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Structural Time Series Modelling of Climate Change Effects on Mortality in a Tropical Developing Country

[1]Robiaatul Adawiah Edrus, [2]Zailan Siri, [3]Farid Zamani Che Rose & [4]Muhammad Aslam Mohd Safari
[1]School of Economics, Finance and Banking, Universiti Utara Malaysia, Malaysia
[1]UUM Institute of Risk Management, Universiti Utara Malaysia, Malaysia
[2]Institute of Mathematical Sciences, Universiti Malaya, Malaysia
[3&4]Department of Mathematics and Statistics, Universiti Putra Malaysia, Malaysia
[3&4]Institut Penyelidikan Matematik, Universiti Putra Malaysia, Malaysia

[*1]robiaatul@uum.edu.my
[2]zailansiri@um.edu.my
[3]faridzamani@upm.edu.my
[4]aslam.safari@upm.edu.my
*Corresponding author

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ABSTRACT

Heat-related mortality has emerged as a critical public health issue, driven by the accelerating impacts of climate change. Most studies establish a direct causative relationship between high temperatures and mortality; however, there is scarce literature studying the climate change mortality ellipse. This study aims to fill this gap by examining the effects of climate change on mortality in the tropical region with consistently high year-round temperatures, specifically in Malaysia. Structural time-series models were applied to annual mortality data for the period 2005 to 2022, obtained from the Department of Statistics Malaysia. Monthly climate data, including temperature, rainfall amount, number of rainy days, and relative humidity, were sourced from the Malaysian Meteorological Department and subsequently aggregated into annual values to ensure consistency in the analysis. The model uses impulse indicator saturation, which makes it easier to spot structural breaks and extreme values, improving the reliability of the results. The analysis indicates that higher rainfall is strongly associated with increased mortality, reflecting the health risks linked to flooding and waterborne diseases. In contrast, periods of higher relative humidity tend to correspond with lower mortality rates. The fully saturated model identifies two key structural shifts in 2006 and 2018, likely caused by abrupt changes in temperature and rainfall. These findings provide a solid foundation for targeted interventions, such as heat-stress regulations and localised air-quality measures, and offer evidence to guide strategies to reduce climate-related health risks in the country, while also supporting broader public health planning.

Keywords: Climate change, impulse indicator saturation, Malaysia, mortality, structural time series model.

INTRODUCTION

The effects of climate change are becoming more evident than in previous times and can be attributed to increased greenhouse gas emissions, rising global temperatures, and global climate change. It is a phenomenon that extends beyond the ecological consequences and encompasses economics, social structure, and the overall status of global public health. The shift in the status of the global climate and climate change is attributable to human action, particularly the burning of fossil fuels, industrialisation, the destruction of the world's forests, and modern farming techniques that disrupt the equilibrium of the earth's atmosphere (Karl & Trenberth, 2003). The most recent concern is the impact of climate change on human health, given that extreme weather events (e.g., heat, floods, droughts, and storms) can cause injury, severely compromise service delivery, particularly in health care, and worsen comorbid conditions (Yewell, 2020). The most vulnerable in this regard are people living in poverty and people living in remote areas. The World Health Organization (2023) predicts that, between 2030 and 2050, climate change is likely to result in approximately 250,000 excess deaths annually, as a result of heat-related illnesses, famine, and communicable diseases, and climate change will be the underlying cause of this. In addition, the degradation of air quality and its impact on the environment are likely to result in more people developing respiratory diseases and in the spread of mosquito-borne communicable diseases (Soomro et al., 2025).

As these global patterns have started becoming more documented, evidence from within Malaysia has been quite limited. Research has documented increasing temperatures (Ng Meng et al., 2005; Tangang, 2007) and alterations in rainfall patterns (Mohamed Shaffril et al., 2015; Suhaila et al., 2010), but the connections between these climatic changes and mortality rates appear weak and insufficiently substantiated. The few studies that exist focus exclusively on climate indicators in isolation and fail to link them to health impacts systematically. Consequently, it creates a vacuum in systematic or integrated analyses, leaving policymakers unable to formulate effective responses or even prepare for impending challenges. This lack of literature is telling, especially as Malaysia, like many other tropical countries, faces its own climate and health-related challenges. This unfortunate combination of high baseline temperature, precipitation, urbanisation, and some social and demographic characteristics creates distinct exposure pathways. Without robust evidence, it is challenging to quantify the health burden of climate change in the Malaysian context or to translate global knowledge into local action.

The present study is motivated by this absence of systematic assessment. It aims to establish empirical evidence on the relationship between climate variables and mortality, thereby contributing to a stronger foundation for risk-reduction strategies and health planning in Malaysia. Although centred on Malaysia, the findings are relevant to other tropical regions with similar climatic and demographic profiles. By linking local observations to the broader international discourse, this research seeks to inform both national policy and global understanding of climate–health dynamics. The article proceeds as follows: the next section reviews literature on climate change and health, with emphasis on the Malaysian context. The methodology, results, and discussion follow this. The paper concludes with key implications for research, policy, and climate–health adaptation strategies.

RELATED WORKS

Defining Key Terms

Climate change refers to long-term shifts in weather patterns primarily driven by human activities, especially greenhouse gas emissions (VijayaVenkataRaman et al., 2012). Its effects include temperature rise, rainfall variability, and extreme weather events, all of which influence public health outcomes. Mortality, in this context, refers to deaths linked directly or indirectly to climate-related exposures such as heat stress, vector-borne diseases, waterborne infections, and respiratory conditions.

Global Evidence on Climate Change and Health

Research has consistently shown that climate change is a major determinant of health worldwide. Studies attribute more than half of the observed global warming trends to industrialised nations, with consequences including heatwaves, wildfires, and floods (Wei et al., 2016). Such events increase mortality both directly, through heat stress and injuries, and indirectly, through malnutrition, vector-borne diseases, and disruptions to health systems (Vicedo-Cabrera et al., 2021; Abbass et al., 2022). In high-income countries, adaptation measures such as improved healthcare access and early warning systems have reduced heat-related deaths, yet extreme events remain a major risk factor (Deschenes, 2022).

Evidence from Malaysia

Compared to temperate regions, research in Malaysia is limited. Sahani et al. (2022) highlighted how climate change exacerbates children's health risks and recommended climate-smart education. Esa et al. (2022) projected cardiovascular mortality under extreme temperatures in Peninsular Malaysia, while Yatim et al. (2021) identified elderly individuals, women, and those with respiratory illness as especially vulnerable. However, these studies tend to focus on specific health conditions rather than overall mortality. Broader assessments suggest that Malaysia faces increasing exposure to extreme heat, rainfall variability, and storm events, with consequences for food security, vector-borne diseases, and long-term health burdens (Barteit et al., 2023).

Climate Change Effects on Mortality

Globally, climate–mortality links are multifaceted. High temperatures have been shown to elevate mortality rates and reduce labour productivity (Stalhandske et al., 2021; Dasgupta et al., 2021). Indirect pathways include food and water insecurity, altered ranges of disease vectors, and increased transmission of respiratory infections (Radović & Iglesias, 2019; Rocklöv & Tozan, 2019; Chen et al., 2021). In tropical countries like Malaysia, vulnerabilities are compounded by ecological diversity and socioeconomic inequalities (Alhoot et al., 2016; Jegasothy et al., 2021). While epidemiological evidence confirms excess mortality during prolonged heat events, comprehensive longitudinal modelling remains scarce (Arsad et al., 2022; Guo et al., 2018).

Identified Gaps and Contribution

Existing research has examined climate change and health across themes such as extreme heat, cardiovascular and respiratory diseases, labour productivity, and vector-borne illnesses. In Malaysia, studies highlight the vulnerability of children, the elderly, and those with pre-existing conditions, alongside rising risks linked to temperature and rainfall variability. Yet, as shown in Table 1, these works remain fragmented, often limited to specific diseases, short-term outcomes, or narrow population groups. Critically, few studies integrate long-term mortality data with climate variables or employ robust statistical methods capable of detecting structural shifts in mortality patterns. This study addresses these gaps by applying Structural Time Series Modelling (STSM) to Malaysian mortality and climate data. By doing so, it provides a more holistic understanding of climate–mortality relationships, generating insights that inform national policy and contribute to the global discourse on health risks in a changing climate.

Table 1

Summary of Related Studies on Climate Change and Mortality

Author(s) (Year)	Focus/Scope	Method/Data	Key Findings & Limitations
Sahani et al. (2022)	Climate change impacts on children in Malaysia	Case study in the education context	Highlighted vulnerability of children's health; limited to educational recommendations, not long-term mortality.
Esa et al. (2022)	Extreme temperatures and cardiovascular mortality in Malaysia	Projection models	Linked heat extremes with CVD risk; lacks broader integration with multi-disease mortality.
Yatim et al. (2021)	Vulnerability to extreme heat (elderly, respiratory diseases, women)	Observational study	Found vulnerable groups at higher risk; limited by exclusion of long-term adaptation effects.
Deschenes (2022)	Heat–mortality trends in the US	Longitudinal analysis (1980–2019)	Showed reduced risk due to adaptation; context-specific to the US, limited transferability to Malaysia.
Abbass et al. (2022)	Climate change impacts across sectors	Systematic literature review	Categorised impacts on agriculture, health, tourism, and economy; broad but not mortality-specific.
Barteit et al. (2023)	Climate change health data in Malaysia	Policy/health data review	Identified limited national data on climate–health impacts; stressed the need for evidence-based interventions.

METHODOLOGY

Overview of the Proposed Framework

STSM is a statistical approach that captures long-term, seasonal, and irregular dynamics in data, making it particularly suitable for analysing complex climate–health relationships. This study proposed an STSM to analyse the relationship between climate determinants and mortality in a tropical developing country. A case study was conducted in the Johor area of Malaysia, covering the period 2005–2022. The proposed framework integrates mortality data with climatic variables, which are temperature, rainfall, number of rainy days, and relative humidity, while accounting for structural breaks and outliers through indicator saturation (IS). The methodology enables the decomposition of mortality trends into underlying components, thereby offering insights into long-term, seasonal, and irregular effects of climate on health outcomes.

Data Sources and Pre-processing

Annual mortality data, including totals of deaths and population estimates, were obtained from the Department of Statistics Malaysia (DOSM) at the state level for Johor, covering the years 2005–2022. These data encompass the entire population of Johor, ensuring comprehensive coverage for the analysis. Climatic determinants for the same period, which are temperature, rainfall amount, number of rainy days, and relative humidity, were retrieved from the Malaysian Meteorological Department (MMD). These variables were originally summarised on a monthly scale and subsequently aggregated to a yearly series to align with mortality data, thereby achieving a consistent chronological framework for regression and estimation. The climate data were extracted from the Senai meteorological station, located immediately northwest of Johor Bahru, the state capital. Given its terminal location and continuous records, Senai provides representative ambient conditions for Johor Bahru and adjacent districts. Despite the spatial mismatch between state-level mortality data and station-based climate exposure, this approach aligns with established practice in climate–health studies, where state-level outcomes are often paired with the most relevant and continuous climate records from a single representative station (Salim et al., 2021; Sa'adi et al., 2024).

Structural Time Series Model

STSM were first brought to the attention of the econometrics and statistics literature approximately three decades ago, most notably by Harvey (1990). Within this framework, a given time series is conceptualised as the superposition of several components: a deterministic or stochastic trend, cyclical influences, seasonality, and an irregular component. The specification of a univariate STSM is summarised by the general form given in Equation 1.

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \varepsilon_t \tag{1}$$

The variable μ_t represents the trend component, γ_t corresponds to the seasonal component, ψ_t indicates the cyclical component, r_t denotes a first-order autoregressive component, and ε_t captures the irregular component of the time series. Each of these components can exhibit either deterministic or stochastic behaviour. The complete mathematical specification of the structural time series, including trend, seasonal, cyclical, and irregular components, is taken from the model set forth by Karimi et al. (2024) and summarised in Equations 2 through 12. The proposed modelling framework facilitates the decomposition of the mortality time series into distinct components, thereby enabling the simultaneous identification of underlying trends, seasonal patterns, and irregular components with climate variables.

The trend component, also known as the underlying trend (Mousavi & Ghavidel, 2019), comprises two components: the level and the slope. Generally, the trend component is modelled using Equations 2 and 3, where Equation 2 defines the level of the trend, μ_t and Equation 3 describes changes in the level or slope, β_t (Harvey, 1990). This component characterises the long-term behaviour of the time series.

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t\ ;\quad \eta_t \sim N\left(0, \sigma_\eta^2\right) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t\ ;\ \ \xi_t \sim N\left(0, \sigma_\xi^2\right) \tag{3}$$

Where t denotes time index. The variable μ_t represents the level of the trend component at time t, while μ_{t-1} denotes the trend level at time $t-1$. The parameter β_t represents the slope, or growth rate, of the trend at time t, and β_{t-1} refers to the slope of the trend at time $t-1$. The term η_t is a disturbance term associated with the level equation and captures random fluctuations in the trend level, whereas ξ_t is a disturbance term associated with the slope equation and represents random changes in the trend slope. The parameters σ_η^2 and σ_ξ^2 denote the variances of the level and slope disturbance terms, respectively. Both η_t and ξ_t are assumed to be independently and identically distributed Gaussion white noise processes with zero mean. Economic time series frequently exhibit pronounced seasonal effects. Researchers typically address these fluctuations through modelling approaches that incorporate either dummy variables, which explicitly mark seasonal peaks or troughs, or trigonometric functions, which offer a compact, continuous representation of cyclical variation. When incorporating stochastic or deterministic dummy variables, the seasonal component is represented by Equations 4 and 5, respectively. The parameter' s' indicates the number of seasonal frequencies within a given period, for instance, s = 12 for monthly data, s = 4 for quarterly data, and s = 2 for semi-annual data.

$$\sum_{i=1}^{s-1} \gamma_{t-i} = \omega_t\ ;\ \ \omega_t \sim N(0, \sigma_\omega^2) \tag{4}$$

$$\sum_{i=1}^{s-1} \gamma_{t-i} = 0 \tag{5}$$

Where γ_t denotes the seasonal component of the time series at time t. The term ω_t is a stochastic disturbance associated with the seasonal component and is assumed to follow a Gaussian white noise process with zero mean and variance σ_ω^2. In Equation 4, the seasonal effects are assumed to have a zero mean. However, due to their stochastic nature, these effects may evolve gradually when the variance is small or more rapidly when the variance is large. Equation 5 represents a special case where the variance is zero, implying that the seasonal effects remain constant over time. The cyclic component can be represented in two forms: deterministic and stochastic trigonometric cycles. A deterministic cycle with a period λ (where 0 < λ < π) is described by Equation 6.

$$\psi_t = \alpha \cos(\lambda t) + \beta \sin(\lambda t) \tag{6}$$

Where ψ_t denotes the cyclical component at time t. The parameters α and β determine the amplitude and phase of the cycle, while λ represents the cyclical frequency measured in radians, with $0 < \lambda < \pi$. When time t is treated as continuous, ψ_t becomes a periodic function with a periodicity of $(2\pi/\lambda)$ and an oscillation amplitude of $\sqrt{\alpha^2 + \beta^2}$. In contrast, when time is discrete, ψ_t is not strictly periodic, except in certain cases where $\left(\lambda = \frac{2j\pi}{k}\right)$, with j and k being integers. Unfortunately, economic time series rarely exhibit sufficiently systematic cycles to be accurately described by a specific periodic function, such as that in Equation 6. Nevertheless, Fourier analysis reveals that complex cyclical patterns can be approximated by a finite sum of sinusoidal functions, as illustrated in Equation 6. As an alternative to identifying deterministic cycles governed by numerous parameters, stochastic cycles can be modelled using the form given in Equation 7.

$$\begin{bmatrix}\psi_t \\ \psi_t^*\end{bmatrix} = \rho \begin{bmatrix}\cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda)\end{bmatrix} \begin{bmatrix}\psi_{t-1} \\ \psi_{t-1}^*\end{bmatrix} + \begin{bmatrix}\nu_t \\ \nu_t^*\end{bmatrix} \tag{7}$$

Where ψ_t and ψ_t^* denote the state variables describing the stochastic cycle at time t. The disturbance terms ν_t and ν_t^* represent stochastic innovations to the cyclical component. In this context, (ρ) represents the cycle adjustment factor, constrained between zero and one. When $\rho < 1$, the cycle is stationary, whereas $\rho = 1$ indicates a nonstationary cycle. The parameter (λ) denotes the cyclical frequency in radians. The terms ν_t and ν_t^* are stochastic error components associated with the cycle, assumed to be independently and identically distributed with zero mean and a common variance σ_ν^2. If the variance equals zero, the cycle reduces to a deterministic form. This model is capable of capturing complex cyclical behaviour in economic time series without requiring the specification of additional parameters. Instead of representing cycles through deterministic (Equation 6) or stochastic models (Equation 7), the cyclical dynamics can be directly modelled using Equation 8.

$$r_t = \rho r_{t-1} + \upsilon_t \ ; \ \upsilon_t \sim N(0, \sigma_\upsilon^2) \tag{8}$$

In Equation 8, r_t denotes an unobserved autoregressive component that follows a first-order autoregressive process, with $-1 < \rho < +1$. Despite its structural simplicity, this component effectively captures much of the inertia observed in business cycles and is commonly found in economic time series. To examine the influence of climate variables on the y_t series, the structural model can be extended beyond univariate analysis by incorporating explanatory variables and lagged values of y_t on the right-hand side of the equation. The general specification of the structural time series regression model is presented in Equation 9.

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j_1}^{J_1} \beta_{1j_1} x_{1t-j_1} + \cdots + \sum_{j_n}^{J_n} \beta_{kj_n} x_{kt-j_n} + \varepsilon_t \tag{9}$$

Drawing on theoretical literature concerning the variables of climate change effects and employing the STSM, the empirical model used to model the effects of climate change on mortality is specified in Equation 10.

$$\begin{gathered} q_t^{mr} = \theta_t + \sum_{i=1}^{I} \alpha_i q_{t-i}^{mr} + \sum_{j=0}^{J} \beta_j p_{t-j}^{temp} + \sum_{k=0}^{K} \delta_k p_{t-k}^{rain} + \sum_{l=0}^{L} \varphi_l \, p_{t-l}^{rd} + \sum_{m=0}^{M} \varphi_m p_{t-m}^{hum} + w_t \lambda \\ + \varepsilon_t \\ \theta_t = \mu_t + \gamma_t + \psi_t + r_t + \varepsilon_t \end{gathered} \tag{10}$$

In Equation 10, variables q_t^{mr}, p_t^{temp}, p_t^{rain}, p_t^{rd} and p_t^{hum} represent the mortality rate, temperature, rainfall amount, number of rainy days, and relative humidity, respectively. All variables are in logarithms. w_t represents the vector of intervention variables, which are typically incorporated into the model as dummy variables to capture the effects of unexpected events. When such an event occurs at time τ and produces a pulse effect, the corresponding intervention variable is defined as shown in Equation 11.

$$w_t = \begin{cases} 1 & \text{for } t = \tau \\ 0 & \text{for } t \neq \tau \end{cases} \tag{11}$$

If an unexpected event occurring at time τ results in a shift in the slope or a change in the trend of the time series, the corresponding dummy variable is specified as shown in Equation 12.

$$w_t = \begin{cases} t-\tau & \text{for } t > \tau \\ 0 & \text{for } t \leq \tau \end{cases} \tag{12}$$

In Equation 10, the variances associated with μ_t, γ_t, ψ_t and r_t are specified as hyperparameters, which may take values of zero or be strictly positive. Table 2 summarises the stochastic or deterministic nature of the unobserved components in the previously modelled time series of mortality rates, depending on whether their variances are non-zero or zero, respectively. The most essential component in this context is μ, as defined in Equation 10.

Table 2

Hyperparameter and Character Components

Character Components	Components and Hyperparameters				
	Trend Level	Trend Slope	Seasonal	Cyclical	Unobserved Autoregressive Component
Stochastic	$\sigma_\eta^2 > 0$	$\sigma_\xi^2 > 0$	$\sigma_\omega^2 > 0$	$\sigma_\nu^2 > 0$	$\sigma_\upsilon^2 > 0$
Fixed	$\sigma_\eta^2 = 0$	$\sigma_\xi^2 = 0$	$\sigma_\omega^2 = 0$	$\sigma_\nu^2 = 0$	$\sigma_\upsilon^2 = 0$

This component is estimated using the Kalman Filter. The Kalman filter is a step-by-step algorithm that helps estimate the state of a system when the available data are noisy or uncertain. It updates estimates by combining information from the system's previous state with new observations, while accounting for possible errors in both. In the following, the estimation of μ for each year is calculated and plotted. Through this method, we examine the dynamic impact of climate variables on mortality rates in Malaysia. Estimation of other parameters in Equation 10 is performed by the maximum likelihood estimator in regression.

Detection Procedure using Impulse Indicator Saturation

The impulse indicator saturation (IIS) technique, first introduced by Hendry (1999), involves adding a series of dummy variables, each representing an individual observation, into a regression model. This approach helps detect outliers and structural breaks within the data. The detection procedure using indicator saturation technique is summarised here. Details procedure of IIS and step indicator saturation (SIS) techniques are presented in (Castle et al., 2015; Che Rose et al., 2021). In summary, the procedure takes the following form when indicators are added to T observations:

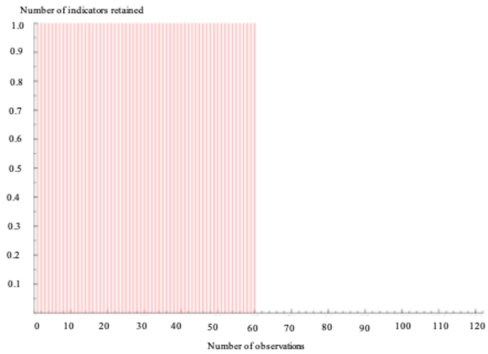
1. The indicators are divided into b = 2 blocks, b_1 and b_2.
2. Estimation of parameters, including the impulse indicators for both blocks, using the ordinary least squares (OLS) method, as shown in Figures 1(a) and 1(c).
3. Selection of retained indicators using a sequential or non-sequential approach at the chosen significance level, as presented in Figures 1(b) and 1(d).
4. Run the model selection using the General-to-Specific (GETS) approach to obtain the terminal model in the first block.
5. Recommence steps 2 to 4 for the second block.

6. Combine all the significant indicators retained from both blocks.
7. Rerun the model selection on retained indicators to obtain the final terminal model as depicted in Figure 1(e).

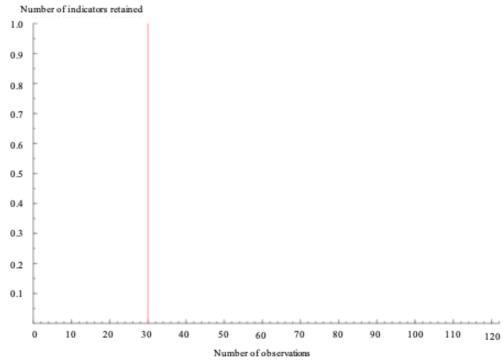
Figure 1

The Impulsive Saturation Algorithm Depicted when the Additive Outlier was Located at t=30 and t=90 (Che Rose et al., 2025)

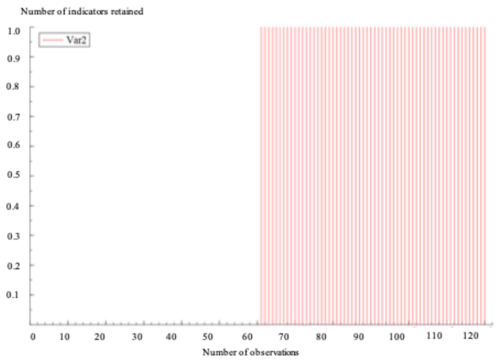
(a) Initial model with indicator variables added in Block 1.



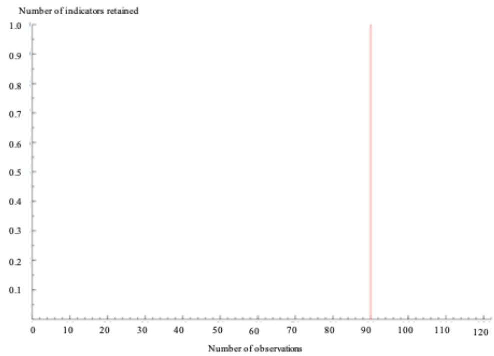
(b) Indicator variables retained in Block 1.



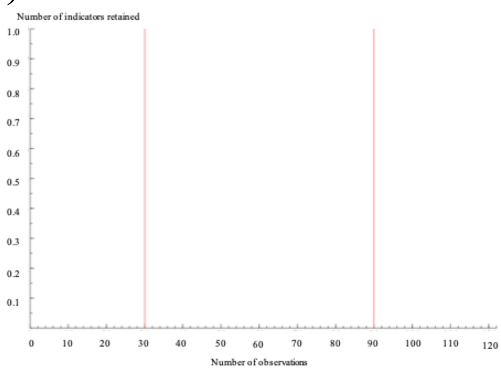
(c) Initial model with indicator variables added in Block 2.



(d) Indicator variables retained in Block 2.



(e) Final model: Combined retained indicator



ANALYSIS AND RESULTS

Descriptive Statistics of Climate and Mortality

Table 3 shows descriptive statistics for each variable: temperature, rainfall amount, number of rainy days, relative humidity, and mortality. The mean temperature is 26.8°C with minimal variation (standard deviation of 0.70°C), reflecting a stable temperature profile. The average rainfall amount is 224.8 mm with a median of 212.0 mm and a standard deviation of 116.93 mm, indicating moderate variability and a likely positive skew in the distribution, as the mean exceeds the median. The number of rainy days averages 16.5 per period, with a median of 17.0 and a standard deviation of 4.85, suggesting a relatively consistent monthly rainfall pattern. The relative humidity averages 84.9%, with a median of 85.4% and a standard deviation of 2.59%, indicating persistently high humidity levels typical of a tropical climate, with slight variation over time. The mean mortality rate is 2.59 deaths per 100,000 population, with a median value of 2.67. The relatively low standard deviation of 0.39 indicates limited variability in mortality rates over time. Overall, the mortality data appear to be relatively stable over time, with no extreme fluctuations.

Table 3

Descriptive Statistics of Climate Variables and Mortality

	Temperature (°C)	Rainfall Amount (mm)	Number of Rainy Days (days)	Relative humidity (%)	Mortality
Mean	26.8449	224.8347	16.5105	84.9307	2.5908
Median	26.8726	212.0000	17.0000	85.4200	2.6740
Standard Deviation	0.6995	116.9264	4.8523	2.5852	0.3947

It is important to note that while the mortality data used for modelling covers the period from 2005 to 2022, the climate data presented in Figures 2(a) to 2(d) extends up to 2025 due to the availability of more recent climate records for the years 2023 to 2025. This extended climate data was included solely for descriptive and visualisation purposes to illustrate recent climate trends and patterns in Johor, Malaysia. However, all modelling and statistical analyses in this study were based solely on climate and mortality data from 2005 to 2022 to maintain consistency across datasets.

Figure 2

Time Series Plot of Climate Variables

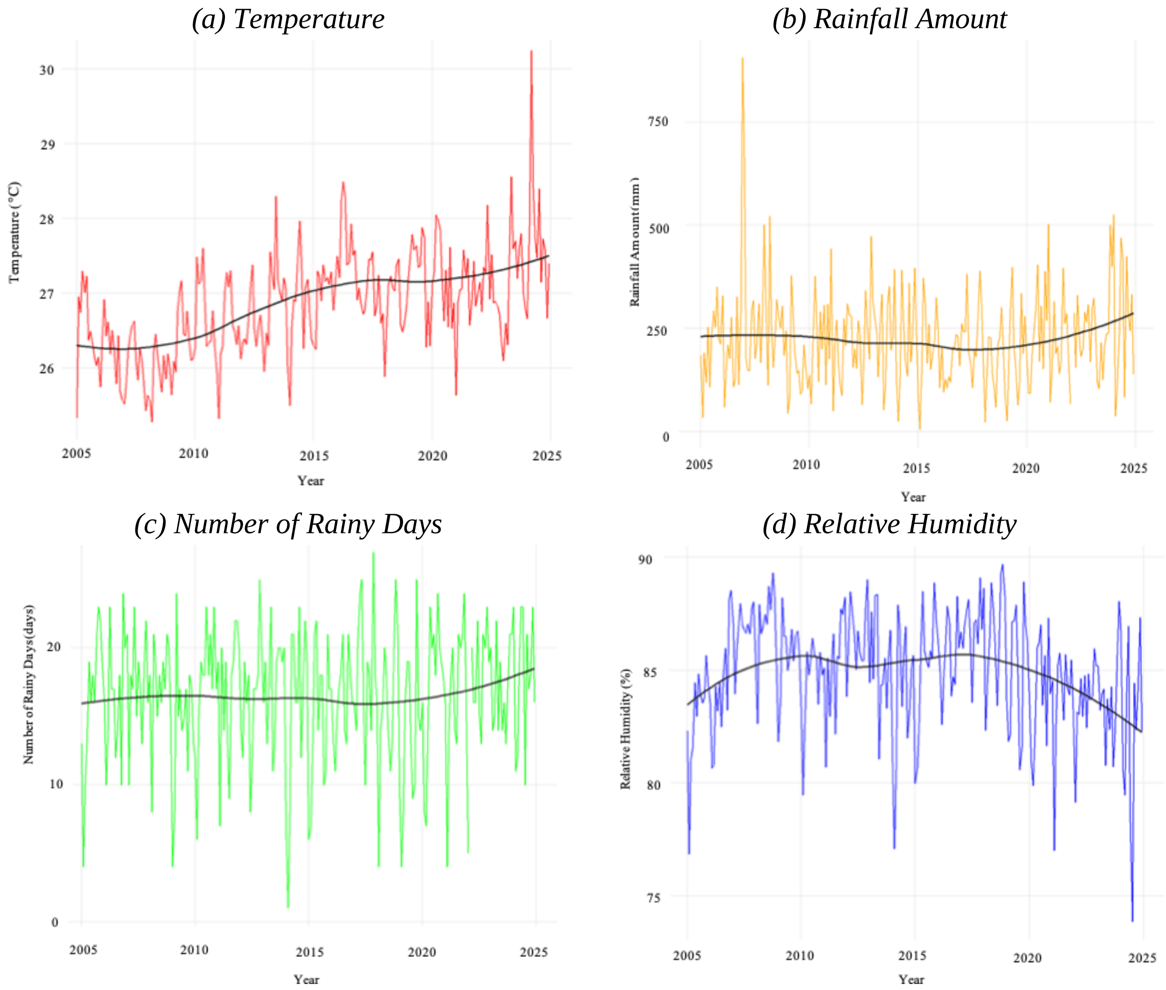
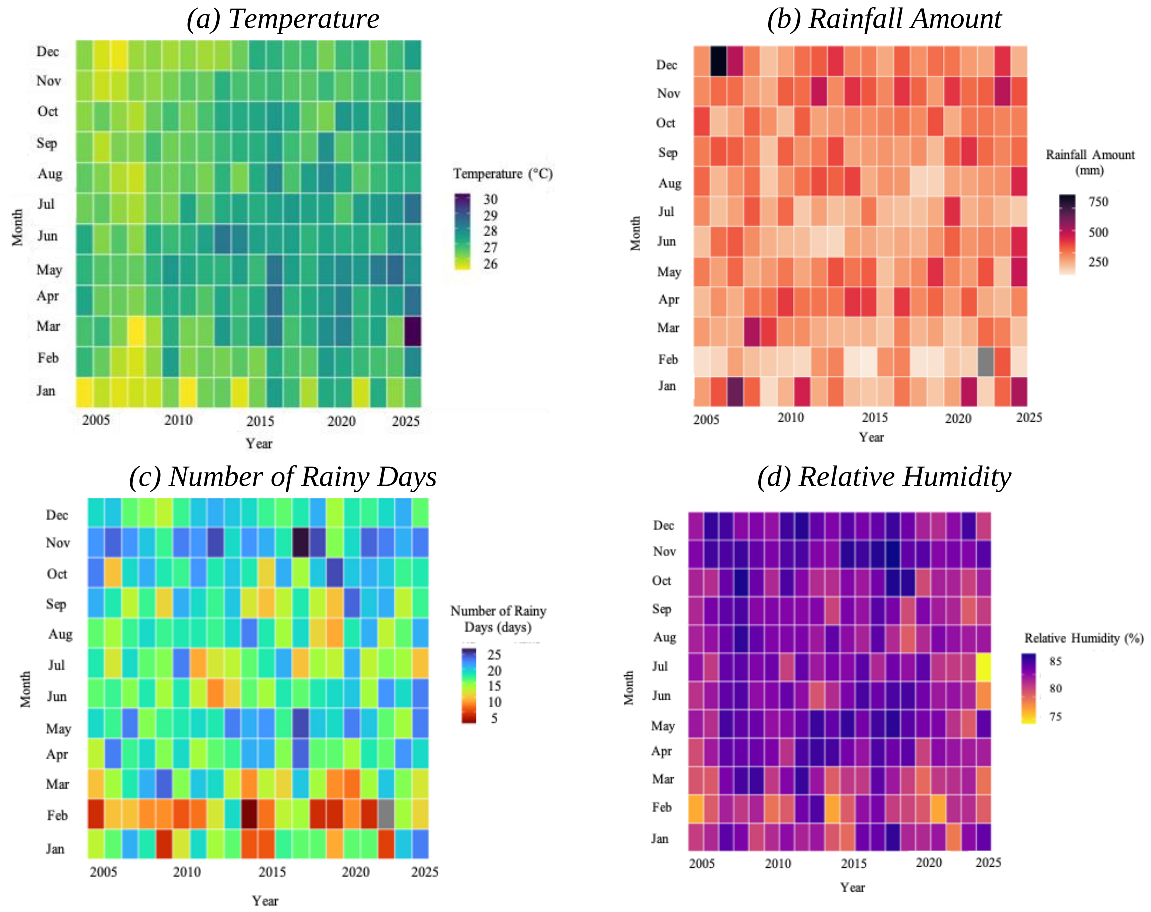


Figure 2(a) shows the time series plot of temperature in Johor, which reveals a gradual warming trend consistent with regional climate change. Seasonal fluctuations are evident, with increasing volatility observed after 2015. A notable anomaly appears in 2023–2024, when average temperatures approach 30°C, suggesting the influence of extreme climate events such as El Niño. Figure 2(b) shows the time series of rainfall amounts in Johor, indicating pronounced interannual variability without a consistent long-term trend. An extreme event occurred in 2007, when rainfall exceeded 750 mm, coinciding with documented flooding. Although fluctuations appear moderate after 2010, episodic extremes persist, reflecting heightened precipitation unpredictability associated with monsoon dynamics.

Figure 2(c) depicts the time series plot of the number of rainy days in Johor, which remains relatively stable, averaging between 10 and 25 days per month. Seasonal variations and occasional sharp dips indicate short periods of unusual dryness, but no significant long-term upward or downward trend is detected. Figure 2(d) shows the time series plot of relative humidity in Johor, which remains consistently high (80–90%), reflecting the state's tropical climate. Despite the stability, short-term oscillations occur due to monsoonal influences, with a notable decline below 75% in early 2021. Such anomalies are relevant for health risk assessments, given their potential impacts on respiratory conditions and heat-related stress.

Figure 3

Heatmap of Climate Variables



Given the availability of climate data for 2023 to 2025, the heatmap was constructed to illustrate climate variables over the full period from 2005 to 2025. Figure 3(a) shows the heatmap of monthly average temperature trends in Johor, Malaysia, from 2005 to 2025. The heatmap shows a seasonal pattern: higher temperatures generally occur between April and August, and lower temperatures between November and February. Several anomalies are visible, including a notably low value in February 2021 and elevated temperatures in April 2010 and March 2015. Figure 3(b) presents a heatmap of monthly rainfall amounts over the same period. Higher rainfall is concentrated in November and December, aligning with the Northeast monsoon, while February and March consistently show lower totals. Notable anomalies include extreme rainfall in January 2021 and unusually low rainfall in December 2016. Figure 3(c) depicts the monthly distribution of rainy days. The darkest blue cells between October and December reflect high frequencies during the Northeast monsoon, while February and March show fewer rainy days. A notable deviation is observed in October 2017, when rainy-day counts exceeded 25. Figure 3(d) shows monthly relative humidity. Values are consistently high (80–90%), with some variation in February and March. A significant anomaly is recorded in July 2021, when humidity exceeded 85%.

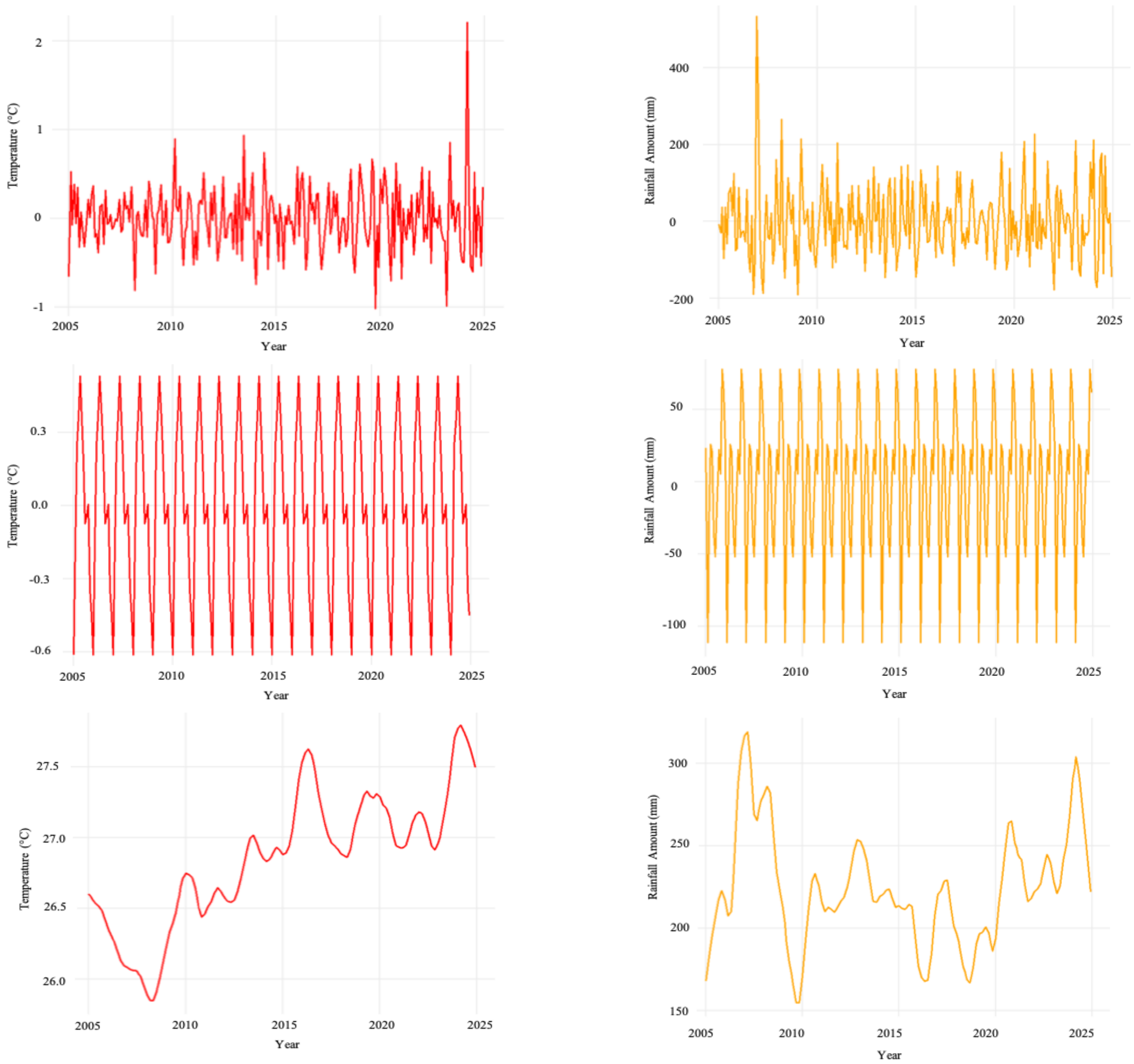
Structural Time-Series Decomposition of Climate Variables

Given the availability of updated climate data up to 2025, the estimation of climate variables, including trend, seasonal, and irregular components was conducted for the full period from 2005 to 2025. This method provides a way to examine recent climate variability more closely while also detecting possible structural changes in the data. In assessing the links between climate and mortality in Johor, Malaysia, this study applied a structural time-series decomposition to four variables, which are (i) temperature, (ii) rainfall amount, (iii) number of rainy days, and (iv) relative humidity. The dataset spans from 2005 to 2025. By breaking down each series into its trend, seasonal, and irregular components, the method helps distinguish long-term shifts from recurring patterns and short-term fluctuations. These decompositions, shown in Figure 4, make it easier to interpret how different aspects of climate behaviour evolve over time.

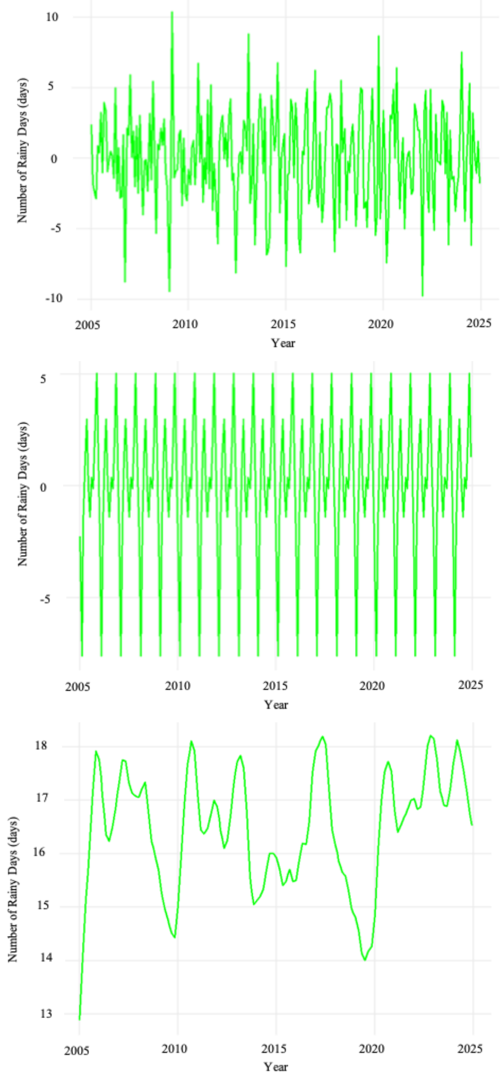
Figure 4

Univariate Estimation of Climate Variables

(a) Temperature *(b) Rainfall Amount*



(c) Number of Rainy Days



(d) Relative Humidity

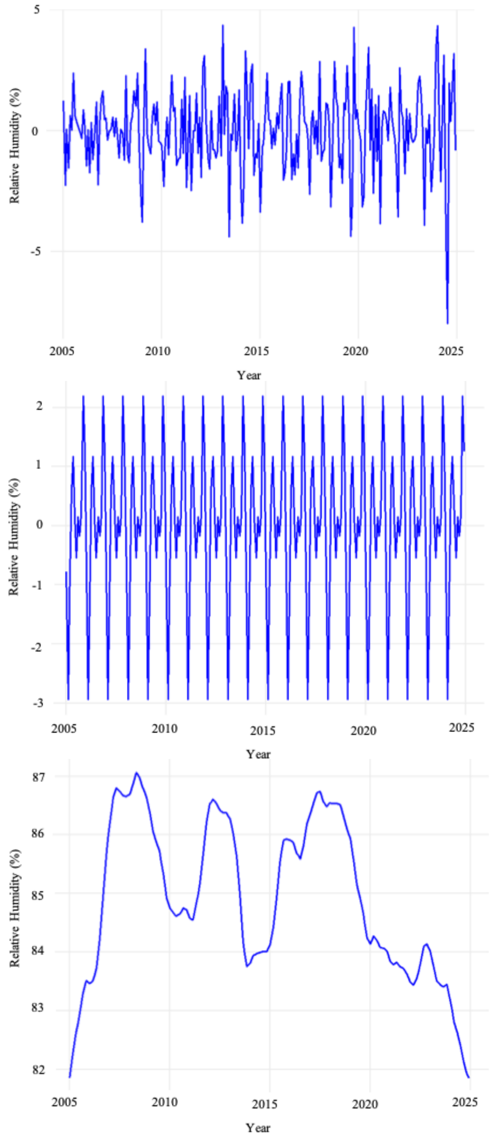


Figure 4(a) shows the temperature time series from 2005 to 2025. The first panel presents the irregular component, followed by the seasonal and trend components. The series exhibits a clear upward trend, particularly after 2015, with a notable spike just before 2025. The seasonal component remains stable, reflecting consistent annual cycles, while the irregular component is largely stationary with occasional short-term spikes in 2020 and 2025. Figure 4(b) shows the monthly rainfall series from 2005 to 2025. The results indicate no sustained long-term trend, though strong seasonal cycles tied to monsoon patterns are evident. Irregular fluctuations are most pronounced before 2010, with several sharp spikes indicating extreme rainfall events. Figure 4(c) shows the number of rainy days from 2005 to 2025. A slight downward trend is observed, suggesting a modest reduction in rainfall frequency. Seasonal cycles remain intact, with predictable wet and dry phases. The irregular component shows occasional short-term spikes associated with unusual weather events. Figure 4(d) shows the relative humidity series from 2005 to 2025. The results display a gradual increase up to around 2013, followed by a modest decline after 2020. The seasonal component remains strong and regular, consistent with monsoonal influences. The irregular component is minor, with only occasional anomalies observed.

To assess the suitability, stability, and predictive accuracy of the STSM applied to each climatic variable, a series of quantitative diagnostic and uncertainty metrics was computed. Table 4 presents the Prediction Error Variance (PEV) statistic, which quantifies the uncertainty in the predicted value over the evaluation horizon. Additionally, residual diagnostic tests, including normality, heteroscedasticity (H(75)), and autocorrelation statistics (Durbin-Watson, r(1), r(q), and Ljung-Box Q statistic), were performed to assess model assumptions. The estimated variances of the state disturbances for the slope, level, seasonal, and irregular components provide insight into the contribution of each unobserved component to the series' total variance. Finally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are reported to facilitate model comparison and selection. Overall, the suite of diagnostic indicators affords a systematic framework for confirming the statistical validity of the fitted models, rendering them appropriate for subsequent analytical applications.

Table 4

Univariate STSM Estimation and Diagnostic for Climate Variables and Mortality

	Temperature (°C)	Rainfall Amount (mm)	Number of Rainy Days (days)	Relative humidity (%)	Mortality
Prediction Error Variance (PEV)	0.1981	11989.3445	14.2372	3.9411	0.1833
Residual Diagnostic					
Normality	52.4120	18.4980	2.1730	10.9500	2.7870
H(75)	2.6208	0.70962	1.2982	2.3234	0.5278
DW	1.8038	1.6679	1.7199	1.7254	1.6293
r(1)	0.0914	0.15956	0.13876	0.1222	0.1719
q	24	24	24	24	5
P	3	3	3	3	2
r(q)	-0.0785	-0.0537	-0.1356	-0.14818	-0.1794
Q(q, q-p)	19.2410	32.1130	31.2210	29.5990	2.8279
Variances of Disturbance					
Slope	1.256×10^{-02} (0.0871)	30.7219 (0.002822)	2.5221×10^{-03} (0.0001702)	0.1490 (0.04420)	0.000266 (0.001761)
Level	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	1.9800×10^{-03} (0.01313)
Seasonal	1.4853×10^{-05} (0.0001030)	1.64193 (0.0001508)	0.0000 (0.0000)	0.0000 (0.0000)	-
Irregular	0.14428 (1.0000)	10885.7 (1.0000)	14.8178 (1.0000)	3.3691 (1.0000)	0.1509 (0.0131)
Model Fit Statistics					
AIC	-1.1298	9.2484	2.9692	1.7431	-1.3634
BIC	-0.8978	9.4804	3.1867	1.9606	-1.2150

Based on PEV values for each variable, rainfall amount has the highest PEV, 11,989.34 mm, reflecting how variable and difficult to predict rainfall is in this dataset. The number of rainy days (14.24) and relative humidity (3.94%) fall in the middle range, indicating moderate levels of forecasting uncertainty. By contrast, temperature (0.1981°C) and mortality (0.1833) have the lowest PEV values, suggesting that both can be forecasted with relatively high confidence. In short, rainfall is the least predictable, while temperature and mortality behave more consistently over time.

Tests for normality indicated that several climate variables deviated significantly from normality. Temperature produced the highest statistic (52.412°C), followed by rainfall amount (18.498 mm). It suggests that both series may be skewed or heavy-tailed, which is not uncommon in climate data. On the other hand, mortality was closer to normal with a test value of 2.787. The Harvey test was used to check for heteroskedasticity. Here, temperature (2.6208°C) and relative humidity (2.3234%) had higher values, suggesting moderate changes in variance over time. Mortality again showed more stability with a much lower value (0.5278). These results mean that for some variables, especially temperature and rainfall, extra care is needed when applying models that assume constant variance.

The Durbin-Watson (DW) results ranged from 1.6293 (mortality) to 1.8038°C (temperature). Since these values are close to the ideal benchmark of 2.0, there is little evidence of autocorrelation in the residuals. It is important because it supports the assumption that the errors are independent. The first-order autocorrelation coefficients, r(1), were small and positive, ranging from 0.0914°C for temperature to 0.1719 for mortality. At the seasonal lag (24 months), the coefficients turned slightly negative but still small, from –0.0537 for rainfall amount to –0.1794 for mortality. The Ljung–Box Q-statistics supported the same conclusion: residuals behave like white noise, and the models appear adequate without signs of serious misspecification.

Regarding disturbance variances, rainfall amount showed the largest slope variance (30.7219 mm), indicating that its long-term trend is the most volatile. By contrast, temperature (0.0126°C), number of rainy days (0.0025 days), and relative humidity (0.1489%) had much lower values, while mortality was even smaller at 0.0003. It suggests rainfall is unpredictable, while the other variables, particularly mortality, are much more stable. All variables had zero disturbance variance at the zero level, indicating their baseline levels did not shift over the study period. Only rainfall amount showed a meaningful seasonal disturbance variance (1.64193 mm), reflecting its recurring wet and dry cycles. The irregular variances, however, were dominant. Rainfall amount (10,885.7 mm) and rainy days (14.8178 days) both had high irregular variances, confirming their random fluctuations, while mortality remained low (0.1509).

The information criteria further highlight the differences among the variables. Temperature had the lowest values (AIC = –1.1298, BIC = –0.8978), which means its model was both accurate and simple. Mortality was also strong (AIC = –1.3634, BIC = –1.2150), even slightly better than temperature. In contrast, rainfall had the highest AIC (9.2484) and BIC (9.4804), indicating the greater complexity required to capture its variability. Rainy days (AIC = 2.9692, BIC = 3.1867) and relative humidity (AIC = 1.7431, BIC = 1.9606) fell somewhere in between. Taken together, these results suggest that mortality and temperature are easier to model parsimoniously, whereas rainfall requires more complicated approaches.

Residual analysis provided further support for model adequacy. The residuals were centred around zero, suggesting that the models did not systematically over- or under-estimate outcomes. Their spread was moderate, and while skewness and kurtosis showed that the errors were not perfectly normal, this was already expected from the earlier normality tests. The Bowman–Shenton (Jarque-Bera) test confirmed the departures from normality, which means results should be interpreted with some caution. Even so, the residuals were close to white noise, which increases confidence that the models capture the main dynamics of the series without leaving strong patterns unexplained.

Structural Time Series Modelling Results

Table 5 displays the residual diagnostic statistics. The residuals' means are close to zero, while their standard deviations are near 1, indicating that the models are well-calibrated in terms of scale. However, the skewness and excess kurtosis statistics reveal departures from normality in some series. For example, temperature (skewness = 0.6767; excess kurtosis = 3.8397) and rainfall amount (skewness = 0.5985; kurtosis = 1.772) exhibit positive skew and leptokurtosis, suggesting asymmetry and a tendency toward outliers, possibly linked to extreme climate events. The Bowman–Shenton (Jarque–Bera) test further supports these findings. Statistically significant results ($p < 0.01$) were obtained for temperature, rainfall amount, and relative humidity, indicating substantial departures from normality. In contrast, the residuals for the number of rainy days were not significant ($p = 0.3672$), suggesting that this series approximates normality more closely. Residual ranges also highlight extreme values, particularly for temperature (–2.67 to 5.71) and relative humidity (–4.25 minimum). These diagnostics confirm that, although some deviations exist, the STSM provides a sufficiently robust basis for subsequent estimation of mortality effects, in line with the study's first objective.

Table 5

Residual Diagnostic Test for STSM

	Temperature (°C)	Rainfall Amount (mm)	Number of Rainy Days (days)	Relative humidity (%)
Mean	0.0425	-0.026097	-0.015055	-0.11842
Standard Deviation	0.9991	0.99966	0.99989	0.99296
Skewness	0.67669	0.59845	-0.22361	-0.47274
Excess Kurtosis	3.8397	1.772	-0.11299	1.0643
Minimum	-2.6701	-2.9875	-3.1503	-4.2497
Maximum	5.7147	4.5284	2.5871	2.1327
Bowman-Shenton	156.77 (0.0000)	43.058 (0.0000)	2.0036 (0.3672)	19.169 (0.0000)

Following the decomposition of climate variables using the STSM, an OLS regression was conducted to estimate the influence of climatic factors on annual mortality in Johor. The results are reported in Table 6. The model, enhanced by IIS, demonstrates strong explanatory power, with partial R^2 values exceeding 0.99. Relative humidity has a statistically significant negative effect on mortality (coefficient = –0.0324, $p < 0.0001$), suggesting that higher humidity is associated with lower mortality rates. It may reflect the moderating role of humidity in reducing heat stress or improving air quality, though further investigation is warranted. By contrast, rainfall amount shows a significant positive effect (coefficient = 0.01166, $p < 0.0001$), with an exceptionally high t-value (625.0). It highlights rainfall as a key driver of mortality variation, possibly linked to flooding, vector-borne diseases, or environmental stressors in Malaysia.

Table 6

Modelling Mortality Rate using OLS Regression

	Coefficient	Standard Error	t-value (t-probability)	Partial R^2
Constant	2.77728	0.04395	63.2 (0.0000)	0.9970
Relative Humidity (RH)	-0.0324002	0.0005264	-61.6 (0.0000)	0.9968
Rainfall Amount (RA)	0.0116563	1.865×10^{-05}	625.0 (0.0000)	1.0000
I:2006	0.00863582	0.002490	3.47. (0.0046)	0.5005
I:2018	0.0128926	0.002728	4.73. (0.0005)	0.6505

Detection of Structural Breaks using Impulse Indicator Saturation

The application of IIS led to the inclusion of two statistically significant impulse indicators: I_{2006} and I_{2008}, corresponding to structural anomalies or outliers in those specific years. These impulses (coefficients = 0.0086 and 0.0129, respectively) are both significant at the 1% level, with t-values of 3.47 and 4.73. Their inclusion indicates that these years exhibited mortality patterns that deviated markedly from what would be expected based on the model's trend and seasonal structure alone. The year 2006 may coincide with public health disruptions, environmental disasters, or data anomalies, while 2018 could reflect extreme climate events or outbreaks (Banwell et al., 2018). Applying IIS at a conservative significance level of 1% to allow outlier in the intercept yield Equation 13.

$$MortalityRate_J = 2.78 - 0.03RH_J + 0.01RA_J + 0.0086I_{2006} + 0.0128I_{2008} \qquad (13)$$

The regression results highlight the significant and opposing effects of relative humidity (RH) and rainfall amount (RA) on mortality, while the implementation of IIS has strengthened the model by accounting for exceptional observations. This approach ensures that the estimation accurately reflects underlying climate-health relationships, free from distortion from irregular events.

Discussions

The findings show that rainfall is the strongest climatic driver of mortality in Johor, reinforcing evidence that excessive precipitation increases risks of flooding, disease outbreaks, and healthcare disruption (Ballester et al., 2016; Pandya-Wood et al., 2024). By contrast, the negative association with humidity suggests a more complex relationship; while higher humidity may ease heat stress (Barreca, 2012), other mechanisms, such as improvements in respiratory health or pollutant dispersion, could also be relevant. These patterns illustrate how climate–health interactions in tropical regions are shaped by overlapping factors rather than single exposures. The detection of anomalies in 2006 and 2018 highlights the importance of accounting for extreme events, since such shocks can magnify risks beyond gradual climatic trends. Methodologically, combining STSM with indicator saturation strengthens analysis by capturing both long-term patterns and sudden disturbances, offering a useful tool for climate–health research in Southeast Asia. Practically, the results underscore the need for stronger flood management, resilient health systems, and targeted interventions during periods of heavy rainfall.

Limitations remain, including reliance on a single weather station, state-level mortality data, and the absence of socioeconomic or demographic variables, all of which limit generalisability. Even so, the study contributes evidence to guide climate-responsive health policy in Malaysia and points to future work that extends the framework across regions and health outcomes.

CONCLUSION

The study identifies rainfall as a major climatic driver of mortality in Johor, a case study of a tropical area in Malaysia, highlighting the health risks associated with flooding, disease outbreaks, and service interruptions, while the negative association with humidity suggests more complex climate–health interactions warranting further study. The STSM with indicator saturation strengthens analysis by capturing both long-term patterns and sudden shocks, providing a robust framework for interpreting climate impacts on health. However, reliance on data from a single meteorological station, state-level mortality figures, and the absence of socioeconomic or demographic factors limit the depth and generalisability of the results. Even so, the findings provide helpful policy guidance, highlighting the need to strengthen disaster preparedness, improve early warning systems, and design health strategies that account for local climate risks. Future work should extend this approach to other states and broader datasets.

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