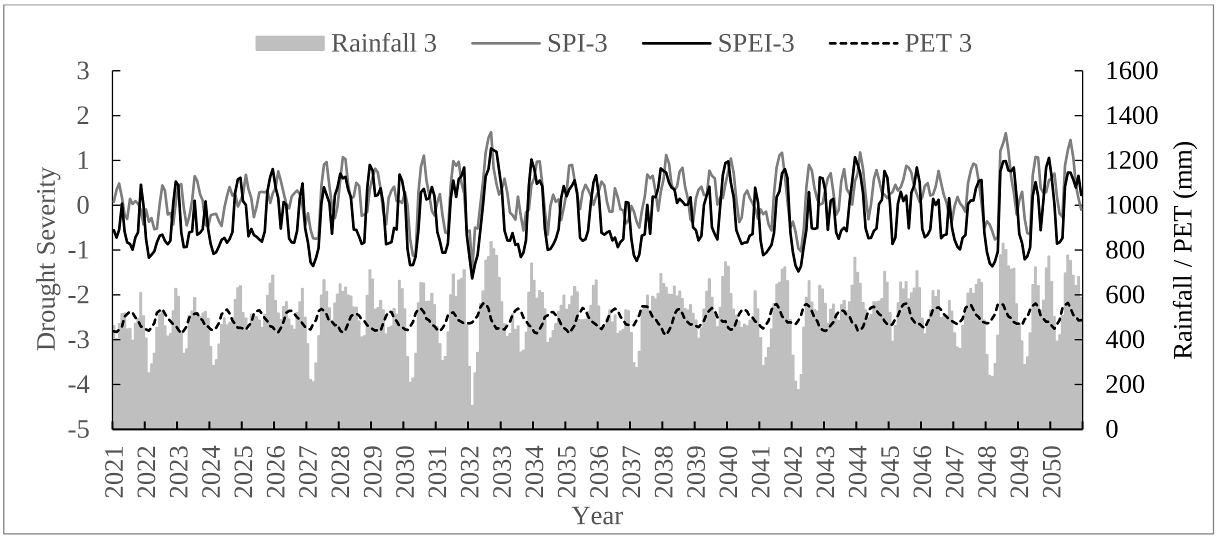

Figure 5. Comparison of projected drought indices (3-month) of year 2021-2050 under AR5 RCP 8.5 scenario with projected rainfall and PET

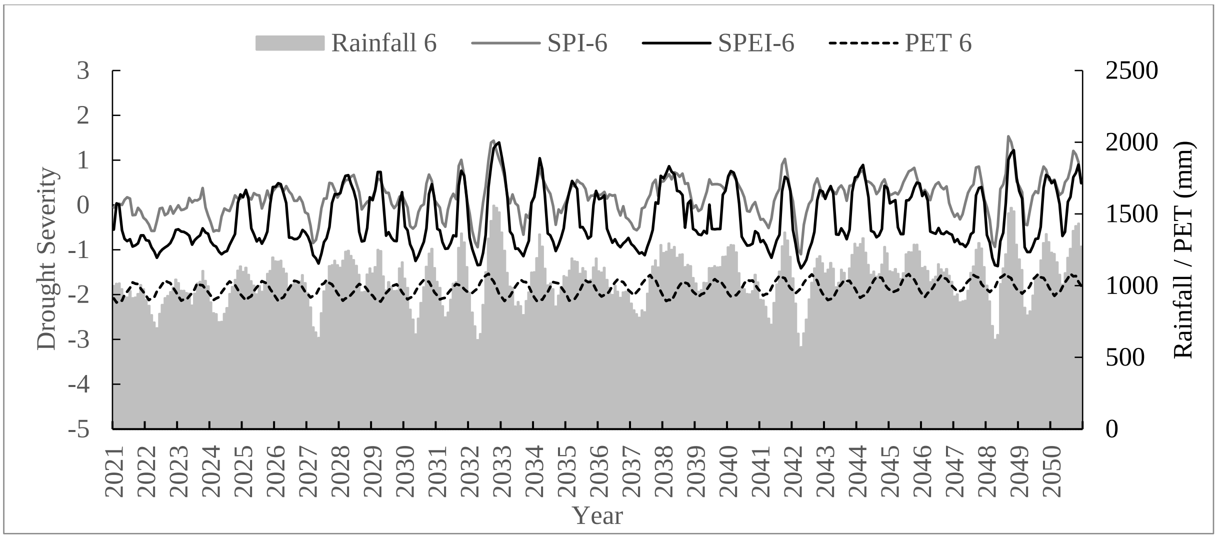

Figure 6. Comparison of projected drought indices (6-month) of year 2021-2050 under AR5 RCP 8.5 scenario with projected rainfall and PET

Table 4. Drought Trends

Trend Analysis		1976-2011						2021-2050					
		SPI-1	SPI-3	SPI-6	SPEI-1	SPEI-3	SPEI-6	SPI-1	SPI-3	SPI-6	SPEI-1	SPEI-3	SPEI-6
Mann-Kendall trend test	Result	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o	Reject H_o
	Z-Value	2.71 (Upward)	2.19 (Upward)	2.11 (Upward)	1.81 (Upward)	1.46 (Upward)	1.43 (Upward)	2.68 (Upward)	3.03 (Upward)	3.21 (Upward)	2.36 (Upward)	2.39 (Upward)	2.18 (Upward)
Sen's Slope		0.016	0.021	0.023	0.011	0.015	0.019	0.007	0.012	0.015	0.007	0.012	0.015

for both periods 1976-2011 and 2021-2050 according to current situation. However, when the magnitude of the trend is considered, it was shown that the magnitude of increasing trend in 2021-2050 has decreased compared to in 1976-2011. This may be due to the projected increasing temperature in 2021-2050. However, the rainfall is also increasing in 2021-2050. Thus, the Mann-Kendall trend test results are still showing positive upward trend but with gentler slope indicated by the lower values in the Sen's Slope test results, giving the evidence that temperature is playing an important role in formation of future droughts.

In general, the occurrence of drought event can be attributed to low rainfall and/or high PET. In this

Table 5. Drought Characteristics

Drought Characteristics	SPI-1		SPI-3		SPI-6	
	1976-2011	2021-2050	1976-2011	2021-2050	1976-2011	2021-2050
Drought Frequency	93	56	38	37	23	21
Mean Drought Duration	1.97	1.89	4.37	3.24	7.78	5.29
Mean Drought Severity	-0.83	-0.39	-0.92	-0.34	-0.87	-0.29
Drought Characteristics	SPEI-1		SPEI-3		SPEI-6	
	1976-2011	2021-2050	1976-2011	2021-2050	1976-2011	2021-2050
Drought Frequency	90	72	47	40	31	25
Mean Drought Duration	2.29	2.22	4.53	4.73	6.71	8.80
Mean Drought Severity	-1.06	-0.77	-1.04	-0.80	-1.06	-0.79

study area, the drought tends to decrease in term of occurrence while the rainfall and PET increase under RCP 8.5 scenario. The drought in the Langat River Basin is believed to be driven by rainfall, yet PET should not be ignored to avoid the underestimation of drought. Hence, SPEI shall be considered to monitor and assess droughts over SPI.

4. CONCLUSIONS

Drought is one of the damaging yet difficult to define natural calamity. Contrary to popular belief that high annual rainfall in a tropical country could always be counted on to provide the more than sufficient water resources, this is no longer holds true since drought is frequently happening, especially with the onslaught of climate change with the much anticipated environmental consequences. Drought monitoring is becoming crucial and using drought indices serves as an important base. Drought indices computed from forecasted rainfall and daily temperature give a better outlook of the potential risk and uncertainty. The usage of the SDSM in future rainfall and temperature downscaling is deemed to be sufficient for drought index computation although the rainfall generation might not provide accurate data. The baselines comparison between the SPI and the SPEI suggests that both indices are correlated to a certain extent. However, the SPEI performs better in the sense of less likelihood of the index to underestimate the drought severity. In this study, climate change and alteration of rainfall and daily temperature patterns have been detected at the Langat River Basin. Generally, the rainfall amount and daily temperature increases in future under RCP 8.5 scenario at this basin. A positive trend of index value detected in both indices implies the occurrence of drought in coming future will be less likely and less severe. The drought indices in this study are for monitoring the evolution of a drought event. With the combination of future rainfall downscaled by SDMS, a framework of future drought event can be generated. This study also offers some insights for future drought planning and management practices.

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