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Comparative Analysis of Single and Multiple Change Points Detection for Streamflow Variations

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ABSTRACT

Abrupt changes in streamflow patterns significantly affect hydrological systems, making their detection critical for effective water resource management. This study uses the annual maximum streamflow (AMS) data to analyze and identify changes at the Kajang Station in the Langat Basin, Selangor, Malaysia. The objective of research is to determine the precise years of abrupt changes in streamflow and examine the underlying factors causing them. The problem lies in the increasing frequency and intensity of streamflow changes that could be related to factors such as changes in land use and climate variation, which require detailed investigation. This study conducts six complementary statistical tests to identify change points in the streamflow data. Six complementary statistical tests were conducted to identify change points. The Pettitt test (statistic: 276, p-value: 0.001), Buishand range test (statistic: 1.5881, p-value: 0.034), and standard normal homogeneity test (statistic: 11.349, p-value: 0.009) consistently identified 2003 as a significant single change point. For multiple change points, the sequential Mann-Kendall test indicated shifts in 2002 and 2007. The multiple structural change method and classification and regression trees revealed significant change points in 1985, 2003, and 2009. These changes are likely due to the 1982 massive flood event and subsequent changes in land use and river encroachments. The findings

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underscore the importance of monitoring and managing river systems, especially given the rapidly occurring environmental changes. It is vital to understand these change points to develop more resilient strategies for water resource management.

Keywords: Buishand range test, classification and regression tree, multiple structural change, Pettitt test, sequential Mann-Kendall, standard normal homogeneity test

INTRODUCTION

Streamflow, the flow of water within a river or other watercourse, is a fundamental component of the hydrological cycle, playing a crucial role in shaping landscapes, supporting ecosystems, and sustaining human activities (Dingman, 2015; Wang et al., 2023). Scientifically, streamflow is characterized by a highly nonlinear distribution and dynamic patterns, driven by the complex interplay of climatic, hydrological, and anthropogenic factors (Yaseen et al., 2018). However, hydrological systems globally are increasingly facing profound alterations, with abrupt changes in streamflow patterns posing significant challenges to effective water resource management (Milly et al., 2008; Saad et al., 2020). These shifts can impact water availability, flood risk, sediment transport, and overall riverine health, necessitating a thorough understanding of their occurrence and drivers.

The study of change points, or abrupt shifts, in streamflow is therefore crucial for understanding the dynamics of hydrological systems and the intertwined influence of both natural and anthropogenic factors (Yusoff et al., 2022). Such change points can indicate significant alterations in climatic, hydrologic, or landscape processes. Detecting and characterizing these abrupt changes is critical for developing informed strategies for water allocation, infrastructure planning, environmental protection, and for robust water resource management and flood risk assessment. Ultimately, this understanding is vital for deciphering the complex effects of climate change and human activities on river systems (F. M. Hamzah et al., 2021; Kundzewicz & Robson, 2004).

The frequency and intensity of abrupt changes in streamflow patterns appear to be increasing globally (Intergovernmental Panel on Climate Change [IPCC], 2023). These alterations can be triggered by a complex interplay of factors, including climate variability, land use modifications, and anthropogenic interventions within river basins (e.g., dam construction, diversions) (F. M. Hamzah et al., 2019; Roy et al., 2022). Understanding the specific timing and magnitude of these changes is essential for attributing their causes and predicting future hydrological regimes (Avinash & Dwarakish, 2023; Kamarudin et al., 2023). The potential for such abrupt changes in the Langat Basin, possibly linked to historical events like massive floods and subsequent alterations in land use and river encroachments, necessitates a detailed investigation to quantify these shifts and understand their temporal characteristics. Without a clear identification of these change points, effective water resource management and the development of resilient strategies to cope with evolving hydrological conditions remain severely challenged. In Malaysia, this urgency is amplified by rapid urbanization, driven by population growth and economic development, which has led to a 30–40% increase in urban land over the past three decades (Hasan et al., 2019), intensifying pressures on river systems and potentially amplifying abrupt streamflow alterations.

While various statistical methods exist for analyzing trends in hydrological time series, identifying the precise timing of abrupt shifts and distinguishing between single and multiple change points requires specific, often complementary, and analytical approaches. Many studies focus on gradual trends, potentially overlooking the critical impacts associated with sudden alterations in streamflow regimes (Danboos et al., 2023). Furthermore, attributing these identified change points to specific underlying factors, such as historical extreme events and long-term changes in land use (Yusoff et al., 2021), requires a robust methodological framework that combines statistical detection with a comprehensive contextual understanding of the basin's history and environmental changes. Therefore, there is a pronounced need for studies that not only pinpoint the years of significant streamflow changes but also explore the potential linkages to specific historical events and evolving basin characteristics.

Recent research has employed a diverse array of methodologies to identify these critical change points in streamflow data across various environments. Nonparametric tests, such as the Pettitt test, have been widely utilized to detect shifts in the central tendency and dispersion of streamflow records, revealing regional and temporal patterns of change (Güçlü, 2020; Kanani et al., 2020; Ryberg et al., 2020). To identify multiple change points and their spatial distribution, spatial clustering techniques have been applied, highlighting the influence of concurrent changes in precipitation and natural climate variability (Ivancic & Shaw, 2017). Other statistical methods, including the Buishand range test (de Jesus et al., 2020), the standard regular homogeneity test (SNHT) for abrupt and gradual trend changes (Pandžić et al., 2020), the sequential Mann-Kendall (SQMK) method for assessing multiple change points (Patakamuri et al., 2020), multiple structural change (MSC) methods (Baltagi et al., 2020), and classification and regression trees (CART) (Yerlikaya-Özkurt & Askan, 2020), further underscore the richness and multidimensionality of change point analysis in environmental and climate variables. For example, CART has been used to analyze the impacts of anthropogenic, climate, and land-use changes on streamflow, as demonstrated in a study in the Talar River basin, Iran, which evaluated the influence of land use changes and climate variations on monthly average streamflow (Ruigar et al., 2023). Their results notably showed that human activities, such as land use changes and point source operations, had a significant impact on streamflow. In specific hydrological settings, such as alpine catchments, wavelet analysis has proven valuable in distinguishing between natural and human-induced breakpoints in streamflow caused by river damming and hydropower operations (Ciria et al., 2019). Furthermore, copula-based methods have been employed to analyze changes in the dependence structure of flood flow characteristics, providing insights into the non-stationary behavior of streamflow due to human activities (Akbari & Reddy, 2020). The diverse approaches and findings from these studies highlight the importance of employing robust methodologies to accurately detect and interpret abrupt changes in streamflow, paving the way for a more comprehensive understanding of hydrological system dynamics. Understanding the underlying factors causing abrupt changes in streamflow is vital for developing socio-hydrological models and predicting future streamflow scenarios. Studies have shown that human activities, such as reservoir operations and water management policies, significantly impact streamflow patterns, often leading to the disappearance of minor periodicities in runoff records (Lan et al., 2020). These findings underscore the importance of integrating change point detection with an analysis of human and natural influences to better manage and adapt to changing hydrological conditions.

This study aims to identify and characterize abrupt changes in the AMS data at the Kajang Station in the Langat Basin, Selangor, Malaysia. Specifically, it conducted exploratory data analysis to pinpoint any shifts in the recorded data and employed robust methods to determine the break or change points within the time series. To achieve these objectives, the study utilized a multifaceted approach, applying the Pettitt test, Buishand range test, SNHT, SQMK analysis, MSC method, and CART method. This comprehensive suite of techniques ensured a thorough investigation into the structural changes or variations present in the streamflow data for the Kajang Station. The diverse methods employed in this study underscore their commitment to conducting a thorough examination of hydrological dynamics at this critical location in the Langat Basin. By achieving these objectives, this research seeks to provide valuable insights into the dynamics of streamflow regimes in the study area, contributing to a better understanding of hydrological change and informing more effective water resource management strategies in the face of ongoing environmental pressures.

MATERIALS AND METHODS

Study Area

The study was conducted at the Kajang Station (station number 2917401), strategically located within the Langat River Basin in Selangor, Malaysia, as depicted in Figure 1. Situated at a latitude of 02°59′40″ N and a longitude of 101°47′10″ E, this gauging station monitors a significant catchment area of approximately 389.4 km^2.

The Langat River Basin itself is one of Malaysia's most critical hydrological systems, spanning approximately 1,815 km^2 between 101°17′E and 101°55′E longitude and 2°40′N and 3°17′N latitude. It originates from the Titiwangsa Range in the northeast of the Hulu Langat District. It ultimately drains into the Straits of Malacca, supplying water to about two-thirds of Selangor's population. Along its course, the Langat River is monitored by four key gauging stations: Lui, Kajang, Semenyih, and Dengkil stations (F. B. Hamzah et al., 2022; Yusoff et al., 2022).

The Kajang Station is situated explicitly within the city of Kajang, a major urban center in eastern Selangor. Located just 21 km from Malaysia's capital, Kuala Lumpur, Kajang encompasses an area of 60 km² and had a population of approximately 300,000 in 2010. It shares its borders with the Cheras, Ulu Semenyih, Semenyih, and Kajang subdistricts.

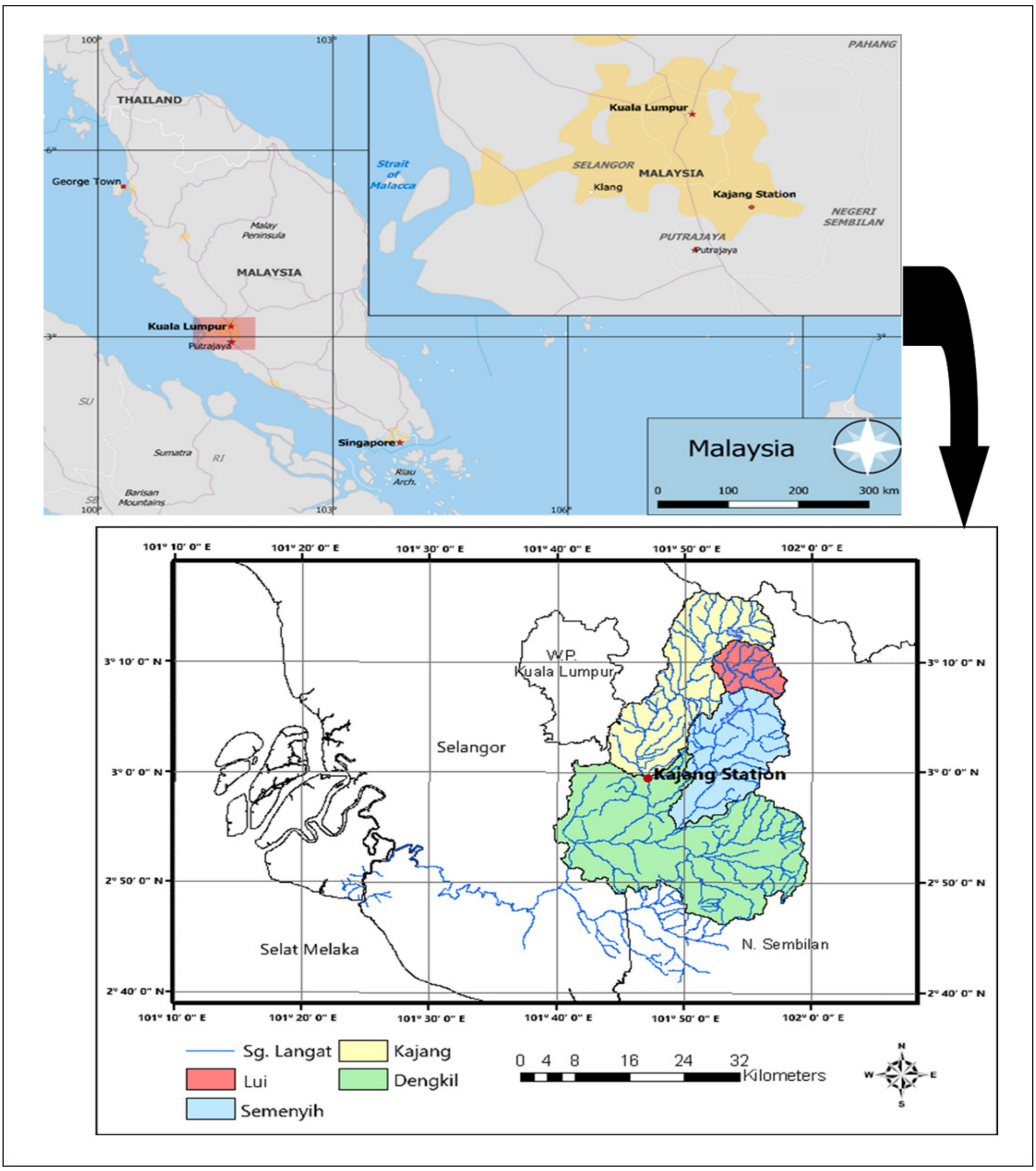

Figure 1. Map of Kajang Station obtained from the Geographic Information System

This area is characterized by high urbanization and dense population. Land use in Kajang is predominantly residential (30.31%), followed by transportation (23.64%), industry (8.13%), public amenities (7.55%), commercial activities (3.03%), and other purposes (1.69%). The extensive urban development in Kajang has notably resulted in the city having a low water retention capacity (Jabatan Perancangan Bandar dan Desa Semenanjung Malaysia [JPBD], 2016), making it particularly susceptible to hydrological changes.

For this research, daily streamflow (m^3/s) data for the Kajang station were analyzed. The streamflow data, spanning the period from 1978 to 2016, were sourced from the Department of Irrigation and Drainage (DID) (Jabatan Pengairan dan Saliran), Malaysia's primary governmental agency responsible for hydrological monitoring. These data, accessed directly from DID, have been subjected to their standard quality control protocols to ensure accuracy and reliability for hydrological analysis.

Single Change Point Detection

Assessment of the change points concerns detecting anomalies in the AMS data. The initial focus is three location-specific tests, the Pettitt test, the Buishand range test, and the SNHT, specifically designed to determine the year a significant break or change is likely to occur in the dataset. The detailed process of change point detection shown in Figure 2 provides a clear and comprehensive overview of the methodology employed to identify and analyze the potential shifts in the streamflow data.

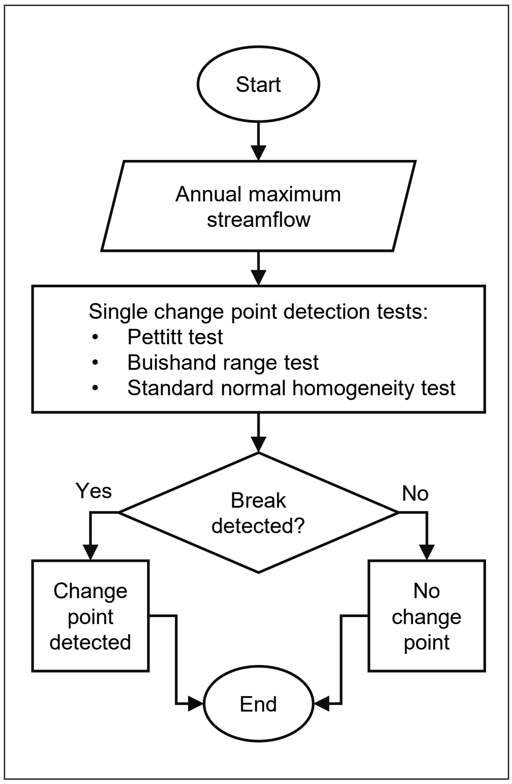

Figure 2. Flowchart for the single change point detection

Pettitt Test

The Pettitt test is a nonparametric tool for examining the homogeneity of a time series and identifying the shifts within the time series. It is specifically formulated to identify breaks in a time series and can efficiently identify the exact year a significant shift occurs. Traditionally used to identify breaks in the middle of a series, the Pettitt test is fundamentally rooted in the rank-based Mann-Whitney two-sample test. It operates on the principle of detecting a shift at an unknown point within a time series, making it a valuable analytical technique for uncovering temporal shifts or structural changes in the investigated dataset (Pettitt, 1979).

The null hypothesis states there is no change in the distribution of a random variable's sequence. The alternative hypothesis states that the distribution function $F_1(x)$ of the random variables, from X_1 to $X_{t,}$, differs from the $F_2(x)$ distribution function of the random variables from X_{t+1} to X_T. Given Equation 1:

$$D_{ij} = sgn(X_i - X_j) = \begin{cases} -1 & ,(X_i - X_j) < 0 \\ 0 & ,(X_i - X_j) = 0 \\ +1 & ,(X_i - X_j) > 0 \end{cases} \qquad [1]$$

where X_i and X_j are random variables, with X_i following X_j in time. It represents the observed values at two different time points, i and j, in the time series. D_{ij} is a sign function that quantifies the relationship between pairs of observed X_i and X_j. The test statistic $U_{t,T}$ is dependent on D_{ij} (Equation 2).

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} D_{ij} \qquad [2]$$

Statistic $U_{t,T}$ is used to analyze samples $X_1, \ldots, X_t$ and $X_{t+1}, \ldots, X_T$ from the same population. $U_{i,T}$ is used to assess all random variables from 1 to T and select the critical change point where the $|U_{i,T}|$ value is large (Equation 3).

$$K_T = max_{1 \le t < T} |U_{t,T}| \qquad [3]$$

A change point occurs at time t when K_T differs significantly from zero at a particular level given by Equation 4:

$$P = 2exp\left(\frac{-6K_T^2}{T^2 + T^3}\right) \qquad [4]$$

The null hypothesis is rejected if the p-value is less than the significance level. α, thus allowing the data to be split into two series, each with different distribution functions (Mallakpour & Villarini, 2016).

Buishand Range Test

The Buishand range test is a parametric test that assumes the data values of the test variables are independent and normally and identically distributed (null hypothesis). The research hypothesis suggests the presence of a shift (break). This Buishand range test is suitable for variables with any distribution. It is sensitive to changes in the middle of a time series (AL-Lami et al., 2014; Wijngaard et al., 2003).

$$s_0^* = 0$$

$$s_k^* = \sum_{i=1}^{k}(X_i - \bar{X}),\ k = 1.2 \dots, N \qquad [5]$$

where $\bar{X}$ is the mean of the time series observation; $X_1, X_2, \dots, X_n$ and k is the number of observations at which a breakpoint occurred.

The rescaled adjusted partial sums are obtained by dividing the s_k^* with the sample standard deviation (Buishand, 1982).

$$D_X = \sqrt{\sum_{i=1}^{N}\frac{(x_i - \bar{x})^2}{N}} \qquad [6]$$

$$s_k^{**} = \frac{s_k^*}{D_X}, \qquad k = 1,2, \dots, N \qquad [7]$$

Equation 8 is the statistics for analyzing homogeneity.

$$Q = \max_{0 \le k \le N} |s_k^{**}| \qquad [8]$$

The value of $Q/\sqrt{N}$ is compared with the critical value recommended by Buishand (1982). The null hypothesis is rejected if a calculated value is larger than the critical value (Arikan & Kahya, 2019).

Standard Normal Homogeneity Test (SNHT)

Alexandersson (1986) as well as Ahmad and Deni (2013) recommended using $T(d)$ to assess the mean (Stone, 2014) of the initial *d* years of the record relative to the mean of the remaining (*n* − *d*) years (Equation 9).

$$T_d = d\bar{z}_1^2 + (n - d)\bar{z}_2^2, \quad d = 1,2, \dots, n \qquad [9]$$

where $\bar{z}_1^2 = \frac{1}{d}\sum_{i=1}^{d}(X_i - \bar{X})\,/s$, $\bar{z}_2^2 = \frac{1}{n-d}\sum_{i=d+1}^{n}(X_i - \bar{X})\,/s$

are the mean values of z during the first *d* years and the last (*n* - *d*) years, respectively. Equation 10 gives the test statistics.

$$T_0 = \max_{1 \le d \le 0} T(d) \qquad [10]$$

The probability of rejecting a null hypothesis when T_0 is greater than a particular critical value depends on the sample size. Therefore, the series is considered inhomogeneous at a given level of significance, such as 95%.

Table 1 presents a comparative analysis of several key characteristics of the Pettitt test, Buishan range test, and SNHT. The Pettitt and Buishand range tests effectively identify the breaks in the middle of the series. In contrast, SNHT identifies the breaks close to the beginning and at the end of the series. The Pettitt test does not require the series to have a normal distribution, but the Buishand range test and SNHT do. Also, unlike the Buishand range test and SNHT, the Pettitt test is less sensitive to outliers.

Table 1
Comparison of the Pettitt test, Buishand range test, and standard normal homogeneity test (SNHT)

Characteristics	Pettitt test	Buishand range test	SNHT
Break	In the middle	In the middle	Near the beginning and at the end of a series
Normality	No normality assumption	Assumes a normally distributed series	Assumes a normally distributed series
Outlier	Less sensitive to outliers	Sensitive to outliers	Sensitive to outliers

Multiple Change Points Detection

This study used specially designed tests, the SQMK, MSC, and CART, to identify the breaks occurring in more than one location in the dataset. These tests efficiently detect shifts across multiple locations. The flowchart in Figure 3 presents the methodology used to identify and analyze the breaks at varying locations.

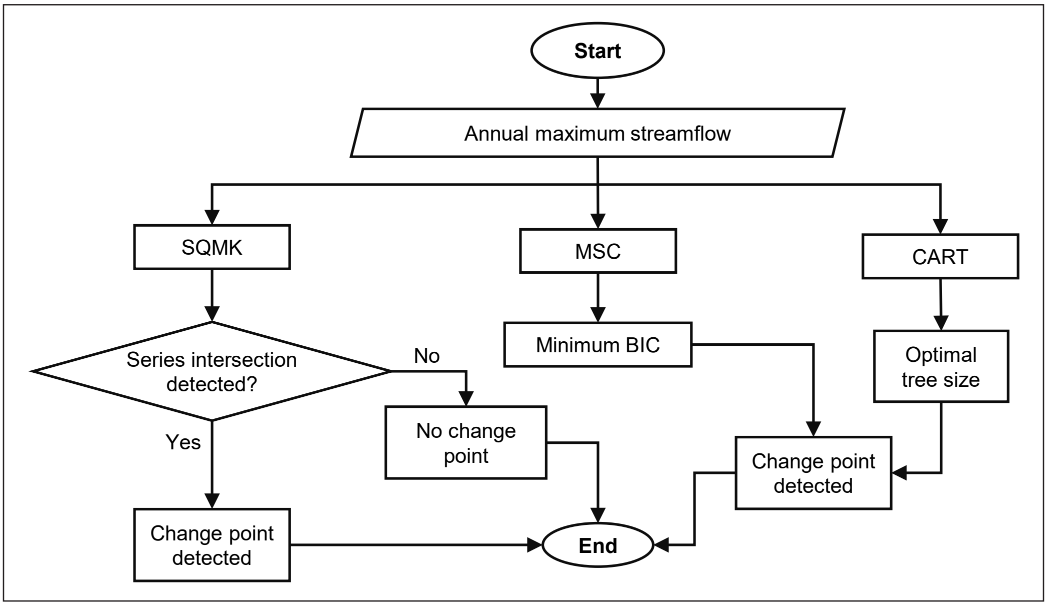

Figure 3. The flowchart for detecting multiple change points
Note. SQMK = Sequential Mann-Kendall; MSC = Multiple structural change; CART = Classification and regression trees; BIC = Bayesian information criterion

Sequential Mann-Kendall Test

Sneyers (1990) introduced the SQMK test, a non-parametric method for identifying a change point or the likely start years for notable trends. The test comprises the forward series *u*(*t*) and the backward series *u'*(*t*). A trend is statistically significant when the series intersects, separates, and exceeds specific threshold values (± 1.96 for a 95% confidence level). *u*(*t*) is a standardized variable with a mean of zero and a standard deviation of one, fluctuating around zero. *u(t)* is the value of the first data point to the last data point. Generally, the SQMK test examines the relative values of the terms in a time series $(x_1, x_2, \dots, x_n)$. The test statistics are calculated as follows:

(i) x_j is the annual mean series $(j = 1, \dots, n)$ evaluated about x_u, $(k = 1, \dots, j-1)$ and the number of cases where $x_j > x_k$ is counted for each comparison and is designed by n_j.

(ii) The calculation of the test statistics uses the following equation.

$$t_j = \sum_1^j n_j \qquad [11]$$

Equations 12 and 13 give the mean and variance.

$$e(t) = \frac{n(n-1)}{4} \qquad [12]$$

$$var(t_j) = \frac{j(j-1)(2j+5)}{72} \qquad [13]$$

(iii) Equation 14 gives the sequential values of *u*(*t*).

$$u(t) = \frac{t_j - e_{(t)}}{\sqrt{var(t_j)}} \qquad [14]$$

The values of *u'*(*t*) are computed in reverse from the end of the series using a similar approach to *u*(*t*). The sequential version of the MK test is an effective tool for detecting the beginning of a trend. The intersection point of the forward and backwards curves indicates the beginning of a trend or change (Zarenistanak, 2019).

Multiple Structural Change Method

Bai (1994) formulated the fundamentals for predicting breaks in time series regression models. Bai and Perron (2003) expanded the equation to account for multiple breaks. They developed an algorithm that allows simultaneous estimation of multiple breakpoints.

Many applications assume the presence of *m* breakpoints at which the coefficients transition from one stable regression relationship to another. The model consists of *m* + 1 segments. Each segment has constant regression coefficients written as follows:

$$y_i = x_i^T \beta_j + \mu_i \quad \begin{cases} i = i_{j-1} + 1, \dots, i_j \\ j = 1, \dots, m + 1 \end{cases} \qquad [15]$$

where, j is the segment index. It is essential to estimate the breakpoints i_j since they are rarely provided externally. The breakpoints estimation is obtained by minimizing the residual sum of squares (RSS) or Bayesian information criterion (BIC) for the above equation (Zeileis et al., 2010).

Classification and Regression Trees

Breiman et al. (1984) developed CART, a recursive algorithm for data mining. It is a non-parametric method that employs input data to develop predictive models. It utilizes historical data to create decision trees. CART builds classification trees when the dependent variable is categorical and a regression tree when the dependent variable is continuous (Choubin et al., 2018). Classification trees classify new observations and organize the dependent variables into the classes specified by the user or calculated using eternal rules. Regression trees aim to predict outcomes. Since they do not have any predefined class, the dependent variables are the response values for the observations within the matrix of independent variables.

This study implemented CART in a structured three-step process. The first step is constructing the maximum tree, which is the most time-intensive phase. The algorithm in regression trees splits and builds the maximum tree by minimizing the squared residuals. Pruning techniques, such as cross-validation and optimization based on the number of points in each node, were used to remove insignificant nodes since the maximum tree, especially the regression tree, can be relatively large. The second step was selecting an optimal tree size using two pruning methods, cross-validation and node point optimization, to determine the appropriate size. In the latter, the splitting process stopped when the number of observations dropped below a predefined minimum. Cross-validation, on the other hand, searched for an optimal balance between misclassification error and tree complexity. The ideal tree size was determined using the complexity parameter (*cp*), where the trial-and-error method was employed to determine the optimal *cp*. Finally, the constructed regression tree predicted the breakpoints for new data to give the response values for each new observation (Choubin et al., 2019; Zhang et al., 2018).

The CART algorithm generates trees with the fewest nodes and cost complexity values to balance simplicity and accuracy. Some of the benefits of this approach are fast computation, easy-to-understand model representation, resistance to irrelevant variables, seamless adaptation to categorical outcomes, single-tuning parameters, and the ability to handle high correlations among variables. However, it is worth noting that CART can sometimes introduce false change points, thus raising false alarms, as observed in a study

Table 2
The advantages of the SQMK, MSC, and CART methods

SQMK	MSC	CART
Detect multiple changes in a time series.	Detect multiple changes in a time series.	Detect multiple changes in a time series.
Non-parametric test.	Use a piecewise linear model.	Fast computations and interpretable model representation
Detect the starting point of trends.	Often applied to data with noise distributions with heavy tails.	Resistant to irrelevant variables and can handle correlation among variables

Note. SQMK = Sequential Mann-Kendall; MSC = Multiple structural change; CART = Classification and regression trees

by Gey and Lebarbier (2008). A notable drawback of the CART method is the potential for error propagation during model construction (Yerlikaya-Özkurt & Askan, 2020). Table 2 compares the advantages and features of the CART, SQMK, and MSC methods.

RESULTS

The Langat Basin has undergone massive changes due to rapid urbanization, industrialization, and intensive agricultural activities. Langat River, an important river in Selangor, is in a fast-transforming area and provides water to 16 intake points in the Langat Basin. The water sources fulfil the diverse water requirements in the region, including industrial, domestic, agricultural, and commercial needs (Abidin et al., 2018). The complex relationship between the river system and the varied demands of a growing urban and industrial area highlights the vital importance of understanding the hydrological dynamics in the Langat Basin in formulating effective management and conservation strategies to preserve the water resources critical for the various sectors in the region.

This study conducted a change point analysis on the AMS data from the Kajang Station in the Langat River Basin. The results of the analysis, as shown in Table 3, indicate that the change point occurred in 2003. Since all methods yielded p-values below the significance level of 0.05, the presence of a structural break is considered plausible. The tests suggest that the shift occurred in a single year. However, it would be ideal to investigate whether the change point may have occurred earlier or developed gradually over several years.

The second group of tests, SQMK, MSC, and CART, lasted more than one year.

The first method involved multi-change point analysis and used the AMS data for the Langat River Station in Kajang in the SQMK test. The $u(t)$ sequence represents the forward series, where the AMS data is from the beginning of the series. The $u'(t)$ sequence is the backwards series, where the AMS data is in reverse and begins at the end of the series.

Plotting the $u(t)$ and $u'(t)$ sequences on the same axis gives an intersection point (Figure 4). In the SQMK method, the intersection of $u(t)$ and $u'(t)$ showed that the change points occurred in 2002 and 2007.

Table 3
Results for the change point for the annual maximum streamflow series from 1978 to 2016

Method	Statistic	*p*-value	Shift	Year of shift
Pettitt test	276	0.001	Yes	2003
Buishand range test	1.5881	0.034	Yes	2003
SNHT	11.349	0.009	Yes	2003

Note. SNHT = Standard normal homogeneity test

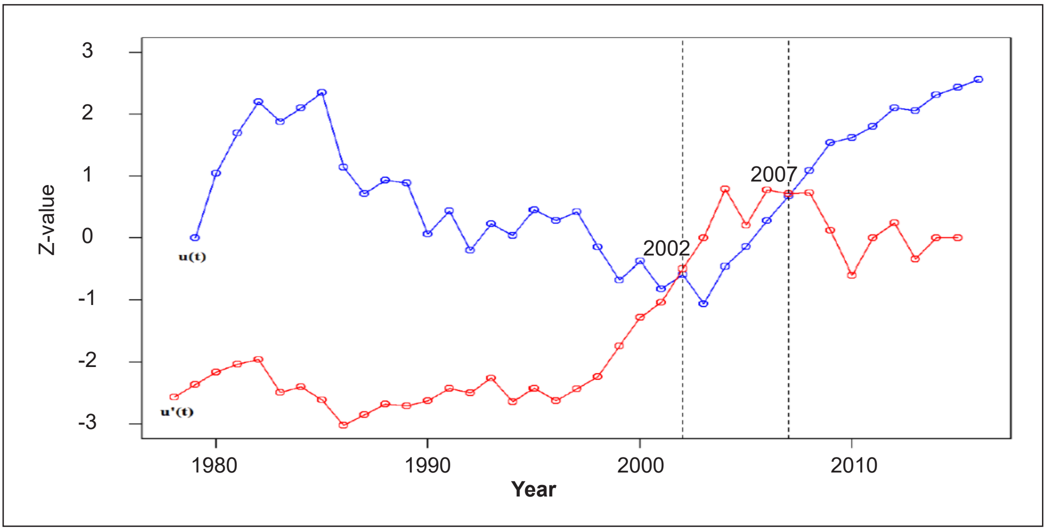

Figure 4. Sequential Mann–Kendall analysis for the Kajang Station

The second method in multichange point analysis uses the MCS methods. The MSC carried out the change point process for the six different breakpoints listed in Table 4 and selected 1985, 2003, and 2009 more frequently than the other years (1982, 1992, and 1997). A comparison of the BIC estimates for different numbers of breakpoints helps determine the optimal number of breakpoints. The BIC selected the lowest value as the optimal number. Table 5 shows the minimum BIC value of 438.8 and two breakpoints. Therefore, the MSC method gives 2003 and 2009 as the years of shift.

The third method, CART, determined that the change points occurred in 1985, 2003, and 2009. Figure 5 shows that the most significant change point was in 2003, and the daily maximum streamflow series comprises two segments. The left tree node is the streamflow series before 2003, and the right tree node is the series after 2003. The left and right nodes represent the second significant change points in 1985 and 2009. The average streamflow values calculated using the change point positions are 67.44, 39.99, 170.80, and 87.58. The primary reason for utilizing the CART method is to detect the change points over time.

Table 4
Number of breakpoints and the respective years

Number of breakpoint	Year					
1					2003	
2					2003	2009
3		1985			2003	2009
4		1985		1997	2003	2009
5		1985	1992	1997	2003	2009
6	1982	1987	1992	1997	2003	2009

Table 5
The Bayesian information criterion (BIC) for selecting the optimal number of breakpoints

Number of breakpoints	0	1	2	3	4	5	6
BIC	445.9	439.3	438.8	444.5	451.6	458.7	466.3

DISCUSSION

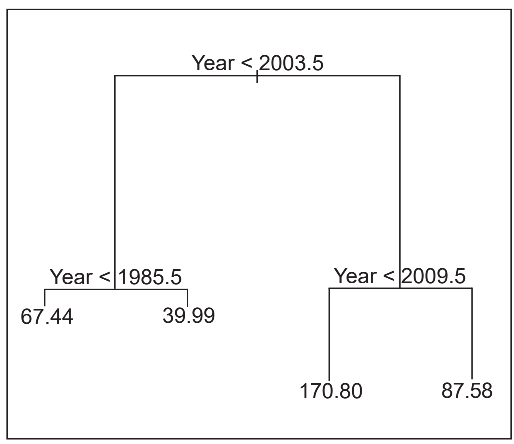

Figure 5. The classification and regression trees

The convergence of results from the single change point detection methods (Pettitt, Buishand range, and SNHT) strongly points to 2003 as a significant year of abrupt change in streamflow characteristics at the Kajang Station. While the SQMK test identified 2002 and 2007 as additional change points, and the MSC method, along with CART, further reinforced the significance of 2003 and 2009, these years collectively indicate a period of pronounced hydrological instability. Notably, CART additionally identified 1985 as a change point. This early identification by CART, coupled with an indication from the analysis that the trend might have begun as early as 1982, aligns critically with the historical flood record for the Langat Basin. Specifically, the flood record details a massive flood event in September 1982, with a stage reading of 26.44 m, almost reaching the dangerous level of 26.50 m. This suggests that the initial abrupt change in streamflow patterns likely commenced around this period, potentially as a direct consequence of or in response to such extreme events. Following this initial shift, the subsequent change points in the early and late 2000s can be linked to the rapid and extensive anthropogenic developments in Kajang. The National Physical Plan (JPBD, 2016) explicitly recognizes Kajang town as an area with a high probability of being inundated. The proliferation of business premises and rapid urbanization in Kajang town have demonstrably contributed to frequent flash floods, often submerging areas like the Kajang market up to one meter and disrupting daily activities (Wan Mohd Rani et al., 2018). The Kajang city center is identified as the area with the highest risk for flash floods, which typically occur within 30 minutes to two hours of excessive rainfall. Thus, the sequence of detected change points, starting with the immediate aftermath of the 1982 flood and continuing through periods of significant urban expansion, provides a compelling narrative for the drivers of streamflow alteration in the Langat Basin.

Langat River flows through various land uses, including commercial, residential, agricultural, and industrial. According to the land use information obtained by Abidin et al. (2018), 183 km^2 (47%) of the land along the one-kilometer buffer of the Langat River is dominated by commercial crops, primarily rubber and palm oil plantations, in the downstream of the Langat Basin. Seventeen per cent (66 km^2) of the land is dominated by commercial, municipal, residential, and other physical development. There is mixed farming, comprising orchards planted with coconuts, bananas, and other fruit trees, for local consumption and market. Ten percent of the land along the Langat River is allocated for this purpose. Most mixed plantations are along the upper and middle streams of the Langat River. Quarrying and mining activities are carried out in an area of 4.35 km^2 along the Langat River, and about 0.6% is for recreational purposes, especially along the upstream of the Langat River. The rapidly changing land use, especially deforestation for agricultural expansion or urbanization, modifies the hydrological areas and exacerbates flood occurrences (Abdullahi et al., 2018). Flash floods in urban areas are indicative of unplanned development, and this is true in Malaysia, where rapid urbanization in the low-lying areas of major cities such as Kuala Lumpur, George Town, and Kota Bharu has worsened flood occurrences (Chan et al., 2019).

The impervious surfaces gradually replacing the green spaces increase the runoff entering the river within a short period. Sand and mud deposits in most rivers have also reduced their drainage capacity. Besides local geomorphological framework conditions, entry products from the upstream area also influence the channel geometry and fluvial dynamics. In the long term, the transport and disposal of sediment from one side to the other result in the formation of specific channel patterns. Any change in the upstream sediment delivery and discharge regimes will alter local channel adaptations (Hohensinner et al., 2008). Jaafar (2009) reported that one of the factors related to water supply disruptions is the reduced water resources that resulted from a change in the land use in the catchment areas, most notably deforestation for agriculture expansion and urbanization.

Active sand dredging in the Langat River directly impacts river morphology (Abidin et al., 2018). Sand mining activities have been identified as the primary contributors to total suspended solids, sedimentation, and turbidity. The influx of high volumes of suspended solids into the river system exacerbates the river conditions during heavy rainfall. Uncontrolled sand mining can pollute the downstream of rivers and damage their aquatic flora and fauna. Additionally, river encroachment when developing urban areas close to the river banks narrows the river channels, damages the river reserves, and destroys the buffer zone (Chan et al., 2020). Aling (2020) reported that the encroachment activities on the banks of the Langat River were one of the causes of the worst flash floods in Kajang after the 2016 flood, and affected 141 families.

From a water resources management and flood prevention perspective, these results provide critical insights into the timing and likely causes of hydrological regime shifts. Identifying specific years linked to major changes in streamflow patterns enables water managers and policymakers to correlate these shifts with land development policies and practices. This can support more effective planning and implementation of mitigation strategies, such as improved land-use zoning, sustainable riverbank management, stricter regulation of sand mining, and the integration of green infrastructure to restore natural infiltration and reduce runoff. Moreover, understanding abrupt changes in peak flows can enhance the design of early warning systems, improve flood forecasting accuracy, and inform the development of resilient flood control infrastructure. Ultimately, this research underscores the importance of integrating hydrological data analysis with land-use planning to ensure sustainable and adaptive water resource management in the face of urbanization and climate variability.

LIMITATIONS AND FUTURE WORK

While this study provides robust evidence for significant abrupt changes in streamflow patterns, certain limitations should be acknowledged. The analysis relied on AMS data for a specific period (1978-2016) at a single station (Kajang Station). Future research should extend the time series of streamflow data to capture more recent changes and long-term trends. Incorporating more detailed spatial data on land use and land cover changes over time will allow for a more granular correlation with hydrological responses. Investigating the impact of specific climate variability indices such as El Niño–Southern Oscillation (ENSO) or the Indian Ocean Dipole could provide additional insight into streamflow dynamics. Coupled hydrological-land use models should be developed to simulate the impacts of various development scenarios. Moreover, studies should explore the socio-economic impacts of these streamflow changes on local communities and aim to create integrated socio-hydrologic models that consider both natural and human systems. Applying these robust methodologies to other river basins in Malaysia could help generate broader regional insights and support national water management planning.

CONCLUSION

The application of a suite of complementary statistical tests has provided robust evidence for significant abrupt changes in the AMS patterns within the study area. Specifically, the Pettitt test, Buishand range test, and SNHT consistently identified 2003 as a key year marking a shift in streamflow characteristics at the analyzed location. Further, the application of methods designed to detect multiple change points, the SQMK test, the MSC method, and CART revealed 2003 and 2009 as significant years of change. The convergence of results across these diverse methodologies underscores the robustness of these identified change points. Notably, the suitability of all employed methods in detecting abrupt shifts within the time series highlights the value of a multi-pronged statistical approach in hydrological change point analysis.

The findings strongly suggest that anthropogenic activities in the vicinity of the Langat River have played a substantial role in altering streamflow behavior and river morphology. The identified change points in 2003 and 2009 appear to coincide with or follow a period of intensified land use activities, including commercial, residential, agricultural, industrial, and sand mining operations. Furthermore, land encroachment on the riverbanks likely contributed to changes in the river's hydraulic characteristics and its response to precipitation events. These activities can lead to increased impervious surfaces, altered infiltration rates, changes in vegetation cover, and modifications to the river channel itself, all of which can significantly impact the magnitude and timing of peak flows.

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