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URBAN PM_{10} MONITORING IN MALAYSIA: A STATISTICAL FRAMEWORK FOR PROCESS STABILITY AND CAPABILITY ASSESSMENT

(*Pemantauan PM_{10} Bandar di Malaysia: Rangka Kerja Statistik untuk Menilai Kestabilan dan Keupayaan* Proses)

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ABSTRACT

This study introduces a novel statistical framework for urban air quality assessment by applying the time-weighted Exponentially Weighted Moving Average (EWMA) control charts and process capability indices (CPI), to simultaneously diagnoses two aspects of the air quality: (1) stability (predictable air pollution behavior); and (2) capability (consistent compliance with national standards) in Four Process States framework to evaluate PM_{10} concentrations in Petaling Jaya, Shah Alam, and Putrajaya from 2015 to 2019 using monthly observations. The dual-analysis approach of this study thereby offers a more comprehensive and diagnostically informative classification of system performance beyond conventional compliance monitoring. The results show that 13 of 15 city-year observations fall under the Threshold Process State, indicating all three urban areas experienced constant non-compliance throughout the study period. Shah Alam went through episodes of Chaos throughout 2015 and 2016. This was due to exposure to persistent elevated PM_{10} levels, which might have posed significant health risks to the public during those years. Putrajaya potentially be a candidate for full compliance. The proposed framework serves as a diagnostic tool in distinguishing between structural pollution issues and temporary fluctuations, hence enabling more targeted and proactive interventions. Rather than relying solely on compliance status, policymakers can assess whether air quality systems are fundamentally capable of meeting regulatory standards. This offers more effective environmental regulation for better long-term urban planning and earlier risk detection. Additionally, it contributes to broader sustainability goals, particularly those related to public health and resilient urban governance.

Keywords: air quality; EWMA; statistical process control; capability analysis; four process states

ABSTRAK

Kajian ini memperkenalkan rangka kerja statistik baru untuk menilai kualiti udara bandar dengan menggunakan carta kawalan Purata Bergerak Wajaran Eksponen (EWMA) wajaran masa dan indeks keupayaan proses (CPI), untuk mendiagnosis dua aspek kualiti udara secara serentak: (1) kestabilan (tingkah laku pencemaran udara yang boleh diramalkan); dan (2) keupayaan (pematuhan yang konsisten dalam mencapai piawaian kebangsaan) dalam sebuah rangka kerja Empat Keadaan Proses. Kualiti udara berdasarkan kepekatan PM_{10} di nilai di tiga bandar utama iaitu Petaling Jaya, Shah Alam, dan Putrajaya bagi tahun 2015 hingga 2019 dengan menggunakan data bulanan. Kajian ini menawarkan klasifikasi prestasi proses kualiti udara yang lebih komprehensif dengan maklumat diagnostik di luar pemantauan pematuhan secara konvensional. Keputusan menunjukkan bahawa 13 daripada 15 pemerhatian mengikut tahun ke atas bandar tersebut berada di bawah Keadaan Proses Ambang yang menunjukkan ketiga-tiga kawasan bandar mengalami keadaan tidak patuh yang berterusan sepanjang tempoh kajian. Khususnya, Shah Alam mengalami episod Keadaan Kekacauan pada 2015 dan 2016 menunjukkan pendedahan kepada tahap PM_{10} yang tinggi secara berterusan yang menimbulkan risiko kesihatan awam yang ketara pada tahun-tahun tersebut. Walau bagaimanapun, Putrajaya muncul sebagai bandar yang paling hampir kepada pematuhan sepenuhnya. Rangka kerja yang dicadangkan boleh membezakan antara isu pencemaran struktur dan turun naik sementara. Ini membolehkan intervensi yang lebih bersasar dan proaktif. Daripada pergantungan semata-mata pada status pematuhan, penggubal dasar boleh menilai sama ada sistem kualiti udara pada asasnya mampu atau tidak untuk memenuhi piawaian kawal selia. Cadangan menawarkan penambahbaikan peraturan alam sekitar, perancangan bandar berjangka panjang dan pengesanan risiko lebih awal. Dapatan ini menyumbang kepada matlamat kemampanan yang lebih luas, terutamanya yang berkaitan dengan kesihatan awam dan tadbir urus bandar yang berdaya tahan.

Kata kunci: kualiti udara; EWMA; kawalan proses statistik; analisis keupayaan; empat keadaan proses

1. Introduction

As urban populations clustered in hubs of economic activity and mobility (Ompad *et al*. 2008), rapid urbanization worsens air quality and poses significant threats to public health, economic productivity, and environmental sustainability. The health impacts of ambient air pollution in Malaysia are significant. It has been reported that the estimated annual economic cost was approaching RM303 billion, which is about 20% of the country's 2019 Gross Domestic Product (GDP) (Centre for Research on Energy and Clean Air 2022). The hazardous air pollution episodes oftentimes occur in urban areas of Peninsular Malaysia due to multiple interacting factors such as rapid urbanization (Shirinkalam *et al*. 2025), tropical climatic conditions, regional geographical influences (Azmi *et al*. 2010), and episodic events, such as El Niño, combined with meteorological factors, especially temperature, can further increase particulate matter concentrations and restrain pollutant dispersion (Mohtar *et al*. 2018; Babu & Thomas 2025). Particulate matter (PM10 and PM2.5) is mostly of particular concern because of its ability to penetrate deep into the respiratory system and contribute to respiratory and cardiovascular complications (Sciaraffa *et al*. 2017; Mahiyuddin *et al*. 2013; World Health Organization 2021; United States Environmental Protection Agency 2025). Studies by Ab Malek *et al*. (2021) and Rahim *et al*. (2023) reveal that particulate matter (PM10 and PM2.5) poses a greater health concern than gaseous pollutants such as O3, CO, NO2, and SO2. Particulate matter, especially PM2.5, can infiltrate deep into the respiratory system, causing respiratory cardiovascular complications (Sciaraffa *et al*. 2017; Mahiyuddin *et al*. 2013; World Health Organization 2021; United States Environmental Protection Agency 2025).

Topics on spatial and temporal urban air pollution have been widely researched in Malaysia. $PM_{2.5}$ dynamics in Petaling Jaya (Mustafa *et al*. 2024), spatial distributions and their impacts in the Klang Valley (Shafie *et al*. 2022), and chronological air quality trends (Amir 2007), are such examples. Recent findings show a strong relationship between particulate matter exposure and adverse health outcomes. Tajudin *et al*. (2024) reported short-term PM_{10} surges in Peninsular Malaysia, which are associated with biomass burning; are significantly correlated to hospital admissions. Prolonged exposure to elevated particulate matter levels has also been shown to be significantly associated with the risk of cardiovascular diseases, stroke, and respiratory illnesses (Guo *et al*. 2023). Measures to control emissions have yielded some improvements, but particulate matter remains the major pollutant. Therefore, continuous monitoring is still needed (Singh *et al*. 2025; World Health Organization 2024). In Malaysia, the continued threat of PM10 is normally associated with emissions from major stationary and urban sources such as power generation (39%), industrial activities (29%), open burning (20%), motor vehicles (12%), and construction activities (Department of Environment Malaysia 2021; Shirinkalam *et al*. 2025).

Air quality monitoring studies in Malaysia primarily employed descriptive analysis, multivariate methods, and time-series modeling, and more recently, machine learning approaches attempt to characterize pollutant trends, identify emission sources, and improve predictive performance (Latif *et al*. 2018; Shaadan *et al*. 2015; Isiyaka & Azid 2015; Hanafi *et al*. 2018; Sentian *et al*. 2019; Ab Malek *et al*. 2021). Such methods are useful for forecasting air pollutant concentrations and for exploring relationships between meteorological or other explanatory variables, but they are not specifically designed to analyze statistically stable processes. While machine learning models often achieve strong predictive accuracy, their results offer limited interpretability, thereby limiting the understanding of process behavior, and failing to capture changes in air quality stability and capability (Karmoude *et al*. 2025). Statistical Process Control (SPC) methodologies, such as control charts, on the other hand, have been designed to monitor process variation and detect small shifts over time to determine whether a process remains in control (stable), whereas capability analysis evaluates if the process is able to meet the specification limits (Borror *et al*. 1999; Montgomery 2020). Despite being established in industrial quality control, control charts have also been adapted to environmental applications (Supharakonsakun *et al*. 2020; Atalay *et al*. 2020). Process capability, which was originally developed for manufacturing, has also been proven to be useful in non-industrial settings (Pan *et al*. 2014; Vännman & Albing 2007). In environmental monitoring, for example, SPC is relevant because pollutant levels are often affected by external shocks like haze, meteorological events, and other long-term systemic patterns. The conventional compliance-based approach is commonly employed to monitor and identify exceedances. Nonetheless, the approach offers limited information on whether the underlying pollution processes are predictable, resilient to external shocks, or capable of sustaining compliance. This is an important limitation for environmental governance, because a clearer understanding of process behaviour, early warning signals, and information on persistent systems deficiencies is equally important for effective management rather than the detection of pollution events. Therefore, the concepts of stability and capability are crucial as a basis for a more systematic diagnosis of ambient air quality systems. Environmental data can be assessed not only in terms of compliance, but also temporal consistency and process performance (Corbett & Pan 2002; Morrison 2008). In addressing this gap, Statistical Process Control (SPC) is applied to evaluate PM_{10} in three urban areas in Malaysia: Petaling Jaya, Shah Alam, and Putrajaya, over the period 2015–2019, using monthly observations. Even though SPC applications are evident in a number of studies that often rely on control charts in isolation, there are scarce studies on SPC applications in urban air quality assessment in Malaysia, let alone embedding SPC techniques within a structured analytical framework.

In this study, the Exponentially Weighted Moving Average (EWMA) control charts and process capability indices are used within Wheeler's (1995) Four Process States analytical framework, which classifies air quality processes into Ideal, Threshold, Brink of Chaos, and Chaos States. This framework allows air quality performance to be assessed from two aspects: stability, that is, predictable air pollution behavior over time, and capability, which reflects whether air quality can consistently remain within the MAAQS regulatory limits (Mulema & García 2019; Corbett & Pan 2002; Pan *et al*. 2014; Azid *et al*. 2014). In doing so, it provides a more comprehensive and diagnostically informative evaluation of system performance than conventional air quality monitoring.

The proposed framework of this study aligns with SDG 3.9 and SDG 11.6, the United Nations Sustainable Development Goals (SDGs), aiming to reduce the health impacts of hazardous air and to minimize cities' environmental footprint. The Malaysian Ambient Air Quality Standards (MAAQS), which adopt the World Health Organization's Interim Targets

(ITs) are the references employed to provide phased benchmarks for pollutant reduction in high-exposure regions (World Health Organization 2006). This study has three objectives: (1) to assess the statistical stability of PM_{10} concentrations of the selected Malaysian cities, (2) to evaluate their capability to meet national air quality standards, and (3) to classify overall system performance using a structured SPC-based framework. Ultimately, this study aimed to contribute to the intersection of environmental science and data analytics by offering a reproducible, policy-relevant approach to understanding the behavior of air quality processes and supporting data-driven environmental governance.

2. Materials and Methods

2.1. *Study area and air quality standards*

This study examines PM_{10} stability and compliance performance in three urban areas in the central region of Peninsular Malaysia: Petaling Jaya, Shah Alam, and Putrajaya. These three study areas are all located within the Klang Valley, Malaysia's most prominent urban and economic agglomeration. The Klang Valley is characterized by concentrated industrial, commercial, administrative, and transport activities, making it a region of substantial anthropogenic pressure on ambient air quality (InvestKL n.d.; World Population Review 2026). Figure 1 illustrates the location of the monitoring stations of the three urban areas in the central region of Peninsular Malaysia. In Malaysia, the Department of Environment (DOE) Malaysia has established fifty-one Continuous Air Quality Monitoring (CAQM) stations, divided into five (5) categories: industrial stations (26%), residential (57%), traffic (2%), background (2%), and specific PM_{10} stations (13%). Petaling Jaya is designated as an industrial station, Shah Alam and Putrajaya are categorized as residential stations. The three urban areas provide a useful basis for comparing PM_{10} behaviour across different urban land-use settings.

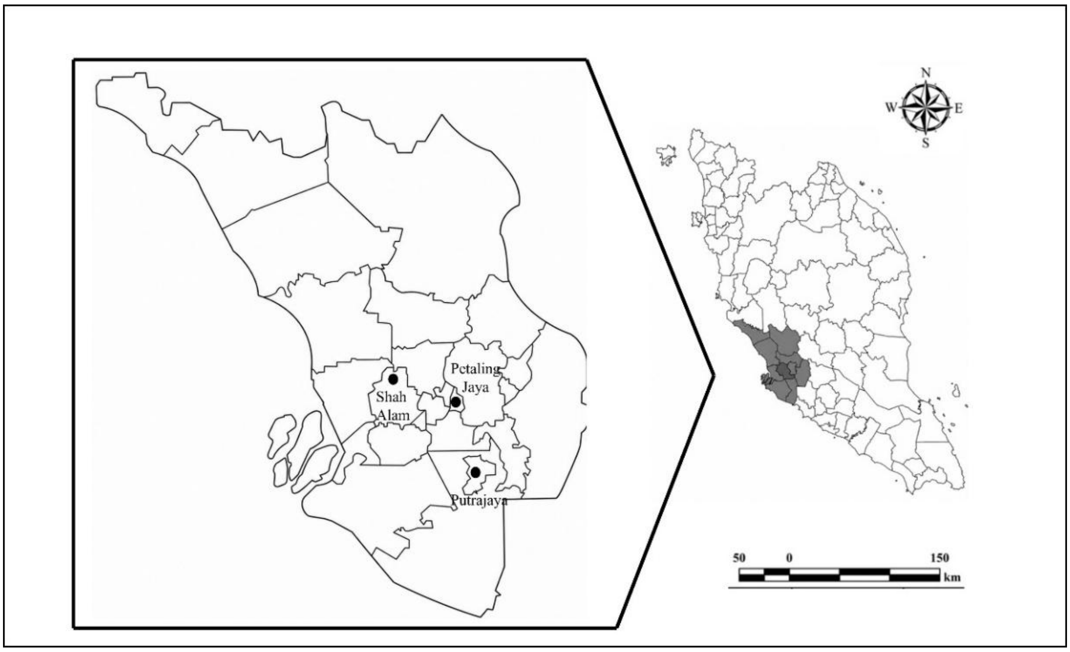


Figure 1: Location of Air Quality Monitoring Stations for Shah Alam, Petaling Jaya, and Putrajaya (adapted from Leeonis *et al*. 2024)

The daily air quality in Malaysia is communicated through the Air Pollution Index (API), which is the highest sub-index among the key pollutants PM_{10}, SO_2, NO_2, CO, and O_3, based on pollutant-specific averaging times (Department of Environment Malaysia 2018). But this current study utilizes the formal Malaysian Ambient Air Quality Standards (MAAQS) rather than API categories as the benchmark for evaluating PM_{10}. The World Health Organization (WHO) provides a set of guidelines to reduce pollutant concentrations through the Interim Targets (ITs). The guideline applies to countries with high air pollution levels (World Health Organization 2006; World Health Organization 2021). The Malaysian Department of Environment introduced similar guidelines known as the Malaysian Ambient Air Quality Standards (MAAQS) (Department of Environment Malaysia 2021), which specify the interim PM_{10} targets for 2015 and 2018, followed by full implementation of the updated standard in 2020. Table 1 shows the WHO interim and MAAQS targets for PM_{10} limits. The differences between MAAQS and the WHO Interims highlight the importance of evaluating PM_{10} performance in Malaysia against the national standards and international health-based benchmarks. Since the dataset used in this study spans the period 2015–2019, the analysis is limited only to the two applicable benchmark stages: Interim Target 1 (IT-1) for 2015 and Interim Target 2 (IT-2) from 2018 onward.

Table 1: PM_{10} ambient air quality standards 2015 – 2020.

Averaging Time	Malaysian Ambient Air Quality Standard (μg/m^3)			WHO Ambient Air Quality Guidelines (μg/m^3)		
	Interim 1 (2015)	Interim 2 (2018)	Standard (2020)	WHO IT-1	WHO IT-2	WHO IT-3
1-year	50	45	40	70	50	30
24-hour	150	120	100	150	100	75

2.2. *Statistical framework for process assessment*

Air quality assessment involves more than measuring pollutant concentrations; it also requires evaluating whether the air pollution process is statistically stable and consistently capable of meeting regulatory standards. In environmental monitoring, stability and capability are two complementary dimensions. Stability reflects whether pollutant levels behave predictably over time, whereas capability indicates whether the process can maintain concentrations within prescribed limits. Assessing both is particularly important in urban air quality studies, where pollutant behaviour is shaped by seasonal variation, meteorological conditions, urbanisation, and episodic pollution events (Borrego *et al*. 2006; Wang *et al*. 2014; Jacob & Winner 2009).

Statistical Process Control (SPC) provides a suitable analytical basis for such assessment because it enables process behaviour to be monitored systematically over time and this tool has been shown to be useful in environmental performance evaluation and monitoring, while air quality itself reflects a dynamic system shaped by pollutant emission, dispersion, chemical transformation, and atmospheric transport (Corbett & Pan 2002; Morrison 2008; Pénard-Morand & Annesi-Maesano 2004). In this context, control-chart analysis offers a useful means of identifying periods of instability and unusual variation in pollutant behaviour, thereby providing insight into process performance over time.

Within SPC, process stability is commonly assessed using time-ordered tools such as run charts and control charts. In this study, run charts were employed as a preliminary visual tool to examine the temporal behaviour of PM_{10} concentrations relative to the applicable interim benchmarks, namely IT-1 for 2015 and IT-2 from 2018 onward. Run charts support an initial assessment of process behaviour by identifying non-random patterns in time-ordered data (Perla *et al*. 2011). The Shewhart control chart, originally introduced by Shewhart (1926), is the earliest and most established SPC tool for evaluating process stability. However, control charts are generally developed under the assumptions that observations are independent, and quality characteristics are normally distributed (Montgomery 2009). In environmental applications, these assumptions are often violated, particularly because time series air pollutant data commonly exhibit non-normality and temporal dependence (Montgomery & Mastrangelo 1991). Under such conditions, conventional Shewhart charts may perform poorly because autocorrelation can inflate false-alarm rates and reduce sensitivity to meaningful process shifts (Montgomery & Mastrangelo 1991; Woodall & Faltin 1993; Bersimis *et al*. 2007). These features prompt the use of more appropriate monitoring techniques. The Exponentially Weighted Moving Average (EWMA) chart is better suited for PM_{10} monitoring, where pollutant concentrations may be skewed and gradual shifts are of practical concern. The EWMA chart improves sensitivity to small changes in the process means by assigning greater weight to recent observations while still incorporating historical process behaviour (Borror *et al*. 1999). The EWMA chart has also been shown to retain good monitoring performance under certain non-normal conditions. To address strong serial dependence, residual-based control charts using autoregressive models such as ARIMA have also been proposed (Lu & Reynolds 1999; Montgomery & Mastrangelo 1991).

Process capability complements stability assessment by evaluating how well a process performs relative to regulatory thresholds. In statistical quality control, capability indices such as the upper process capability index are used to determine whether a process can consistently operate below an upper specification limit. In environmental applications, similar indices have been adapted to quantify the degree to which air quality systems comply with upper regulatory standards (Corbett & Pan 2002; Pan *et al*. 2014). Studies such as Azid *et al*. (2014) further demonstrate the usefulness of integrating capability indices with control chart methods for environmental assessment. However, capability analysis is only meaningful when interpreted together with process stability, because a stable process may still be incapable if pollutant levels remain predictably above the required threshold, whereas an unstable process may occasionally meet the standard but remain unreliable due to erratic variation (Deming 1982; Mulema & García 2019; Hoffmann *et al*. 2021).

Evaluating both stability and capability is therefore essential for a more complete diagnosis of air quality system performance. This combined perspective extends beyond conventional exceedance-based monitoring by distinguishing between processes that are (1) predictable and compliant, (2) predictable but non-compliant, (3) unstable but temporarily conforming, or (4) both unstable and non-compliant. In the present study, this logic underpins the Four Process States framework, which is used to classify PM_{10} behaviour across three selected Malaysian urban areas and to identify whether the air pollution process is approaching deterioration or requires urgent intervention (Wheeler 1995).

2.3. *EWMA control chart for process stability*

The EWMA control chart is suitable for small, gradual changes in time-dependent processes and has been widely applied in environmental monitoring (Lu & Zhen 2015; Mulema & García 2019; Supharakonsakun *et al*. 2020). EWMA-based control charts have successfully been applied to detect subtle shifts and persistent deviations in pollutants such as CO, NO_2, SO_2, O_3, and PM_{10} (Martínez *et al*. 2014; Lu & Zhen 2015; Harrou *et al*. 2016; Al-Rashed *et al*. 2019; Supharakonsakun *et al*. 2020). The use of EWMA and related SPC tools for detecting non-random variation is evident in assessing the stability of environmental processes (Shafii *et al*. 2017; Kamaruzzaman *et al*. 2017).

Originally introduced by Roberts (1959), the EWMA chart is a memory-type SPC method that monitors process behaviour by combining the current observation with information from past observations. It assigns exponentially decreasing weights to older data, thereby making it more responsive to persistent small shifts than the Shewhart chart. The exponentially weighted moving average is defined as Eq. (1).

$$Z_i = \lambda X_i + (1-\lambda) z_{i-1} \tag{1}$$

where Z_i is the ith EWMA, X_i is the ith observation, Z_0 is the starting value (required with the first sample at i = 1) and the average from the historical data, so that $Z_o = \mu_o$. For this study, the relevant interim air quality targets (IT-1 and IT-2) are used to evaluate the stability of the PM_{10} process. λ is a smoothing constant where $0 < \lambda \leq 1$.

The EWMA control chart is constructed by plotting z_i against time, with the centre line and control limits given in Eq. (2) to Eq. (4), respectively.

$$\text{Upper Control Limit} = \mu_O + L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \tag{2}$$

$$\text{Centre line} = \mu_o \tag{3}$$

$$\text{Lower Control Limit} = \mu_O - L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \tag{4}$$

where L is a positive coefficient that determines the width of the EWMA limits (often set to 3 for "3-sigma" limits, and applied in this study), and σ is the process standard deviation. Based on Montgomery (2009), smoothing values (λ) of $0.05 \leq \lambda \leq 0.25$ work well in practice. This study used λ = 0.20, as this value is frequently employed in the control charting literature and has been shown to perform well under various conditions, following the recommendations of Lucas and Saccucci (1990) and Supharakonsakun *et al*. (2020). A smoothing constant of 0.20 is also commonly employed in the SPC literature (Montgomery 2009). It strikes a balance between sensitivity to small shifts and smoothing of short-term variation, hence making the control chart sensitive to small and critical changes in air quality. This is essential for early detection and quick response to any environmental issues. For this study, the PM_{10} process is considered statistically in control (stable) when all points lie within the control limits, indicating that the observed variation is attributable solely to common-cause variation. Any point outside the control limits was interpreted as evidence of an out-of-control condition, indicating special-cause variation and instability in the air-quality process. The EWMA chart, therefore, provides a formal basis for assessing whether PM_{10} concentrations in the three study areas behaved in a predictable, statistically controlled manner over time. The suitability of EWMA for environmental monitoring has been demonstrated in several studies. EWMA control charts have been employed in several studies to monitor the Air Pollution Index during haze in Kuala Lumpur and on autocorrelated $PM_{2.5}$ and CO air pollutants (Sharifuddin *et al*. 2019; Supharakonsakun *et al*. 2020; Al-Rashed *et al*. 2019), where the EWMA control charts provide early signals for air pollution time series. These applications demonstrate EWMA as a robust method for monitoring air quality with autocorrelated data, moderate non-normality, and common serial dependence. In such cases, where serial dependence is present in air quality time series data, slight modifications are essential (Mulema & García 2019). Here, the ARIMA model is fitted to time-series data for each location to assess the temporal structure. To assess the presence of serial dependence, residual diagnostics such as the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Ljung–Box test are used. If the serial dependencies are found to be insignificant, the residuals are treated as approximately white noise and used to construct the subsequent EWMA chart. If not, charting an EWMA control chart based on residuals rather than raw observations is particularly appropriate for environmental monitoring. This approach provides a more reliable assessment of whether instability remains after the underlying temporal structure has been accounted for.

2.4. *Process capability and Four Process States classification*

In this study, the primary concern is to assess whether pollutant concentrations exceed the applicable MAAQS regulatory standard. Another SPC tool, process capability analysis, was employed to assess if the PM_{10} concentrations remain within the two relevant interim targets: IT-1 (50 µg/m³) and IT-2 (45 µg/m³). PM_{10} concentrations exceeding these limits would generally lead to greater health risks. By adopting the one-sided upper capability analysis, this study uses the interim target as the upper specification limit (USL).

The application of traditional capability indices assumes that the process data are normally distributed, with the process mean as the central reference value (Montgomery 2020). However, PM_{10} concentrations that are influenced by extreme pollution series, thus, typically exhibit non-normal behaviour (Georgopoulos & Seinfeld 1982). For this reason, the present study uses the median rather than the mean, as it provides a more robust measure of central tendency under skewed conditions, while retaining the standard deviation to represent process dispersion. The one-sided upper process performance index (PPU) is therefore defined as in Eq. (5).

$$PPU = \frac{USL - Median}{3\sigma} \tag{5}$$

where USL is the MAAQS interim benchmarks, Median is the median PM_{10} concentration and σ is the corresponding standard deviation. The median-based formulation is adopted because it provides a more robust and operationally straightforward assessment for skewed PM_{10} data. Since the median is less sensitive to outliers and asymmetrical than the mean, it is a more appropriate measure of process center under non-normal conditions. Moreover, research on robust process capability proven non-normal capability assessment can be strengthened by using robust measures of location rather than relying on specific distribution assumptions (Kashif *et al*. 2017). Accordingly, the present study uses the median-based PPU formulation to evaluate compliance with the applicable PM_{10} upper limit in a way that is both interpretable and less dependent on parametric distributional assumptions. A process is said to be capable when the PPU is larger than 1. The larger the PPU values, the stronger conformity of the relevant PM_{10} concentrations; whereas the smaller PPU, indicate the less capable the PM_{10} concentrations to remain within the prescribed threshold. What it shows is that the center of PM_{10} concentrations is either too close to the regulatory threshold or has already exceeded the regulatory threshold. This signals severe non-compliance, and urgent policy attention is needed. Additionally, a PPU which is below 1.00 implies excessive variability, which actually led to exceedances even though the process is stable.

For a more complete diagnosis of PM_{10} concentration performance, the Four Process States framework proposed by Wheeler (1995), which combines capability results and the stability analysis based on control chart applications (Aba & Hayden 2013). The Four Process State framework, the stability and capability status of each urban area for the year under study is classified into one of four process states: Ideal (stable and capable), Threshold (stable but incapable), Brink of Chaos (unstable but capable), and Chaos (unstable and incapable). In the present study, stability was determined using the EWMA control chart, while capability was assessed from the upper-sided PPU value using the interim target. Based on this framework, the performance of PM_{10} for each study year can be interpreted into four states: (1) predictable and compliance, (2) predictable non-compliance, (3) temporary conformity despite instability, and (4) severe process deterioration. This four-state assessment of PM_{10} system performance is more informative than the conventional monitoring of Interim Standard compliance. The Four Process States and their corresponding interpretations are shown in Figure 2 and detailed in Table 2.

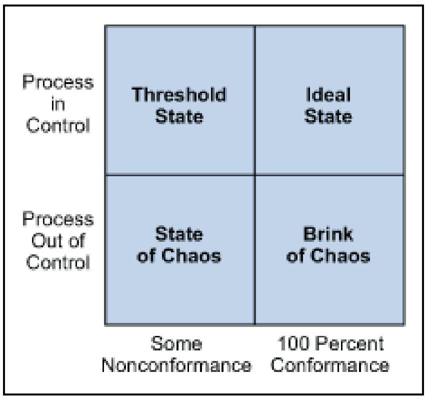


Figure 2: Four Process State Source: (Aba & Hayden 2013; Wheeler 1995)

Table 2: General description of the Four State Process

Process State	Stability	Capability	Description	Health Implication
Ideal	Stable	Capable	Air quality is predictable and consistently meets health-based standards.	Minimal health risk; supports long-term public health and sustainable urban planning.
Threshold	Stable	Incapable	Predictable pollutant behavior but consistently exceeds safe limits.	Chronic exposure risk requires policy intervention despite statistical control.
Brink of Chaos	Unstable	Capable	Air quality meets standards but fluctuates unpredictably.	Risk of sudden exceedances; monitoring and control systems may be insufficient.
Chaos	Unstable	Incapable	Air quality is erratic and frequently violates health thresholds.	High health risk; urgent need for systemic intervention and emission control.

2.5. *Data preparation and preprocessing*

The original PM10 concentration obtained from the Department of Environment (DOE) Malaysia for the period 2015 to 2019 was hourly data. Preliminary inspection of the dataset shows there are missing data in observations between mid-April and July 2017. Upon confirmation from the DOE Malaysia, there were missing data identified and this because of the transition process of new monitoring instruments concession holders. When involving time series data like the case of this case study, this is a typical missing data situation, among others, as a result of sensor malfunction, power outages, and operational disruptions (Hua *et al*. 2024). To decide on the missing data treatment method, a quick run chart analysis on the original data were set on all three urban areas. There are seasonal patterns and strong autocorrelation (temporal dependence). The subsequent observations are affected by past values. Given this seasonal variability condition, the seasonal mean method is used to impute the missing data. During the pre-processing stage, the missing PM_{10} values for each affected month were replaced by the average of the corresponding months from other years. This approach is suitable for environmental time series with recurring seasonal data patterns (Wijesekara & Liyanage 2020; Shaadan & Rahim 2019; Layanun *et al.* 2017). After preprocessing, the cleaned hourly data were aggregated into monthly mean concentrations, which is the analytical time scale for this study. The aggregation was adopted to assess the patterns of PM_{10} concentration in terms of stability and capability. The monthly aggregation will smooth the short-term extremes and reduce SPC methods' sensitivity to abrupt changes. This is appropriate because, rather than capturing isolated hourly pollution episodes, the primary objective of this study is to evaluate the long-term stability and capability of PM_{10} as an urban air quality process. Additionally, monthly aggregation supports the investigation of broader trends and seasonal patterns by reducing high-frequency fluctuations, thereby improving interpretability when assessing the relevant environmental policy (Nguyen *et al*. 2023; Zhao *et al*. 2018). The use of monthly average pollutant concentrations is evident in previous similar studies on long-term air quality behaviour (Rahman *et al*. 2015).

Upon completing preprocessing, the sample size of 60 across the three urban areas for the study period from 2015 to 2019 is ready for analysis. This is an ample sample size for assessing both process monitoring and capability, given that 20-30 observations are required for robust parameter estimation and stable control limits (Montgomery 2020). To implement the EWMA control chart, a minimum of 25 samples in the timeframe of this study already exceeds this requirement (Montgomery 2020). The second preliminary diagnostic check of statistical assumptions is a crucial stage before conducting SPC analysis. Normality checks via boxplots for each urban area reveal a long upper tail, indicating non-normality of the PM_{10} distribution. The second diagnostic check is to examine for autocorrelation, which is important as standard control chart methods generally assume independence among observations, whereas prior findings indicate that environmental time-series data exhibit serial dependence. To examine the presence of autocorrelation and significance of serial dependence in the monthly PM_{10} series, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were used (Box *et* al. 1994). Results from these preliminary checks would form the basis for selecting the control chart for the formal stability assessment.

2.6. *Analytical framework*

Figure 3 presents the analytical framework for this study. It begins with the original PM_{10} dataset received from DOE, which undergoes preprocessing and preparation, diagnostic checks, and formal assessment of process stability and capability. The final stage of classifying the three urban areas by plotting stability and capability of the cities through the study period using the Four Process Stage framework. This is a stepwise, systematic assessment of PM_{10} process behavior relatable to the Malaysian PM_{10} interim quality standards.

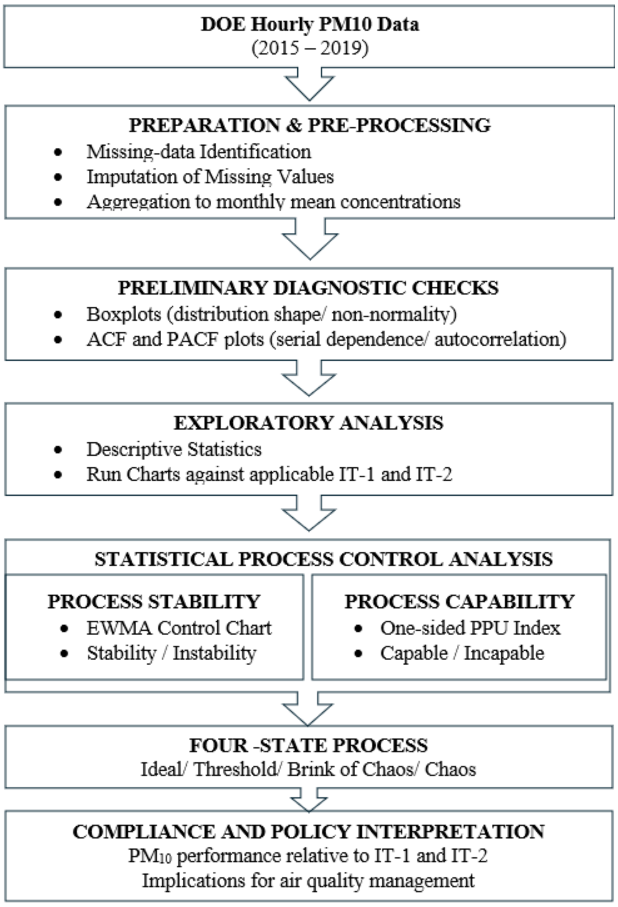


Figure 3: Analytical framework

3. Results and Findings

3.1. *Preliminary diagnostic check*

The boxplots in Figure 4 indicate that PM_{10} distributions under IT-1 and IT-2 across the three urban areas exhibit outliers, especially in 2015, suggesting non-normality in the data distribution. Specifically, the positive skewness suggests an increased incidence of extreme PM_{10} concentration during that year. The box plots in Figure 4 also show increased variability, with certain years seeing PM_{10} averages up to 50 µg/m³, and several values exceeding 200 µg/m³ during IT-1 in Petaling Jaya, Shah Alam, and Putrajaya. These are instances of non-compliance with MAAQS air quality standards. This may correspond to episodic haze events and transboundary pollution episodes.

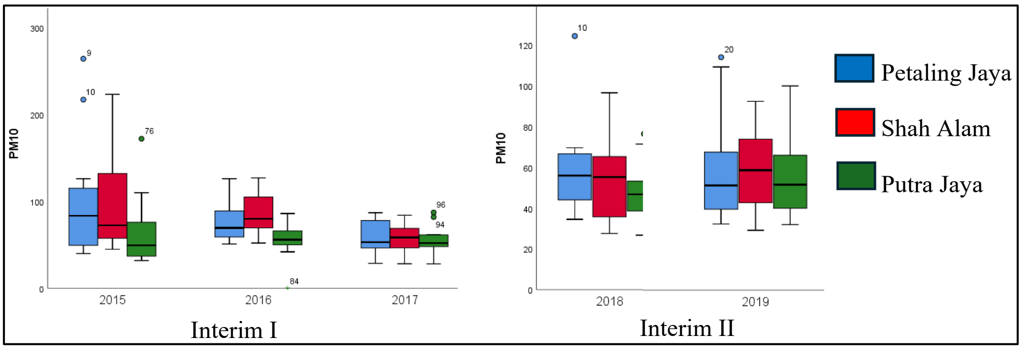


Figure 4: Boxplots of PM concentration (µg/m³) for three urban areas for Interim I and Interim II

Nonetheless, variability was much reduced during Interim II across all three urban areas, the medians even approaching the interim target of 45 µg/m³ in 2018. Putrajaya exhibits the most favorable average values with the smallest median and range. Despite being stable, increased variability in PM_{10} concentrations was observed in 2019, with median values remaining above 45 µg/m³ across the three cities.

For autocorrelation checks, Figure 5 shows significant autocorrelation in the PM_{10} series for Shah Alam, Petaling Jaya, and Putrajaya at the 5% level, indicating the presence of serial dependence. This simply means PM_{10} values were influenced by previous observations. All cities depict dependence, with Petaling Jaya reporting the strongest autocorrelation. The PACF plots show that much of the dependence is concentrated at the initial lags. These results further support the conclusion that the independence assumption is violated and strongly suggest using ARIMA modeling before applying the EWMA control chart. This is a common strategy to assess the process instability after removing serial dependence (Montgomery & Mastrangelo 1991; Lu & Reynolds 1999).

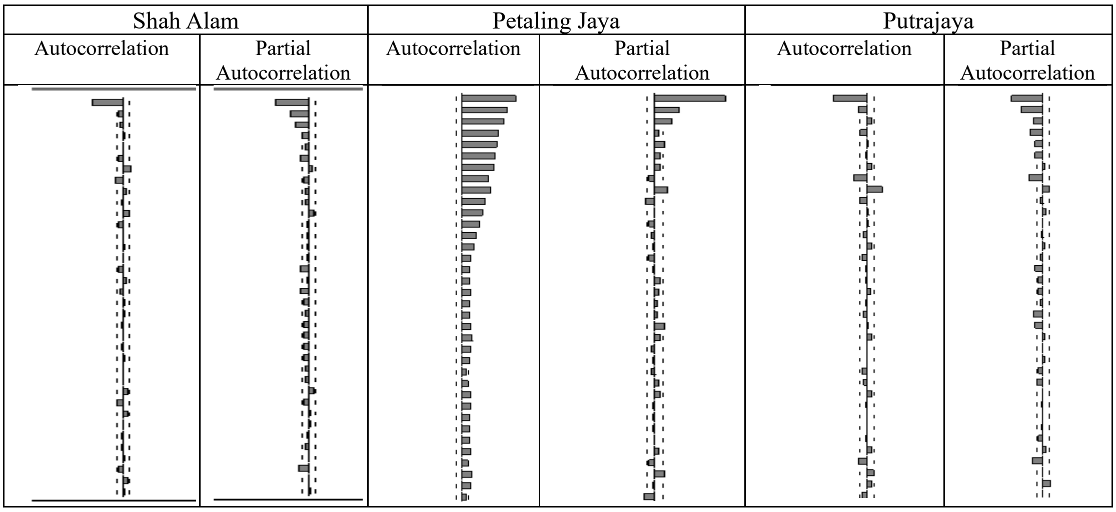


Figure 5: ACF and PACF plot of PM10 at three cities

3.2. *Descriptive analysis*

Table 3 presents the descriptive statistics of PM_{10} concentrations in Petaling Jaya, Shah Alam, and Putrajaya (2015 - 2019), which covers Interim I and Interim II. The annual mean benchmark of 50 µg/m³ was exceeded in all three cities during Interim I, indicating persistent non-compliance on average per month throughout the years. Among the three locations in 2015, Petaling Jaya recorded the greatest variability and the average PM_{10} of 267 µg/m³.

Table 3: Descriptive Analysis of PM_{10} of Petaling Jaya, Shah Alam and Putrajaya (2015-2019).

Interim	Year	Descriptive/ Summary Statistics	Petaling Jaya	Shah Alam	Putrajaya
Interim I	2015	Mean	102.08	100.5	64.25
		Standard Dev.	70.70	60.08	41.57
		Minimum	40	45	32
		Median	83.5	72.5	49.5
		Maximum	264	223	172
		Skewness	+0.79	+1.40	+1.06
	2016	Mean	76.58	85.83	55
		Standard Dev.	23.41	24.90	21.34
		Minimum	51	52	0
		Median	69.5	80	56
		Maximum	126	127	86
		Skewness	+0.91	+0.70	+0.57
	2017*	Mean	63.7	62.9	55.79
		Standard Dev.	19.70	18.36	16.61
		Minimum	28.76	28.2	28.09]
		Median	65.62	67.20	54.2
		Maximum	93.29	90.26	87.21
		Skewness	-0.29	-0.70	+0.29
Interim II	2018	Mean	58.95	54	48
		Standard Dev.	24.00	19.98	14.09
		Minimum	35	28	27
		Median	56.06	55.22	46.79
		Maximum	124	97	76
		Skewness	+0.36	-0.21	+0.35
	2019	Mean	60	59	55
		Standard Dev.	27.28	20.37	18.75
		Minimum	33	29	32
		Median	51.41	58.87	51.77
		Maximum	114	93	100
		Skewness	+0.90	+0.02	+0.56

The run charts for Petaling Jaya, Shah Alam, and Putrajaya under MAAQS Interim 1 and Interim 2 are shown in Figure 6. The charts confirm ongoing non-compliance across most of the study period; PM_{10} concentrations in all three cities frequently exceeded their respective interim limits. Significant variability and major spikes exceeding 250 µg/m³ were also clearly evident in 2015, in Petaling Jaya and Shah Alam. The pattern shown by the run charts is consistent with the high mean values, large standard deviations, and positive skewness of the PM_{10} distribution. However, the average PM_{10} concentration in Petaling Jaya and Shah Alam remains above the IT-1 standard, indicating prolonged non-compliance. Only Putrajaya showed a less extreme condition with general stability throughout 2016 and 2017. A more stable condition was observed in all three cities during Interim II, but most PM_{10} readings still remained above 45 µg/m³. PM_{10} levels in Putrajaya showed the most favorable pattern, showing better potential for short-term compliance. The box plots in Figure 4 confirm increased variability, with several outliers exceeding 200 µg/m³ in 2015 during Interim I for Petaling Jaya, Shah Alam, and Putrajaya, which obviously depict instances of non-compliance with Interim I air quality standards.

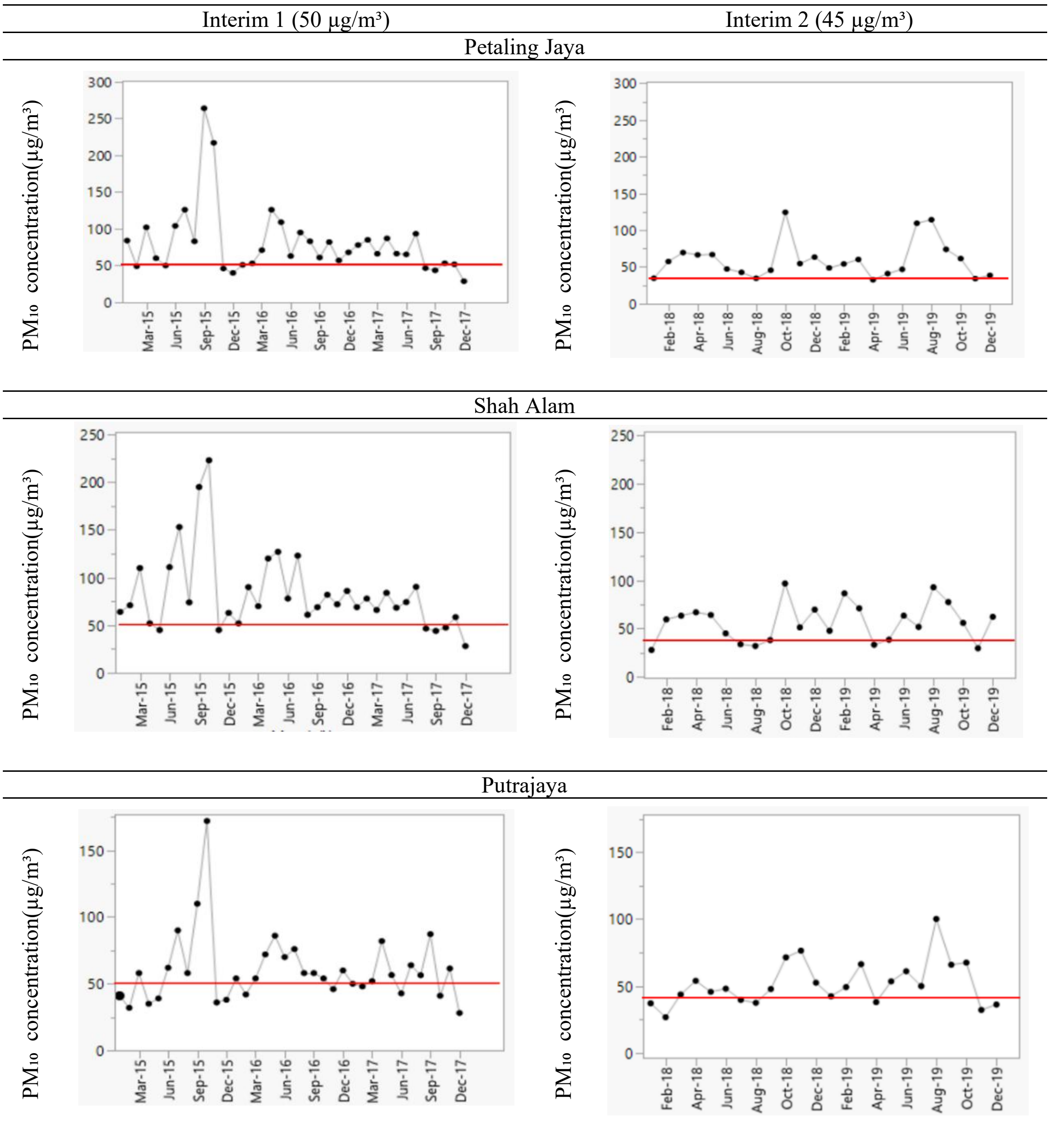
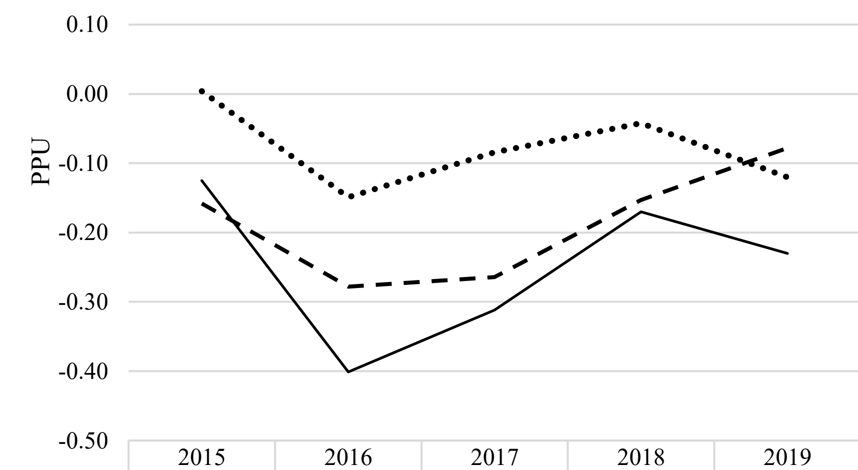


Figure 6: Run charts for monthly PM_{10} concentration (µg/m³) of Petaling Jaya, Shah Alam, Putrajaya (Interim 1 and 2)

3.3. *Capability analysis*

The capability formulas for PM_{10} are adapted to focus on the upper specification limits (USL) only (Vännman & Albing 2007; Borucka *et al.* 2023), which measure how far the process mean is from the USL, and the results are presented below.

Figure 7 shows that the PPUs for all three cities are less than 1.00. This confirms that average PM_{10} levels are beyond the interim threshold, so all areas are non-compliant.



	2015	2016	2017	2018	2019
Petaling Jaya	-0.158	-0.278	-0.264	-0.153	-0.078
Shah Alam	-0.125	-0.401	-0.312	-0.17	-0.23
Putrajaya	0.004	-0.149	-0.084	-0.042	-0.12

Figure 7: The Process performance upper (PPU) of Petaling Jaya, Shah Alam, and Putrajaya (2015 – 2019)

3.4. *Stability analysis*

To evaluate PM_{10} process stability, the EWMA control chart is applied (Figures 8 and 9). During MAAQS Interim I, EWMA control charts for Shah Alam and Putrajaya reveal an initial period of instability followed by a gradual trend towards stabilization. While the early 2015 period shows lines close to the target, the mid-year 2015 period shows a sharp, sustained increase, with the line exceeding the upper control limit, indicating an unusual pollution spike. Although PM_{10} remains within the control limits after a series of spikes reflecting a return to statistical control, PM_{10} remains above the target for most of 2015 and 2016. Towards the end of 2017, the EWMA line moved closer to the target, indicating some long-term improvement, though again still exceeded the desired MAAQS target.

Interim 2 sets a new target of 45 mg/m^3, reflecting a stricter target. PM_{10} process levels in Petaling Jaya and Shah Alam demonstrated significant improvement, with overall consistency and minimal signs of instability, indicating that all cities are statistically stable. However, the points remain above the new target throughout 2018 and 2019. The upward trend towards late 2019 further suggests the risks of deteriorating air quality. In the case of Putrajaya, EWMA statistics initially fall below the target, but the upward trend away from the standard throughout 2018 and 2019 demonstrates Putrajaya drifting away from a compliant to non-compliant state.

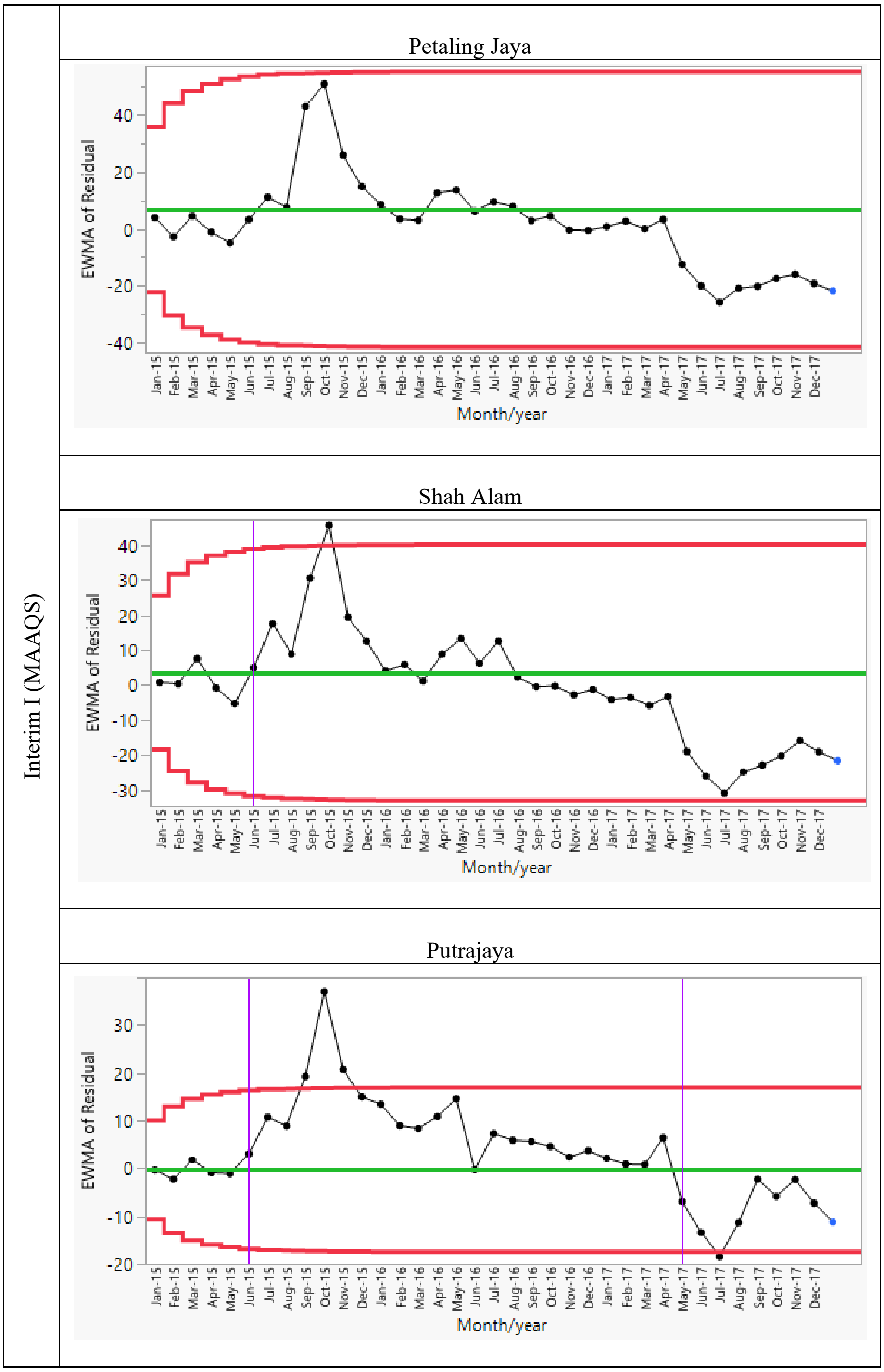


Figure 8: EWMA control charts of three urban areas for Interim I

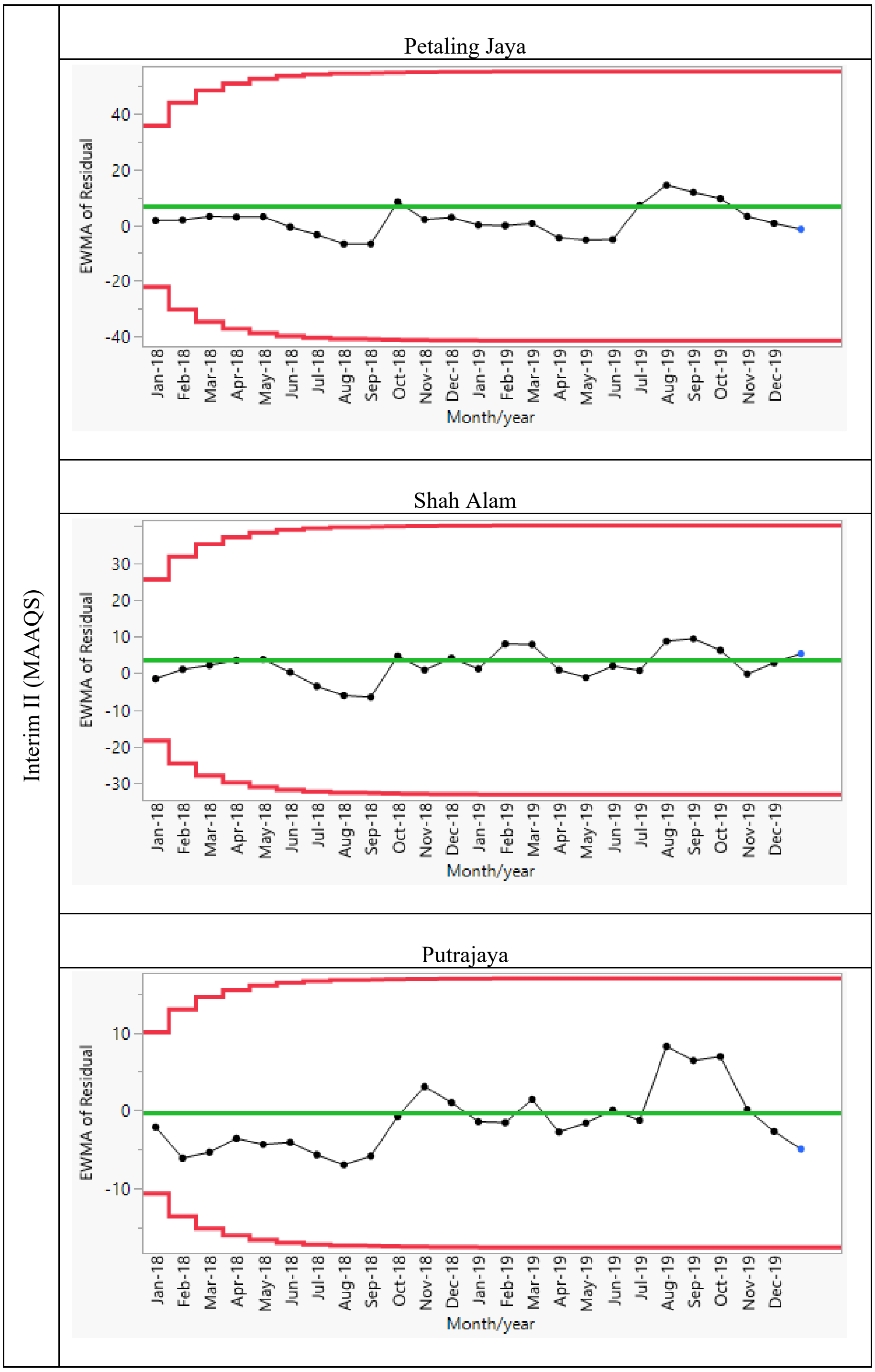


Figure 9: EWMA control charts of three urban areas for Interim II

3.5. *Four process states of PM_{10}*

Based on the stability and capability analysis conducted for the three urban areas: Petaling Jaya (PJ), Shah Alam (SA), and Putrajaya (PUTJ), the proportion of non-conformance (i.e. months exceeding MAAQS PM_{10} regulatory standards) and out-of-statistical control points (derived from EWMA control charts) were evaluated. The process states of PM_{10} are classified into four distinct conditions: 1) Ideal state, 2) Threshold state, 3) Brink of chaos, and 4) State of Chaos. The corresponding results for each city in the respective years are presented in Figure 10.

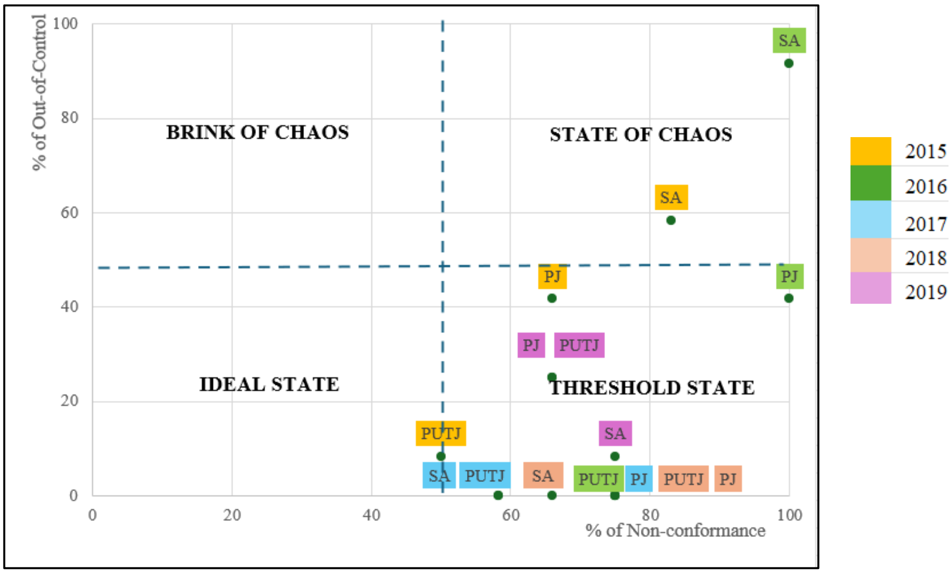


Figure 10: Four Process States – PM_{10} Compliance and Stability by area and Year (2015-2019)

Figure 10 shows that most observations, 13 out of 15 categories across the three cities, fall within the Threshold State. As most observations fell under this classification, this indicates that even though the processes were statistically in control, PM_{10} concentrations failed to meet the MAAQS standards. By being in the Threshold State for five years, Petaling Jaya was not able to meet the target standards, despite exhibiting good statistical stability, with the out-of-control state ranging from 0% to at most 25%. Shah Alam was in the State of Chaos in 2015 and 2016, non-conformance and out-of-statistical conditions being high (≥75% and ≥58%, respectively). The combination of high non-conformity and high process instability reflects poor air quality and unpredictable pollution behaviour in Shah Alam during those years. Nonetheless, Shah Alam shows marked improvement from 2017 onwards, transitioning back to the Threshold State with a more stable process, although it still did not fully comply with the MAAQS PM_{10} standards.

Table 4 summarizes the diagnostic outcomes across the cities, reinforcing the value of SPC tools in guiding targeted, system-informed interventions for urban air quality management. Overall, during the 2015–2019 period, the SPC analysis shows that all three urban areas were predominantly incapable of meeting MAAQS limits as indicated by the consistently NC capability results. This means that although air quality performance often became more statistically stable over time, it generally remained stable yet inadequate, reflecting persistent non-compliance rather than fully acceptable air quality, indicating the dominance of the Threshold state where PM_{10} concentrations remained structurally above the required limit despite becoming more statistically controlled. Shah Alam recorded the weakest performance in the earlier years, as it experienced the greatest volatility when it entered a State of Chaos in 2015–2016, before stabilizing post-2017. Although stability improved from 2017 onward, leading to an in-control classification, the process still remained incapable, shifting Shah Alam into the Threshold state from 2017 to 2019. Thus, Shah Alam appears to have experienced the most severe early deterioration before progressing to a more predictable yet still non-compliant condition. Petaling Jaya showed the clearest transition from early instability to later stability. In 2015, it was out of control, with extreme peaks, and in 2016, it remained close to control despite high volatility. From 2017 onward, however, the process became in control, with fewer variations, although PM_{10} levels remained above the target. This led Petaling Jaya to remain in the Threshold state throughout the study period, suggesting that its main issue was chronic incapability rather than continuing instability. Putrajaya displayed the most favourable stability pattern among the three cities. Aside from being mostly in control in 2015, it was classified as stable from 2016 to 2019, with fewer spikes and comparatively moderate fluctuations. Nevertheless, it was still categorized as Threshold every year, indicating that even the relatively better-performing city did not achieve capability. This suggests that Putrajaya had the most stable PM_{10} behaviour, but not full compliance with the required standard. Overall, the findings indicate that the dominant air quality condition across the three urban areas was not severe instability, but rather predictable non-compliance.

Table 4: Summary of Findings from the SPC analysis

City / year	Run Chart (pattern)	EWMA (Stability)	PPU (Capability)	Process State	Diagnostic Classification
Petaling Jaya					
2018	Near stable but mostly > target	In-Control	NC	Threshold	Stable but
2019	Less variations, non-compliant	In-Control	NC	Threshold	Incapable
Shah Alam					
2015	High spikes, erratic	Out-of-Control	NC	Chaos	Extreme peaks
2016	Persistent exceedances	Out-of-Control	NC	Chaos	High volatility but decreasing
2017	Mild variations but > target	In-Control	NC	Threshold	Stabilized but above target
2018	Fluctuations, not consistent	In-Control	NC	Threshold	Stable but
2019	Consistent ups and downs	In-Control	NC	Threshold	Incapable
Putrajaya					
2015	Moderate, few exceedances	Mostly In-Control	NC	Threshold	
2016	Less variation, fewer spikes	Stable	NC	Threshold	Stable but
2017	Close to the target	Stable	NC	Threshold	Incapable
2018	A few months < target	Stable	NC	Threshold	
2019	Moderate fluctuations	Stable	NC	Threshold	

Note: NC indicates non-compliant

4. Discussion

This study highlights that the dominant air quality condition in Petaling Jaya, Shah Alam, and Putrajaya throughout 2015 to 2019 was stable but incapable. These processes correspond to the Threshold state in the Four-State Process Framework. The PM_{10} concentrations have shown significant improvement over the two interim periods IT-1 and IT-2, proven by their statistical stability, but also continued to be non-compliant (NC) with the MAAQS PM_{10} standard. This suggests that the principal air quality problem was not persistent instability alone, but rather predictable non-compliance. This suggests that the main air quality issue was not only non-compliance (measured through capability analysis) but also persistent exceedance of the MAAQS interim limit (as indicated by stability measured through control charts) over the five-year study period. The distinction between stability and capability is important because it clarifies that statistical stability does not necessarily imply the capability of air quality to meet performance standards. This is consistent with the previous work on environmental process capability and compliance assessment (Corbett & Pan 2002; Pan *et al*. 2014; Azid *et al*. 2014).

Shah Alam recorded the weakest performance in the early stage of the study and was classified as in the Chaos state in 2015 and 2016, marked by sharp spikes, erratic variation, and persistent exceedances. Clearly, the PM_{10} pollutant in Shah Alam was in a state of instability and was incapable. Such findings align with earlier studies that relate the local pollution patterns in Shah Alam to industrial activity and source-related variation. These are the typical characteristics of an urban-industrial area with sustained pollution pressure (Zakaria *et al*. 2017). Hence, Shah Alam just shifted from Chaos to Threshold, where the air quality improvement was mainly in predictability rather than in regulatory performance. A recent study on trend analysis still found no significant improvement in overall air quality, suggesting conditions have remained unchanged over time (Mohammed *et al*. 2024). Moreover, another study of the broader Klang Valley continues to place Shah Alam among locations with relatively increased PM_{10} burdens (Azhari *et al*. 2021).

Petaling Jaya showed a slightly different pattern: from early instability, with extreme peaks and substantial variability in 2015, to improved stability in 2016 approaching to the control limits. Both conditions in Shah Alam and Petaling Jaya are consistent with recent haze-related evidence from the 2015 haze episode, with PM_{10} concentration levels exceeding Malaysian guideline levels plus considerable variability (Rahim *et al*. 2023; Mead *et al*. 2018). Remaining in the Threshold state throughout a five-year period suggests that the city's main challenge was not ongoing instability, but chronic incapability. It means that the air quality process had been stabilized at a pollution level and remained unsatisfactory from a regulatory perspective for a considerable time.

In the case of Putrajaya, despite portraying the most favorable stability profile which is consistent with earlier studies suggesting that Putrajaya generally experiences lower or more moderate pollution levels than the more industrialised parts of the Klang Valley, the local air quality patterns remained (Mutalib *et al*. 2013) being in the Threshold state for most of the study years – stable and yet not a fully capable to comply to the MAAQS standards.

Overall, Petaling Jaya appears especially sensitive to haze-related PM_{10} variability, Shah Alam reflects persistent urban-industrial pollution pressure, and Putrajaya performs relatively better in absolute terms but is not necessarily improving or fully compliant. Taken together, these patterns signify the broader Klang Valley context where PM_{10} has been strongly shaped by urbanization, industrial activity, traffic, and haze transport (Azhari *et al*. 2021).

The uncompromising PM episodes in Malaysia are not only driven by local urban and industrial emissions but should also be interpreted in light of broader climatic and transboundary influences. Seasonal meteorological variability, tropical climate, and large-scale events such as El Niño tend to prolong dry conditions and favour pollutant accumulation (Latif *et al*. 2018; Mohtar *et al*. 2022). The major regional contributor to worsening air quality in Peninsular Malaysia has also been repeatedly pointed to the transboundary haze coming from the biomass burning in Indonesia. Such an example is the major haze year of 2015 (Latif *et al*. 2018; Samsuddin *et al*. 2018; Rahim *et al*. 2023). The external pressures amplified PM_{10} variability across the Klang Valley, explaining the pronounced spikes and unstable behavior observed, particularly in Shah Alam and Petaling Jaya during the study's early years. From an analytical perspective, these findings highlight the value of the Four Process States framework, as it distinguishes between severe instability and incapability on the one hand, and stable but structurally non-compliant systems on the other.

The practical perspective of the Four Process States framework is clear and can serve as a basis for linking statistical classification to different policy responses. The Threshold classification dominated in Petaling Jaya and Putrajaya, indicating the PM_{10} non-compliance process has consistently shown to go beyond the required standard. In such cases, the policy implication is not merely to intensify short-term monitoring but to address the structural drivers of pollution, for example, through tighter industrial emission controls, transport demand management, land-use planning, and sustained urban pollution mitigation. On the other hand, Shah Alam, which was classified under Chaos State in 2015 and 2016, reflects a far more critical condition where PM_{10} behaviour is both unstable and incapable. This state implies the need for urgent intervention, including intensified surveillance, rapid identification of dominant emission sources, short-term control measures during high-risk periods, and stronger enforcement. This is because both unpredictable and persistent exceedances pose a major threat to public health. On the contrary, stability and capability offer distinct yet complementary insights into more accurate forecasting, earlier detection of deterioration, and more targeted intervention, whereas instability often reflects uncontrolled or episodic influences, such as traffic surges, industrial discharges, or transboundary haze. More importantly, this study confirms that stability alone is insufficient. This study has shown that an air-quality process can be statistically stable yet remain environmentally unacceptable.

Another critical implication revealed by this study is that the three urban areas are not only struggling to achieve Malaysia's own PM_{10} targets but are also further from meeting the more stringent WHO interim benchmarks. Although the Malaysian interim standards are less stringent than the corresponding WHO limits, there has been persistent non-compliance with the national benchmarks. This could suggest that Malaysia has an even wider gap from internationally recommended health-protective thresholds. This reinforces the need for stronger and more sustained air quality management, particularly in the urban centres, if Malaysia is to move toward genuinely health-protective standards.

The Four Process States framework has practical value because it sheds light on whether the air quality problem arises from instability, structural non-compliance, or a combination of both, hence, guides the scale and urgency of any air quality intervention. In this sense, the study advances air quality assessment beyond simply reporting exceedances; it provides a stronger basis for targeted intervention, early warning, and strategic policy design. Continued emission controls, tighter urban pollution management, and sustained regulatory reinforcement are necessary for these urban areas to move from the Threshold state toward genuine and lasting compliance.

5. Conclusion

Statistical Process Control (SPC) tools have been applied within the Four Process State framework on long-term PM_{10} data for Petaling Jaya, Shah Alam, and Putrajaya. The first objective has been met by using EWMA, stability has generally improved over time, particularly in Petaling Jaya and Putrajaya, while Shah Alam exhibited greater instability in the earlier years. Similarly, the second objective to assess air quality process capability analysis using the Process Potential Upper (PPU) index was achieved and revealed that the three cities consistently exceeded the Malaysian Ambient Air Quality Standards (MAAQS) throughout the study period. These findings confirm that an air quality process needs to be consistently statistically in control (stable) and capable of meeting the MAAQS limits. The third objective put forth the importance of the Four Process States framework in classifying system performance more systematically. By integrating run charts, EWMA control charts, and process capability analysis, the framework combines the assessment of stability and capability, offering a more informative diagnosis of the performance of the air-quality process. The assessment is not only about meeting the MAAQS standards but also about whether the air quality system is stable, capable, and sustainable to meet the standards. This study offers an enhancement of the Malaysian environmental governance. It supports a shift from reactive compliance checking to proactive, capability-based policy. As shown in this study, persistent Threshold conditions require structural emission-reduction strategies. A state of Chaos requires urgent intervention and close monitoring. This study offers diagnostic analysis for data-driven policy enhancement, regulatory enforcement, and urban planning.

This study is limited to PM_{10} and to only three urban centers. This may not capture the complexity of regional air quality dynamics. Future research should extend the framework to multivariate SPC approaches that simultaneously monitor $PM_{2.5}$, NO_2, SO_2, CO, and O_3, and incorporate meteorological and emissions data to enhance predictive capability. Overall, the study shows that a more meaningful air quality assessment must extend beyond asking "Are we meeting the standard?" toward "Is the system stable and capable of meeting the standard sustainably?"

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