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Assessing the Drought Index and Water Scarcity Nexus: Case Study for Langat River Basin

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ABSTRACT

Climate change has resulted in the increase of surface temperatures, which has significantly affected water availability, disrupting economic development and quality of life. Thus, the application of drought index and water scarcity for analysis is essential, as they accurately estimate the impact of water availability. This study quantifies drought and water scarcity using SPEI and WEI+, respectively, and investigates their interrelationship in the Langat River Basin. The results revealed a strong positive correlation between the drought and water scarcity index, with correlation coefficients of 0.9677, 0.9545, and 0.9633 for SPEI-3, SPEI-6, and SPEI-12, respectively. The frequency analysis of the drought index showed 54 occurrences for SPEI-3, 58 for SPEI-6, and 61 for SPEI-12. Meanwhile, the water scarcity index was quantified for the period from 2015 to 2018, yielding values of 2.60×10^{-3} in 2015, 3.81×10^{-3} in 2016, 3.39×10^{-3} in 2017, and 3.68×10^{-3} in 2018. Overall, these findings provide valuable insights and form a robust basis for developing effective mitigation strategies and informed decision-making in water supply planning and river basin management, thereby reducing potential adverse impacts on water resources.

Keywords: Climate change, drought index, water resources, water scarcity index, water supply

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INTRODUCTION

Urbanisation is a dynamic phenomenon of economic and social capability shifting from rural areas with an agriculture-based economy to urban areas with industry and

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services sectors. In fact, urbanisation with high urban densities is also capable of structuring the economic patterns of resource consumption and worldwide environmental quality (Shahbaz et al., 2015). However, climate change is one of the effects of uncontrolled urbanisation and leads to an increase in surface temperature, which contributes to the changes in the atmosphere and has a significant effect on the availability of water. The possibility of climate change for an area is dependent on the historical situation or the prediction of potential climates such as drought, floods, and monsoons (Othman et al., 2018). Drought is a stochastic and persistent natural hazard that has costly and destructive effects on the availability of surface and groundwater, crop production, quality of ecological water, production of electricity (hydropower), modern industrial production, and waterborne transportation (Tri et al., 2019). The effect of climate change on the water resources of Karaj River Catchment was investigated and showed that the decreasing on precipitation in the coming decades resulting the increasing of river discharge (Azizi et al.,2017). Many scientists have made several attempts to examine drought, which consists of spatial and temporal drought variations (Lana et al., 2001), the drought impact reduction (Huang et al., 2008), drought frequency analysis (Mondal et al., 2015), and drought prediction based on different indices of atmospheric circulation (Cordery, 2000). Two aspects that had been considered for drought analysis were classification of drought severity and estimation of drought vulnerability (Natarajan et al., 2022).

Standardised Precipitation Evapotranspiration Index (SPEI), Standardised Precipitation Index (SPI), and Effective Drought Index (EDI). Standard Index of Annual Precipitation (SIAP), Z-Score Index (ZI) and Standardised Water Storage Index (SWSI) are several available drought indices. However, among them, the SPEI is most preferable due to its integration of precipitation and temperature effects, multi-timescale flexibility, and suitability for assessing drought under climate change conditions (Isia et al., 2023). The other indices, such as SPI and EDI, are used to evaluate the severity, period and extent of drought occurrence (Huang et al., 2016). Meanwhile, the SIAP used for meteorological drought, and SWSI used for hydrological drought which effective in predicting hydrological and meteorological drought very close to the observed values (Khan et al., 2018). The Z score Index can be calculated by subtracting the long-term mean from an individual rainfall; however, it cannot represent the shorter time scales as well as the SPI (Edwards & McKee, 1997). The main reason SPEI has been chosen because it can detect drought better than other indices because the data used is a long base period (30 -50 years besides able to monitor and explore the impact of global warming, which another index cannot do.

Water scarcity plays an important role in evaluating the continuity of water supply as well. Water scarcity can be defined as the water shortage in a water supply system that can be caused by drought or by human actions, such as increasing water usage over renewable natural water supplies, which normally happen in a greater population and a lack of natural water supplies (Fan et al., 2018). Water Poverty Index (WPI), Water Exploitation Index

(WEI), Water Exploitation Index Plus (WEI+) and Water Stress Index (WSI) are among the available water scarcity indices. WPI is developed for water scarcity assessments at the scale of local communities and the ability to adapt this index for different scales (Shalamzari et al., 2018). Meanwhile, the WEI+ represents the level of pressure that human activity puts on a specific area's natural water supplies (Fan et al., 2018), and the WEI is obtained through the percentage of mean annual total demand of freshwater with respect to the long-term mean annual freshwater resources (Pedro-Monzonís et al., 2015). The WSI calculates the availability of total water resources in a region based on the actual ratio of water withdrawal to hydrological availability (Sondermann et al., 2022). WEI+ is preferred over WPI, WEI, and WSI because it provides a physically based, basin-scale assessment of water scarcity that accounts for consumptive use, return flows, and environmental requirements, while remaining compatible with climate-driven drought analyses.

Malaysia is blessed with abundant rainfall, averaging around 2,000mm annually. However, due to recent climate variations, the country has experienced and is expected to face more drought events. A series of droughts occurred in Malaysia in 1997, 1998, and 2014, with the severe one in 2014 affecting around 1.8 million residents in southern Kuala Lumpur. During these years, Malaysia faced significant water scarcity due to reduced rainfall, which led to drought conditions (Shaaban et al., 2003). There were a few studies related to the drought assessment that had been conducted in Malaysia, such as SPI and NDVI methods in determining the risk vegetation area that was impacted during the drought event in Kedah (Othman et al., 2016), determination of the drought event in Langat River Basin using SIAP and SWSI (Khan et al., 2018), and the potential of evapotranspiration (PET) based on temperature variables in determining the trend analysis with respect to the drought episode (Hui-Mean et al., 2018). As for the water scarcity index, the existing studies have primarily focused on the WSI, and the conducted research is assessing water scarcity in Malaysia, especially in rice production, which indicates Malaysia are heavily dependent on precipitation to meet the demands of rice production (Hanafiah et al., 2019). Another study on the reserved forest in Kelantan, which assesses the WSI as a role in producing, maintaining, and reserving water for natural ecosystems and human usage (Samsudin et al., 2020). These studies highlight the critical role of WSI in understanding and managing water resources in Malaysia, especially in the face of changing precipitation patterns and increasing water demand. Despite extensive research on drought assessment and water scarcity in Malaysia, existing studies have largely addressed these issues independently, with drought characterised using precipitation- or temperature-based indices and water scarcity primarily assessed through the Water Stress Index.

Besides, limited research has investigated the SPEI and WEI+ quantitative relationship within humid tropical river basins. Existing studies have largely focused on arid and temperate climates, where hydro-climatic responses differ substantially from those of tropical monsoon systems. Consequently, the extent to which drought circulates into water scarcity under tropical climatic conditions remains poorly understood. Hence, the exploration of drought and water scarcity indices under tropical climate are very crucial as the indices can represent and portray the value of drought and water scarcity indices based on accurate experience and able to provide accurate conditions locally, which relates to the drought assessment and the drought legislation is more effective as the drought management can be planned earlier. (Hui-Mean et al., 2018; Iglesias et al., 2007). The neglecting of this issue will affect society's agriculture in the long term, as it is an important environmental issue that needs to be addressed (Payus et al., 2020). Thus, this study addresses the gap by integrating SPEI and WEI+ using an Artificial Neural Network (ANN) in order to quantify the drought–water scarcity nexus in the Langat River Basin, Malaysia and this will be able to provide a proper planning for the water management stakeholder especially in drought management.

METHODOLOGY

LRB has been chosen as the location of study due to the major transformation of land use due to rapid urbanisation. The development areas around the basin extended to 23.5% in 2013 compared to 2.4% in 1974 (Farid Ahmed et al., 2023). Figure 1 shows the map of LRB, which ranges around 1815 km^{2,} and the river's major course is 141km.

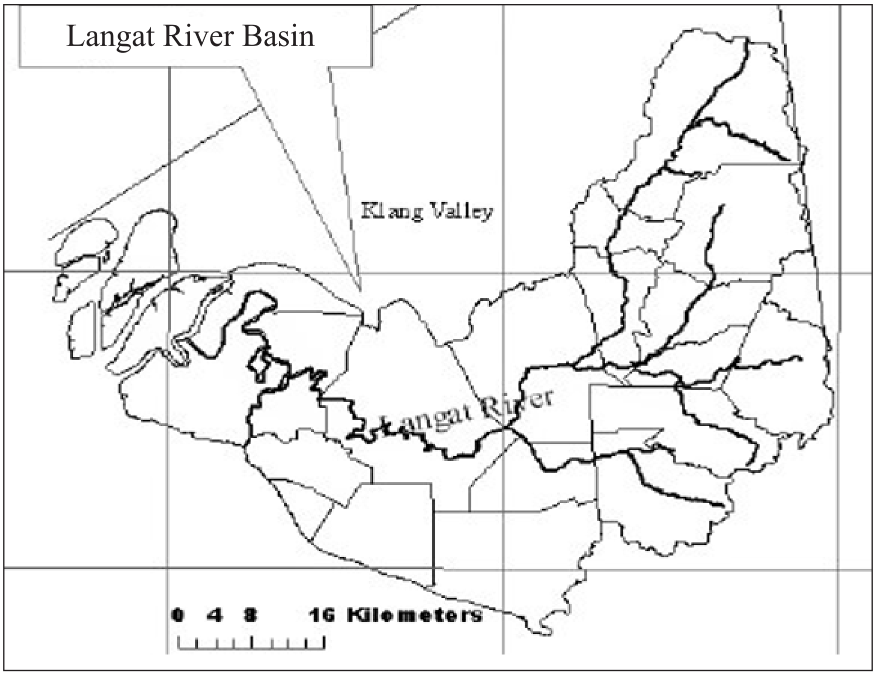

Figure 1. Map of Langat River Basin (LRB) (DID, 2017)

The location of LRB lies between latitude N 2° 40’ 0” and N 3° 20’ 0” and between longitude E 101° 20’ 0” and E 102° 0’ 0”. The LRB have a population of 1,184,917 in the year 2000 with a rate of growth of 7.64%, then grew to 4,266,011 in 2013 as reported by the Department of Statistics Malaysia (Elfithri et al., 2018). The Langat catchment provides water supply to approximately 1.2 million people from 14 towns include dense towns such as Cheras, Kajang, Bangi and the Government Centre of Putrajaya. There are two (2) reservoirs located under LRB, which are Semenyih and Hulu Langat Dam and eight (8) water treatment plants located within the catchment. The land use trend had a major transformation in LRB because of rapid development.

SPEI and WEI+ Assessment

The SPEI monthly time scales are being considered, with the calculation according to the water deficit or surplus between the precipitation and evapotranspiration, based on various time scales. In this study, 3-month, 6-month, and 12-months timescales were used in the analysis, and the analysis was conducted using R Studio software. The 3-month and 12-months value of SPEI reflected short-term and long-term moisture conditions and provided a seasonal estimation of precipitation deficiency (Quang et al., 2021). The computation equation is depicted as in Equation 1, and the classification for SPEI can be categorised as in Table 1. The data for rainfall, temperature and evaporation for SPEI calculation were obtained from the Drainage Irrigation Department Malaysia and Met Malaysia in accordance with the selection station within the catchment from 1998-2018, as displayed in Table 2.

Table 1
Drought classification based on the (SPEI) values

Drought Classification	SPEI Values
Extremely wet	2.00 or more
Severely wet	1.50 to 1.99
Moderately wet	1.00 to 1.49
Near normal	-0.99 to 0.99
Moderately drought	-1.00 to -1.49
Severe drought	-1.50 to -1.99
Extreme drought	-2.00 or less

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad [1]$$

where

$W = [-2\ln(P)]^{0.5}$ for $P \leq 0.5; P = 1 - F(x);\ C_0 = 2.515517,$
$C_1 = 0.802853, C_2 = 0.010328;$
$d_1 = 1.432788, d_2 = 0.189269$ and $d_3 = 0.001308$

Table 2
List and location of the rainfall station

No	Station	Latitude	Longitude
1	Tadika Kemas Kg. Tg. Sepat	2° 40’ 53”	101° 33’ 49”
2	P/A Sg. Pelek Sepang	2° 37’ 58.9”	101° 37’ 26.2”
3	P/A Kg. Tali Air Morib	2° 44’ 39”	101° 27’ 02”
4	Kg. Salak Tinggi	2° 47’ 19.2”	101° 44’ 31.1”
5	P/A Kelanang	2° 48’ 44”	101° 25’ 6”
6	Pejabat JPS Sg. Manggis	2° 49’ 35”	101° 32’ 30”
7	Ldg. Brooklands	2° 49’ 40”	101° 33’ 15”
8	P/A Pekan Banting	2° 48’ 38”	101° 30’ 30”
9	P/A Sg. Sedu	2° 51’ 21.1”	101° 30’ 53”
10	Dengkil	2° 51’ 20.8”	101° 40’ 53.1”
11	KLIA	2° 48’ 17.5”	101° 41’ 30.5”
12	RTB Bukit Changgang	2° 48’ 41”	101° 39’ 15”
13	Bukit Changgang	2° 48’ 48.5”	101° 38’ 30.9”
14	Paya Indah	2° 52’ 44”	101° 37’ 09”
15	Kg Jenderam Hilir	2° 51’ 41”	101° 44’ 7”
16	Sek. Men. Bandar Tasik Kesuma	2° 53’ 55.47”	101° 52’ 13.3”
17	P/A Bt. 9 Sijangkang	2° 57’ 23”	101° 26’ 03”
18	P/A Bt 7 Sijangkang	2° 57’ 23”	101° 26’ 03”
19	Ldg. Bkt. Cheeding	2° 54’ 40”	101° 34’ 35”
20	Puncak Niaga Putrajaya	2° 54’ 40”	101° 41’ 50”
21	RTM Kajang	2° 59’ 46”	101° 47’ 8.9”
22	Kolam Takungan Sg. Merab	2° 56’ 43”	101° 44’ 60”
23	Stor JPS Hulu Langat	2° 56’ 10”	101° 45’ 49”
24	Kajang	2° 59’ 33.7”	101° 47’ 7.8”
25	Sg. Rinching	2° 54’ 54.7”	101° 49’ 18.9”
26	Sg. Raya Bt.9 Hulu Langat	3° 04’ 04”	101° 46’ 19”
27	Sg. Serai Bt.12 Hulu Langat	3° 05’ 58”	101° 47’ 51”
28	Empangan Semenyih	3° 04’ 43”	101° 52’ 50”
29	Kg. Pasir	3° 00’ 48.4”	101° 51’ 57.8”
30	Ldg. Dominion	3° 00’ 13”	101° 52’ 55”
31	TNB Pansun	3° 12’ 34.7”	101° 52’ 33.1”

Note. Adapted from (Department of Irrigation and Drainage, 2017)

Meanwhile, WEI+ can be obtained through the total amount of water supplies, water usage, inflow, outflow and reservoir impoundment. The index focuses on the net consumption assessment at the monthly level as shown in Equation 2 (Sondermann et al., 2022).

$$\text{WEI+} = \frac{(AB - RE)}{RWR} \qquad [2]$$

where

AB = the total amount of water abstracted from the river basin, including surface water resources and groundwater resources,

RE = the amount of water returning to the hydrological cycle after being used by human activities,

RWR = renewable water resources, and is measured by using natural streamflow as shown in Equation 3.

$$RWR = Outflow + (abstraction - returns) - \Delta Sart \qquad [3]$$

where,

ΔSart = change in storage of artificial reservoirs.

Data for WEI+ calculation, such as water abstraction and sewerage treatment plant, were obtained from Selangor Water Management Authority (LUAS), and Indah Water Konsortium (IWK) Selangor, as depicted in Table 3. However, there is a limitation in terms of data for water abstraction and sewage treatment plant for the Langat River Basin, as the availability of these two data is only available from 2015-2018.

Table 3
Summary of data collection for the Langat River basin

List of Data	Type of Data	Duration
Evaporation	Monthly	1988 – 2018
Water abstraction	Yearly	2015 – 2018
Sewage treatment plant	Yearly	2015 – 2018

To quantify the relationship between SPEI and WEI+, an Artificial Neural Network (ANN) was used to calculate the correlation coefficient, and the Pearson method was chosen to identify the relationship. The value nearly +1.0 shows a perfectly positive and good relationship.

RESULTS AND DISCUSSION

Drought Assessment for LRB

The drought years were identified based on the computed value to plot the SPEI trend. Table 4 shows the summary of major drought and wet events identified using SPEI in the Langat

Table 4
Summary of major drought and wet events identified using SPEI in the Langat River

Year	SPEI frequency	Drought Classification	Duration (months)	Minimum SPEI	Severity (Magnitude)
1995	SPEI-3	Near Normal	12	0.15	7.33
1998	SPEI-6	Moderate Drought	5	-1.48	-4.71
1998	SPEI-3	Severe Drought	6	-1.61	-6.80
1999	SPEI-12	Moderate Drought	12	-1.50	-14.78
1999	SPEI-12	Severe Drought	12	-1.50	-14.78
2012	SPEI-12	Near Normal	12	0.77	10.72
2013	SPEI-6	Moderately Wet	12	-0.19	7.03
2016	SPEI-3	Moderately Wet	12	-0.64	4.38
2017	SPEI-6	Near Normal	12	0.12	6.87

Table 5
Frequency of drought based on SPEI values for LRB

SPEI Values	Drought Classification	Frequency		
		SPEI-3	SPEI-6	SPEI-12
2.00 or more	Extremely wet	0	0	0
1.50 to 1.99	Severely wet	0	0	0
1.00 to 1.49	Moderately wet	11	8	3
-0.99 to 0.99	Near normal	304	301	304
-1.00 to -1.49	Moderately drought	52	58	60
-1.50 to -1.99	Severe drought	2	0	1
-2.00 or less	Extreme drought	0	0	0

River. It presents the monthly SPEI values corresponding to the representative wet, normal, moderate drought, and severe drought events that were identified in the Langat River Basin. Representative years were selected to illustrate the temporal evolution of drought classification at different frequencies (SPEI-3, SPEI-6, and SPEI-12). The magnitude represents the cumulative SPEI values over the corresponding event period, where larger negative values indicate greater drought severity, while positive values indicate wetter-than-normal conditions. Meanwhile, Table 5 depicts the frequency of drought based on SPEI values for the Langat River basin. According to Table 4 and Figures 2 to 4, the moderate wet occurs in 2016 for SPEI-3, 2013 for SPEI-6 and SPEI-12. It covered 10 months in 2016 for SPEI-3 with a magnitude of 4.38, and July was characterised as a moderately wet month, with the value of SPEI being 1.32. For SPEI-6, the year was moderately wet in 2013, with the magnitude value of 7.03, and the value of SPEI is 1.34. In that year, 10 months of moderate wet event occur, and February was the most moderate wet. For SPEI-12, the most moderate event occurs in February in the year 2013, with the SPEI value of 1.13, and it covered 12 months of moderate wet events with the value of magnitude of 10.14.

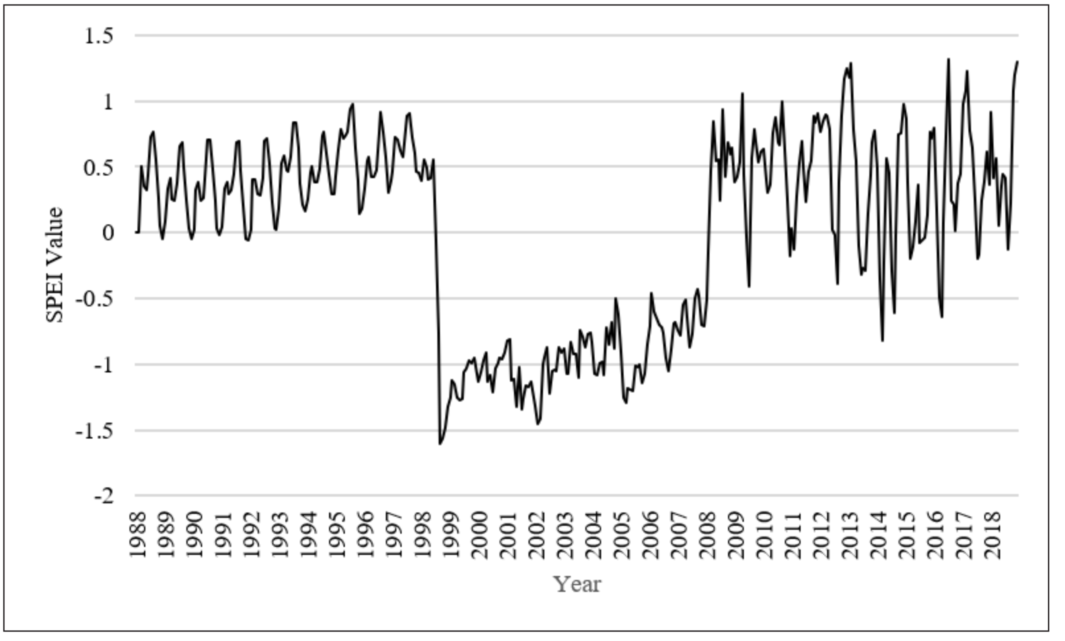

Figure 2. Temporal trends of SPEI 3-months over years

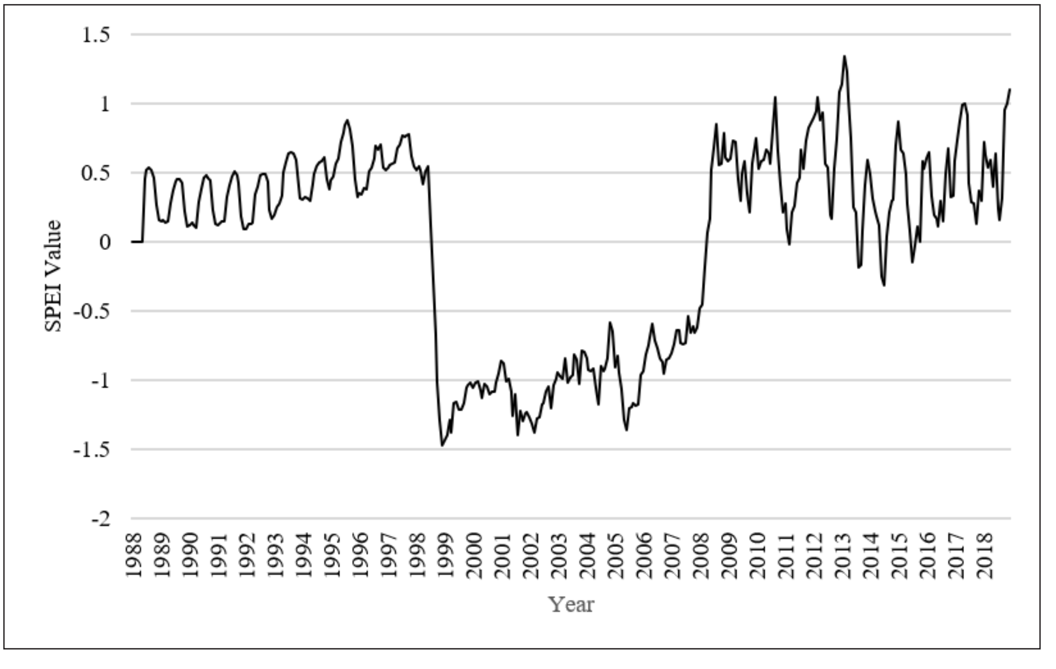

Figure 3. Temporal trends of SPEI 6-months over years

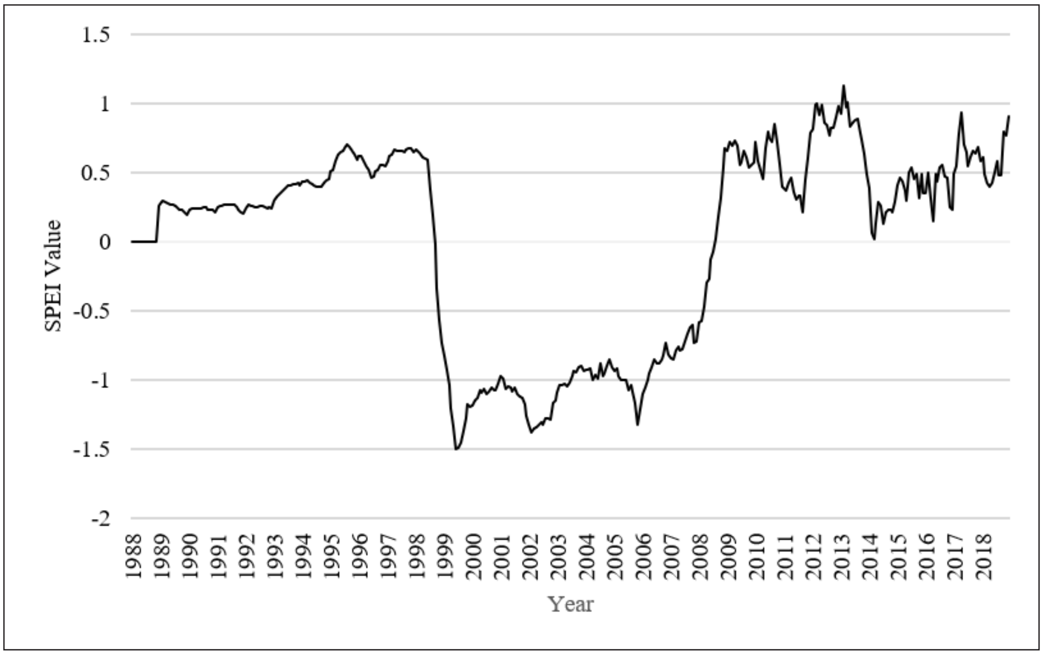

Figure 4. Temporal trends of SPEI 12-months over the years

For near normal occurrences in 1995, 2017, and 2012 for SPEI-3, SPEI-6, and SPEI-12, respectively. In the year 1995, the most normal occurrence in August had a SPEI value of 0.98, and it covered 12 months of near-normal events with a magnitude value of 7.33. For SPEI-6, the near-normal event occurred in 2017, with the most near-normal month being April, and the value of SPEI is 0.99. Meanwhile, the value of magnitude for that year is 6.87, which is covered by 12 months event. For SPEI-12, the year occur near normal event is 2012, which is 12 months event, and the most near normal month is February and May, with the SPEI value of 0.99 for both months, while the magnitude value for that year is 10.72. The moderate drought event is being identified from 1998 to 2006 for SPEI-3, SPEI-6, and SPEI-12. Figure 2 shows that the highest value for moderate drought is in 1998 for SPEI-3. It covered 6 months of drought events, and the highest value of severity is -1.49, which is in November, with the value of magnitude -6.80. Meanwhile, for SPEI-6, the year of the highest value for moderate drought is the same as SPEI-3, which is in 1998, and it covered 5 months of drought events. The most severe month is in December, with the value of severity is -1.48 and the magnitude value is -4.71. For SPEI-12, the highest value of moderate drought occurs in the year 1999, and it covers 12 months. The most severe month is July, with a severity value of severity is -1.49 and a magnitude value of -14.78. For severe drought, the year identified is 1998 only for SPEI-3 and SPEI-12. There are 6 months of drought for SPEI-3. The most severe occurs in September, with the value of severity being -1.61, and the magnitude value is -6.80. For SPEI-12, there are 12 months of drought, and the most severe occurs in June, with the value of severity is -1.50 and the magnitude value is -14.78. Like Fung et al. (2020), the conducted study demonstrates that SPEI effectively characterises drought variability in tropical climate conditions. Moreover, the drought characteristics observed in the Langat River Basin are consistent with those reported for the Muda River Basin, where drought variability was governed primarily by rainfall deficits despite the humid tropical climate (Luhaim et al., 2021). The event exacerbated by climate variability and increasing water demand for urbanization and understanding the dynamics of drought patterns (Dai et al., 2020; Lam et al., 2023). Singh et al. (2022) reported that the number of drought months under the categories of severe and moderate could be higher for 3 and 6 months compared to 12 months' time step. Besides, the location of the station and the lower annual precipitation rate are among the factors that influenced the magnitude of drought (Fung et al., 2020; Wu et al., 2009).

There are many factors that contributed to the effect of drought pattern trend, such as rainfall amount, pattern of rainfall and land use characteristics. However, a certain factor caused by climate change modifies the form, intensity and timing of water demand, precipitation, and runoff. The availability of water becomes less predictable due to the contribution of the increased period of drought and higher temperatures. The irregularity of rainfall patterns can be observed over the last two decades, which affected the annual precipitation and daily temperature, thus prolonging the incidences of dry periods for a few years in Malaysia (Yusof et al., 2013). Besides, the deterioration of water quality and groundwater also contributed to the degradation of the water supply. Instead, the increasing water demand due to the higher growth of population and economic development, changes in the rainfall pattern due to climate change has led to prolonged duration and magnitude of the drought events. According to Tan et al. greater increase in the warm index was found in the southern part of peninsular Malaysia, indirectly due to climate change, rapid urbanization and industrialization which have induced more warm days in the last decade (Tan et al., 2021).

Land use changes are basically involved with human use, for examples terrestrial space for economic, residential, recreational, conservation and government purposes, such as deforestation, has significantly increased the temperature. Furthermore, the changes in land use patterns and climate change are interrelated, where the changes in land use patterns change the concentration of greenhouse gases, thus contributing to climate change (Li et al., 2022). The urban area, which already has the changes of the land use pattern significantly impacting the drought propagation, can be observed clearly in LRB as changing rapidly compared from 1974 to 2013 (Farid Ahmed et al., 2023) with the population of 1,184,917 in 2000 and increasing to 4,266,011 in 2013 based on the report by the Department of Statistics Malaysia (Elfithri et al., 2018).

Zhou et al. (2021) have conducted a study to investigate the relationship between drought indices and concluded that forest and cover types were significantly affected since climate change influences the growth of vegetation due to the conversion of forest land for economic development reasons.

WEI+ Assessment for LRB

The calculated values of the WEI+ for LRB from 2015 to 2018, according to the availability of data, are displayed in Table 6 and show the increasing trend of WEI+ yearly. These reflected the increasing of water consumption from 2015 until 2018 due to rapid urbanisation development, increasing of population and the usage of water for household purposes, as the location of LRB is located at urbanised area. Besides, the renewable freshwater resources (RWR) also increased from 2015 until 2018, and the accumulation of RWR depended on several factors such as the development of water catchment and the increasing of precipitation volume during that year. The change of WEI+ values is related to the parameters such as abstractions, returns, and outflows. Thus, the average net water consumption, renewable water resources, and WEI+ from 2015 to 2018 are 690 million m^3, 9.744×10^{10} m^3, and 3.37×10^{-3} respectively.

Table 6
The calculated WEI+ values from 2015 to 2018

Year	Water Consumption (m^3) ($\times 10^8$)	RWR (m^3) ($\times 10^{10}$)	WEI+ ($\times 10^{-3}$)
2015	6.80	8.98	2.60
2016	6.88	8.84	3.81
2017	6.83	9.97	3.39
2018	7.12	11.14	3.68
Average	6.90	9.73	3.37

Figure 5 and Figure 6 show that the water consumption and RWR value are increasing over the year due to increasing on the population, expansion in urbanisation, industrialisation, as well as irrigation (Ahmed et al., 2014). This condition aligned with the LRB, which is located at urbanized and industrial area, thus contributing to the increasing of water consumption. Meanwhile, the increasing of RWR value depends on several factors such as the development of the water catchment and the increase in precipitation volume during that year. The similar factors occurred at LRB as well, thus contributing to the increasing RWR values at LRB. According to the previous research, the WEI+ value varies between 0 and 1, and if the WEI+ value is below 20%, it can be defined as a non-stressed period, exceeds 40% is a severe water stress period, and above 60% is a highly stressed period (Sondermann et al., 2022). Therefore, according to the results obtained, it can be concluded that the values of WEI+ are below 20%, which is recognised as a non-stressed period.

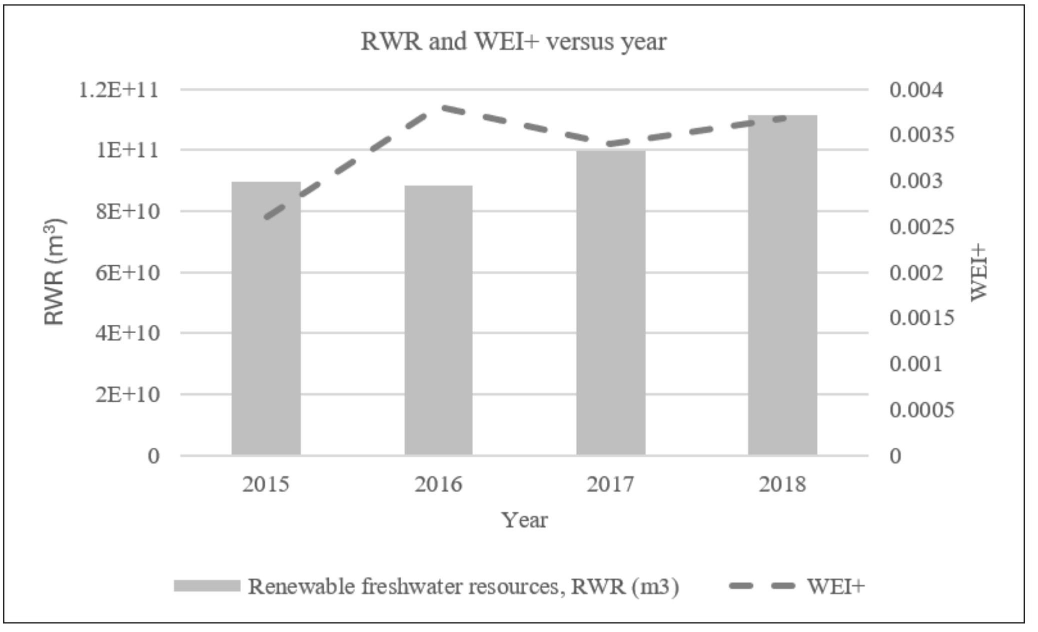

Figure 5. Renewable freshwater resources and WEI+ versus the year

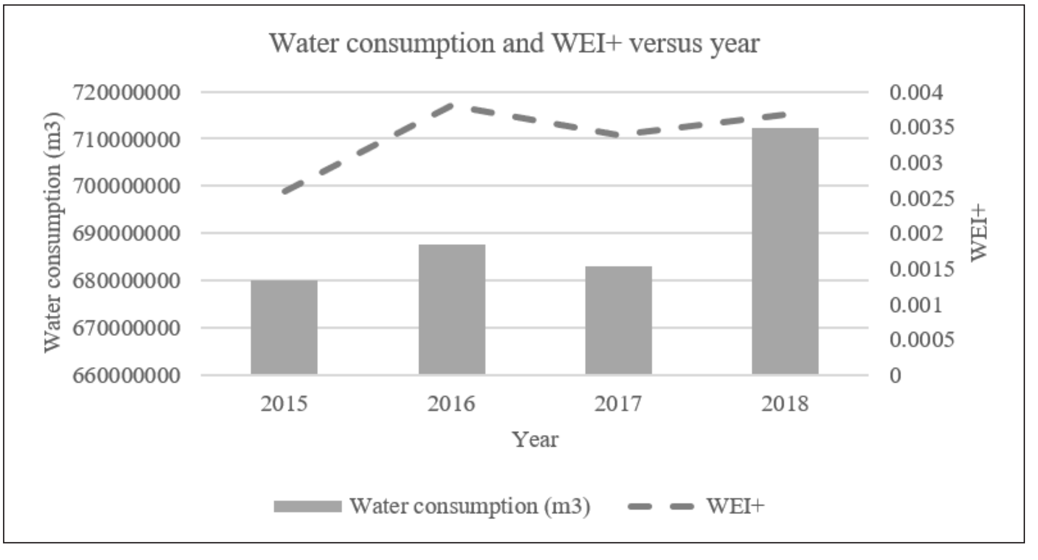

Figure 6. Water consumption and WEI+ versus the year

Relationship between SPEI and WEI+

Table 7 depicts the relationship between SPEI-3, SPEI-6, SPEI-12 and WEI+, respectively, using the artificial neural network (ANN) to identify the value of the correlation coefficient, R. The results show the correlation coefficient, R, is 0.9677 for SPEI-3 versus WEI+, 0.9545 for SPEI-6 versus WEI+, and 0.9633 for SPEI-12 versus WEI+, thus indicating the strong positive correlation relationship between SPEI-3, SPEI-6, and SPEI-12 against the WEI+. A similar behaviour has been observed between SPEI-3 and SPEI-12 due to the hydrological characteristics of the Langat River Basin. Although SPEI-3 represents short-term drought and SPEI-12 reflects long-term drought, the basin is characterised by a humid tropical monsoon climate with high dependence on seasonal rainfall for river discharge and reservoir storage. Consequently, prolonged rainfall deficits can simultaneously influence short-term and long-term drought conditions, resulting in similar temporal responses between SPEI-3 and SPEI-12. Furthermore, water demand in the Langat River Basin remains relatively stable throughout the year due to continuous domestic, industrial, and agricultural consumption. Therefore, fluctuations in water availability are primarily governed by climatic variability rather than abrupt changes in water abstraction, contributing to the consistently strong relationship between SPEI and WEI+ across different time scales.

Table 7
Relationship between SPEI and WEI+ using ANN

No	Relationship	Correlation Coefficient Value, R
1	SPEI-3 and WEI+	0.9677
2	SPEI-6 and WEI+	0.9545
3	SPEI-12 and WEI+	0.9633

The obtained finding aligned with the previous study by Fan et al. (2018), where the dependency between SPEI and WEI+ was 0.658, and indicated a positive dependence between these two variables. The same vein found in Guan et al. (2025) showed a strong correlation between water resources and SPEI, which emphasises the importance of water management strategies. According to the mechanism of drought and water scarcity, meteorological drought may happen when natural precipitation is not enough for a certain period and when water supply cannot meet the needs of water consumption for society, then water scarcity may happen (Fan et al., 2018).

CONCLUSION

This study demonstrates that drought conditions have significantly influenced water availability in the LRB. The application of the SPEI and the WEI+ was proven effective in characterising drought conditions and water scarcity, respectively. The strong positive correlations identified between SPEI and WEI+ across multiple time scales, as revealed through the artificial neural network (ANN) approach, indicate a clear and quantifiable linkage between climatic drought and basin-scale water stress. The increasing frequency of drought events at short-, medium-, and long-term time scales, together with the observed upward trend in WEI+ values between 2015 and 2018, highlights the growing vulnerability of water resources in the basin.

These findings underscore the importance of integrating climate-sensitive drought indices with physically based water scarcity indicators to support informed water resources planning and river basin management. The results provide empirical evidence that drought conditions, when combined with increasing water exploitation, can substantially aggravate water scarcity, posing risks to socio-economic development and environmental sustainability.

Even though this study provides valuable insights into the relationship between drought and water scarcity in the Langat River Basin, several limitations should be acknowledged. First, the analysis relied on historical data datasets and data available up to 2018, which may not fully capture future climatic variability under changing climate conditions. Second, the assessment employed SPEI and WEI+ and this index has been widely accepted, but they did not explicitly account for reservoir operation and land-use change, which also may influence the water availability.

Based on the outcomes of this study, it is recommended that water management authorities incorporate integrated drought–water scarcity assessment frameworks, such as the combined use of SPEI and WEI+, into routine monitoring and early warning systems. The adoption of data-driven tools, including machine learning techniques, can further enhance predictive capability and decision-making under climate uncertainty. Additionally, demand-side management strategies, protection of environmental flows, and adaptive water allocation policies should be prioritised to mitigate the impacts of prolonged droughts. Besides, the continuous monitoring will further improve the reliability of drought prediction and support adaptive river basin management.

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LIST OF ABBREVIATIONS

ANN	:	Artificial neural network
EDI	:	Effective drought
LRB	:	Langat River Basin
PET	:	Potential of evapotranspiration
SPEI	:	Standardised precipitation evapotranspiration index
SPI	:	Standardised precipitation index
SIAP	:	Standard index of annual precipitation
SWSI	:	Standardised water storage index
WPI	:	Water Poverty Index

WEI	:	Water exploitation index
WEI+	:	Water exploitation index plus
WSI	:	Water stress index
ZI	:	Z-Score index

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