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A robust calibration approach for PM_{10} prediction from MODIS aerosol optical depth

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Abstract

Investigating the human health effects of atmospheric particulate matter (PM) using satellite data are gaining more attention due to their wide spatial coverage and temporal advantages. Such epidemiological studies are, however, susceptible to bias errors and resulted in poor predictive output in some locations. Current methods calibrate aerosol optical depth (AOD) retrieved from MODIS to further predict PM. The recent satellite-based AOD calibration uses a mixed effects model to predict location-specific PM on a daily basis. The shortcomings of this daily AOD calibration are for areas of high probability of persistent cloud cover throughout the year such as in the humid tropical region along the equatorial belt. Contaminated pixels due to clouds causes radiometric errors in the MODIS AOD, thus causes poor predictive power on air quality. In contrary, a periodic assessment is more practical and robust especially in minimizing these cloud-related contaminations. In this paper, a simple yet robust calibration approach based on monthly AOD period is presented. We adopted the statistical fitting method with the adjustment technique to improve the predictive power of MODIS AOD. The adjustment was made based on the long-term observation (2001–2006) of PM_{10}-AOD residual error characteristic. Besides, we also incorporated the ground PM measurement into the model as a weighting to reduce the bias of the MODIS-derived AOD value. Results indicated that this robust approach with monthly AOD calibration reported an improved average accuracy of PM_{10} retrieval from MODIS data by 50 % compared to widely used calibration methods based on linear regression models, in addition to enabling further spatial patterns of periodic PM exposure to be undertaken.

1 Introduction

The interest in using earth observation satellites to measure atmospheric aerosols has progressed from climate studies to the more important topic of human health. This is due to a satellite's unique ability in providing a synoptic view over large areas in a uniform, repetitive and quantitative way. Atmospheric aerosols originate from both natural and anthropogenic emission sources. The latter are considered to have major implications to human health as they are highly related to mortality and morbidity as already shown by many researchers around the world (Bell et al., 2007; Dominici et al., 2006; Franklin et al., 2007; Gent et al., 2003, 2009; Schwartz et al., 1996; Slama et al., 2007; Hu et al., 2009). Most of the recent studies highlighted $PM_{2.5}$ as the main contributor towards health effects. However, $PM_{2.5}$ is a portion of PM_{10} and can be estimated ith a known constant (Marcazzan et al., 2001). In many developing countries PM_{10} is still being measured instead of PM_{10} due to limited resources. For example, in Malaysia, PM_{10} is being measured and used in the Air Pollution Index (API) to assess regional air quality.

Satellite data can be used as a surrogate to monitor regional air quality due to the fact that there are limited ground monitoring stations where many regions are left unmonitored (Schaap et al., 2009; Engel-Cox et al., 2004b). The widely-used method of predicting PM concentration from satellite data is by empirical analysis, where in-situ PM measurement are linearly regressed with the corresponding satellite AOD. In order to improve the predictive power of the linear regression models, related parameters such as local meteorological and land use information were also used as an input into PM prediction (Liu et al., 2009). However, these models generally predict < 60 % of the PM variability (Hoff and Christopher, 2009). The latest model developed by Lee et al. (2011) uses a mixed effect model to establish daily specific AOD-$PM_{2.5}$ relationship and then predicts daily $PM_{2.5}$ concentrations with $R^2 = 0.62$. Besides, Lee et al. (2011) also hypothesized that the relationship between $PM_{2.5}$ and AOD varies daily due to time-varying parameters influencing the PM-AOD relationship, such as PM vertical and diurnal concentration profiles, PM optical properties, and others. Therefore, a linear AOD-PM relationship on a long-term daily monitoring is rather limited (Xen Quan et al., 2011), and in fact the time-varying assumption by Lee et al. (2011) that varies minimally spatially on a given day over a specific spatial scale is rarely valid for humid tropical weather over the equatorial regions where the high probability of cloud-cover

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exists, and also dependent on the surroundings maritime environment. Thus, it is more practical and efficient for the calibration of the satellite data to be based on a monthly basis.

The monthly calibrated satellite data is useful in improving the air pollution indicators of Environmental Performance Index (EPI) reporting in this region. The EPI is a system used to evaluate countries based on 22 performance indicators that focus on environmental issues for which governments can be held accountable (Emerson et al., 2012). Atmospheric PM derived from monthly average satellite data is one of the performance indicators used in EPI evaluation for environmental health. Without the robust calibration, errors in the datasets resulting from systematic error and local climatic effects such as the monsoon and site specific error may occur. These will lead to poor representation of PM concentration and EPI derived from satellite measurements, having consequences of misinterpretation by policy makers around the world.

In this paper, a robust calibration approach is introduced by incorporating a simple adjustment technique into a statistical model that is developed to predict PM concentrations using MODIS AOD monthly average data sets. The MODIS AOD is calibrated by minimizing the inherent systematic and random errors (i.e. from sensor and site specific ones) in order to improve the AOD-PM relationship. The adjustment in the statistical model was made based on a long-term (2001–2006) analysis of the residual bias of MODIS AOD. In addition, this statistical model was adjusted for site errors which accounted for time varying parameters on a monthly basis. From the literature search, there are no specific similar robust calibration approaches for satellite AOD which have been reported to date. The result of this study can provide an improved AOD-PM prediction for EPI and PM human health exposure study as well as for the investigation of PM spatial patterns.

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2 Methodology

Our study is focused on Peninsular Malaysia. In order to calibrate the MODIS AOD data for this region, PM_{10} was sampled at 34 air stations as shown in Fig. 1 for a period of six years (i.e. 2001 to 2006). The monthly corresponding PM_{10} values for each of the 34 air stations were averaged out from the daily PM_{10} concentrations measurements. On the other hand, the calibration on MODIS AOD data was done by using the in-situ PM_{10} measurements. Here, the calibration was performed independently for each monitoring site using multiple regression method to identify the random error to be included into the statistical model. Thus, this accounts for the spatial variability of the random errors on a monthly basis. After that, a single monthly AOD-PM_{10} relationship was established using all the parameters from the 31 monitoring stations. The predicted PM_{10} concentration from this method was validated independently in three sites, namely, in the northern, central and southern part of Peninsular Malaysia.

2.1 MODIS derived AOD

MODIS is a space sensor aboard the National Aeronautics and Space Administration (NASA)'s Terra Earth Observing System (EOS) satellite launched in December, 1999. Operating at an altitude of approximately 700 km, this polar-orbiting satellite is able to provide aerosol data on a daily basis. MODIS Terra satellite crosses the equator at about 10:30 a.m. (descending orbit) local sun times, with a scanning swath of 2330 km (cross-track) by 10 km (along-track at nadir). MODIS has a total of 36 different wavelength channels suited for a wide range of applications. AOD was retrieved by using the second generation operational algorithm (Collection 5) developed by Levy et al. (2009). In general, seven out of 36 wavelength channels (between 0.47 and 2.12 µm) are used during the AOD retrieval.

According to the MODIS AOD retrieval algorithm (Collection 5) by Levy et al. (2009), three different channels of 0.47, 0.66, and 2.12 µm are primarily employed for land aerosol retrievals, while others are used to the screen out cloud, snow-cover, and ice-

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cover. The reported AOD by MODIS at the wavelength of 0.55 µm is the result of simultaneous inversion from these 3 channels. The accuracy of MODIS AOD data is expected to be $\pm 0.05\tau$ at best (under very clear atmospheric condition) and $\pm 0.15\tau$ (τ indicates AOD) for slight contamination or disturbance in the atmosphere over land. More details about the retrieval of MODIS satellite aerosol data are reported in Remer et al. (2005) and Levy et al. (2007, 2009, 2010). The MODIS AOD value ranged from 5.0 to −0.05. In this study, negative values were omitted, to avoid any bias that may have occur during the calibration.

To conduct this study, level 2 MODIS Terra AOD product (MOD04) data were collected for a period of six years (2001 to 2006). However, aerosol data are often missing due to clouds, high surface reflectance (e.g. snow- and ice-cover), and retrieval errors. For Malaysian climatic conditions, cloud cover is a serious issue that causes failure in AOD retrieval by MODIS in most of the region.

To overcome this problem, an averaging algorithm of a 5 × 5 window was used (Xen Quan et al., 2011). The algorithm assumes that the neighbouring 5 pixels with no AOD retrieval have the same value with the reference pixel with a valid retrieval. This means that if there is no retrieval of AOD in that particular area, then the nearest 5 pixel (50 km) retrieval will be used. In this regard, the number pixels without AOD information due to cloud cover can be reduced. If there is a continuous valid AOD retrieval, a normal averaging scheme will be applied by ignoring pixels with no AOD retrieval. On averaging multiple pixels, it is expected to reduce the influence of random errors associated to the retrieval of AOD. Besides, a 5 × 5 window averaging has been widely used in MODIS validation work, which is in agreement with the average speed of aerosol air mass transport in the mid troposphere in the Atlantic (Ichoku et al., 2002; Remer et al., 2005). However, as the average wind speed near the earth surface is much less than mid troposphere, a 5 × 5 window is consider appropriate. On the other hand, if a 3 × 3 window is used, we found that there are many voids left in the imagery that resulted in the poor retrieval of the overall MODIS AOD in Peninsular Malaysia.

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2.2 Statistical model

Recent work by Lee et al. (2011) states that AOD-PM relationship is influenced by time-varying parameters such as relative humidity, PM vertical and diurnal concentration profiles, and PM optical properties. Thus, Lee et al. (2011) developed a mixed effect model which allows for day to day variability with a hypothesis of little spatial variability over the study region. In this study, a monthly observation is performed.

The statistical model proposed in this study, therefore, uses a monthly input parameter. Here, we hypothesis that the time-varying parameter exhibits a certain pattern in Peninsular Malaysia as a result of the peninsula's climate. Therefore, the monthly spatial variability of the time-varying parameter is statistically estimated from the AOD-PM_{10} relationship and plotted to characterize its overall pattern across Peninsular Malaysia. This time-varying parameter is then further included into the statistical model to predict PM_{10} concentrations of the study region.

The statistical model used to predict PM_{10} concentration is summarized by the following equation:

$$E(Y)_{mn} = \alpha_{\text{fix}} + \beta_{\text{fix}}(\text{AOD}_{mn} - [\varepsilon_{mn} + \varepsilon_{\text{fix}}]) \quad (1)$$

Where, $E(Y)_{mn}$ is the estimated PM_{10} concentration in month m, at site n; AOD_{mn} is the MODIS AOD value in the grid cell corresponding to month m, at site n; α_{fix} and β_{fix} fix is the intercept, and slope; ε_{mn} random error for month m, and site n; ε_{fix} fix error or adjustment derived from longterm observations of MODIS AOD. Here, the AOD fix effect represents the average effect of AOD on PM_{10} concentrations. The long term observations showed that there is a linear pattern of error in the AOD data where the error is directly proportional to the AOD data with an R^2 of 0.653. Therefore, we added a constant that is derived from this observation to minimize this error.

On the other hand, the AOD random effects represent the monthly variability in the PM_{10}-AOD relationship. The site bias may arise since an AOD value in a 10×10 km grid cell is an average optical depth in the given grid cell, while the PM_{10} concentrations

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measured at a given site may not be representative of the whole grid cell. In short, it represents the bias due to their spatial locations and meteorological condition in relation to the surrounding attribute. Therefore, the site bias is different for every location. To control for this site bias, we added a site term as a random effect into the statistical model. The bias value was computed from ground measurements and interpolated to represents the approximate ground conditions. From the monthly observations, the spatial pattern of the site bias exhibit three general patterns due to the meteorological conditions, i.e. the monsoon effect. From here, we average the spatial distribution of the site bias (random effect) according to the monsoon period. Once this parameter has been entered into the statistical model, the PM_{10} concentration was estimated for the whole study area using the MODIS AOD.

2.3 Model validation

This model is analyzed throughout Peninsular Malaysia by using a cross-validation (CV) method to examine whether the statistical model is applicable to our study region. There are a total of 31 sampling sites which were used in establishing the model and three independent sampling sites were used to validate the model. From the 31 sampling sites, a statistical model was developed to predict PM_{10} in Peninsular Malaysia. To assess the relationship between the predicted and measured PM_{10} concentrations for each site, the Pearson correlation coefficients were used. A high correlation indicates that the MODIS AOD data can be used to assess human health exposure investigations and can be applied in establishing the EPI for Malaysia. This validation is important to investigate the reliability and accuracy of the predicted PM_{10} concentration to assess the spatial accuracy of the predicted PM_{10}.

2.4 PM_{10} in Malaysia

In Malaysia, severe cases of air pollution are generally affected by our neighboring country as a result of forest fire and monsoon wind. This event usually occurred during

Southwest Monsoon season that occurred between May till September, which brings haze from Sumatra region to the western side of Peninsular Malaysia. Other local sources of air pollutions include vehicle emission, power generation, industrial emission, open burning and forest fires (Afroz et al., 2003; Azmi et al., 2010; Dominick et al., 2012). Besides, west peninsular Malaysia where major cities resides usually has a higher PM_{10} concentration compare to other region due to anthropogenic activities (Azmi et al., 2010).

3 Results and discussion

3.1 Descriptive statistics

The mean concentrations of PM_{10} in our study site are summarized in Table 1. From Table 1, there are several sites that exhibits high mean (SE) PM_{10} concentrations across Peninsular Malaysia. For example, Perai, Melaka, Kuala Selangor, Klang, KL, Shah Alam and Manjung. These sites are mainly industrialized regions that are affected by heavy traffic and seasonal haze. Surprisingly Bukit Rambai, Melaka has the highest mean (SE) PM_{10} concentration at 74.9 (1.81) $\mu g m^{-3}$ and followed by Klang at 72.3 (3.04) $\mu g m^{-3}$. The exceptionally high PM_{10} concentration in Bukit Rambai is mainly a result of local anthropogenic activities as it is situated in an industrial district with a secondary impact from seasonal haze (Mahmud et al., 2010). The average number of monthly sample points, (n) across peninsular Malaysia was 61. A total of 433 (17.69 %) monthly samples points were discarded due to the unavailability of a corresponding point with the MODIS AOD samples.

3.2 PM_{10} prediction

In the statistical model, the random error for all 72 months were generated (from year 2001 to 2006) and are summarized in Table 2. The random error was attributed to

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site and time varying errors. It has a seasonal pattern across Peninsular Malaysia as shown in Fig. 2. From Table 2 and Fig. 2, regions of densely developed sites have a high negative random error. This shows that these regions tend to have an overestimated AOD value. Therefore, it is necessary to include the random error into the statistical model to perform the adjustment. The fixed error or adjustment effect ξ_{fix} represents the monthly effect of MODIS AOD on PM_{10} for all study days. This constant is derived from Eq. (2) as shown below:

$$\xi_{\text{fix}} = \alpha - \beta(\text{AOD}_{mn}) \tag{2}$$

Where, α and β is the intercept, and slope for the relationship of the long term observations of MODIS AOD and error measurement for PM_{10} concentrations. This equation is obtained from a long term observation of the MODIS AOD residual effects on the in-situ PM_{10} concentrations measurement. The relationship between the fixed error, ξ_{fix} and AOD_{mn} is statistically significant with R^2 =0.653 where intercept, $\alpha = 0.214$ [(SE = 0.00379), $p < 0.0001$] and slope, $\beta = 0.653$ [(SE = 0.0105), $p < 0.0001$].

In the statistical model, the seasonal pattern of random error clearly shows the effects of the monsoon wind on our study region. The negative (red) region denotes the overestimated value from MODIS AOD that needed to be trimmed down. Similarly the positive (blue) region indicates an underestimation of the MODIS AOD, so that enhancement is needed. The overestimation of MODIS AOD may be due to the effect of unscreened cloud resulting from the MODIS cloud screening algorithm (Lee et al., 2011). This was also demonstrated in the work of Holben et al. (1998) where level 2 (AERONET) data was compared with MODIS AOD where unscreened cloud causes a positive bias in the predicted particulate matter concentration. Besides, bright surface condition also may also increase the error as a result of poorer visible to infrared (2.12 µm) band relationship (Levy et al., 2009). Besides, the overestimation of the AOD may also be related to the natural multiple scattering effect of the atmospheric particulate matter (pollutant). Thus, most of the well develop regions (having bright surface) tend to be overestimated. In Fig. 2, the effect of the monsoon wind was clear as it

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drifted the overestimated region further inland towards East Peninsular Malaysia. In contrast, the occurrence of the underestimated MODIS AOD values was common only during the inter-monsoon season and in some rural areas. The Inter-monsoon is the interval when a change of monsoon wind direction occurs. During this period, most of the atmospheric particulate matter concentrations recorded originated from local anthropogenic activities due to the stagnant wind condition. Thus, the underestimated MODIS AOD value at this period could be due to lower pollution levels in that particular area,compared to its surroundings that resulted in a plunge of offset in the observed MODIS AOD value below the apparent value.

The predicted PM_{10} concentrations from the statistical model are also prone to errors attributed from the difference in AOD retrieval and in-situ measurements of the PM_{10} concentrations. This is due to the fact that the in-situ measurements were point measurements, whilst the AOD was based on 10 × 10 km grid cells. However, this error was not taken into account due to the fact that the in-situ measurements were a 24 h average. Here, if the surrounding (within 10 × 10 km) PM_{10} concentration of a particular station was to represent the 10 × 10 km grid cell, it would most probably have been measured by the monitoring station within 24 h. Thus, the 24 h in-situ PM_{10} concentrations averaged to represent the 10 × 10 km grid cell, would most probably resemble the predicted PM_{10} concentration from MODIS AOD. Besides, the comparison of a 10 × 10 km grid cell with a point measurement was a common practice among researchers such as Chu et al. (2003), and Koelemeijer et al. (2006). However, for a monitoring station that is close to the pollution source such as Bukit Rambai in Melaka, the random error would appear higher due to the point measurement as it does not represent the 10 × 10 km^2 grid cell. Therefore, it is important to avoid sampling in close proximity to a pollution source, when the aim is to compare it to a large grid cell.

3.3 Accuracy assessment

In order to examine the accuracy of the predicted monthly PM_{10} concentrations, the monthly in-situ PM_{10} concentration and the monthly predicted PM_{10} concentration were

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regressed as shown in Fig. 3. The statistical model explained 77 % of the variability in the monthly measured PM_{10} concentration for a period of six years (i.e. 2001 till 2006). From Fig. 3, the relationship of the predicted PM_{10} concentration using the statistical model approximate the ground condition [slope = 1; intercept = 2×10^{-05}; $n = 1895$, $p < 0.0001$]. Further validation from three independent ground stations (i.e. Johor Bahru, Shah Alam and Pengkalan Chepa which are situated in southern, central and northern parts of Peninsular Malaysia) that were chosen to assess the predicted PM_{10} concentration also shows a promising result when regressed with the measured PM_{10} concentrations [slope = 1.085; intercept = 5.515; $n = 181$; $p < 0.0001$] (Fig. 4). This slope presented in Fig. 4 shows that the predicted PM_{10} concentration had a high agreement with the in situ PM_{10} concentration measurement and the intercept represent the noise in the predicted PM_{10} concentration dataset which is considerably lower.

Besides, the ability of the statistical model to predict the PM_{10} concentration was compared to a linear regression model by using Pearson correlation, R and root mean square error, RMSE (Table 3). The linear regression model has been widely used by many researcher (Chu et al., 2003; Engel-Cox et al., 2004a,b, 2005, 2006; Lee et al., 2011) to establish the AOD-$PM_{10 \text{ or } 2.5}$ relationship, and therefore is regarded as a common and valid methodology to predict particulate matters of different sizes (10 µm and 2.5 µm in diameter). Since the R does not quantitatively reflect the difference between the measured and predicted PM_{10} concentrations, RMSE is necessary to better assess both models. In Table 3, the performance of the statistical model has significantly improved the accuracy of the predicted PM_{10}, compared to the linear regression model. Overall, the long term Pearson correlation, R of predicted PM_{10} concentration has improved from 0.60 to 0.88 using the statistical model. Similarly, the RMSE of the predicted PM_{10} concentration of the statistical model improvised the linear regression model by an average of $\pm 6.18\,\mu g\,m^{-3}$ annually. In other words, the accuracy of the statistical model was superior and has improved approximately 50 % compared to the conventional linear regression model. This was further confirmed by the ANOVA test (p-value ≈ 1) which suggest that the predicted PM_{10} concentration using our method

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are in high agreement with in situ measurements. From this performance test, the statistical model appeared to be a better solution in producing a reliable concentration map for both environmental and health effect studies.

4 Conclusions

To date, there has been an increase in the adoption of satellite AOD data into air pollution, health effects and environmental studies. The awareness of the potential of remote sensing technologies to enhance ground-level particulate matters monitoring networks has further encouraged the many government and private agencies to look into its practicality. In Malaysia, the used of satellite derived parameters as performance indicators in EPI is one of the highlights to bring forward these technologies. However, the application of satellite data has always been received with skepticism in this region due to cloud cover and low predictive power. The proposed statistical model suggested in this paper has shown that this calibration method can be reliable in producing a better PM_{10} concentration map for this region. Taking into account the site specific random error and the fixed errors, the accuracy of the satellite data improve significantly.

Next, we anticipate that the outcome of this method will be increasingly used for health effects, pollution and environmental related studies. Future satellite technologies are expected to improve spatial and temporal resolutions in the near future, resulting in an even more accurate retrieval method. As the satellite data is readily available, monitoring and predicting the atmospheric pollution such as PM_{10} can be made in a cost-effective way. Another focus of our future research will be to study atmospheric particulate matter and other atmospheric trace gases that are harmful to human health.

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Table 1. Longterm (2001–2006) descriptive statistics of PM_{10} concentration ($\mu g\,m^{-3}$) observed at 34 monitoring stations.

Site Location	Latitude	Longitude	Mean ($\mu g\,m^{-3}$)	SE	*n*
Pasir Gudang	1.4704	103.8940	48.1863	1.0899	63
Teluk Kalung, Kemaman	4.2658	103.4323	42.7493	1.4158	60
Taman Inderawasih, Perai	5.3711	100.3891	67.9593	2.9404	51
Bukit Rambai, Melaka	2.2586	102.1727	74.9056	1.8103	57
Jerantut	3.9706	102.3477	40.9819	1.2827	66
Jalan Tasik, Ipoh	4.6294	101.1166	51.5535	1.2655	69
Perai	5.3982	100.4039	62.8881	1.7725	61
Nilai	2.8216	101.8114	58.9865	1.5094	73
Klang	3.0100	101.4085	72.3269	3.0406	61
Indera Mahkota, Kuantan	3.8193	103.2965	35.6930	1.1265	46
Balok Baru, Kuantan	3.9607	103.3822	58.6329	1.1805	64
Petaling Jaya (PJ)	3.1092	101.6387	56.7447	1.8507	66
Sg. Petani	5.6315	100.4697	52.1768	1.3659	67
J.Bahru	1.4974	103.7268	41.9780	1.4483	57
Taiping	4.8987	100.6792	46.6497	1.2714	65
Pangkalan Chepa, Kota Bahru	6.1591	102.2880	44.6054	1.3353	61
Kota Bahru	6.1587	102.2510	41.7383	1.3460	63
Kajang	2.9939	101.7417	49.2644	1.7183	64
Paka-Kertih	4.5980	103.4349	34.8524	0.8947	58
Shah Alam (SA)	3.1047	101.5563	62.3982	2.3494	65
Langkawi	6.3316	99.8583	41.1803	1.2462	57
Kangar	6.4240	100.1841	50.2028	1.3886	63
Kuala Terengganu	5.3076	103.1202	55.5998	1.3245	61
P. Pinang	5.3575	100.2944	41.4968	1.4140	60
Alor Star	6.1372	100.3466	37.0292	1.2113	45
Manjung	4.2003	100.6633	64.9669	2.1603	69
Bachang	2.2131	102.2343	45.0230	1.7305	62
Muar, Johor	2.0397	102.5769	54.5739	1.7906	69
Tanjung Malim	3.6878	101.5244	44.2118	1.2914	70
Pegoh 4, Ipoh	4.5533	101.0802	50.5180	1.3745	69
Seremban	2.7236	101.9684	46.2812	1.3255	71
Kuala Selangor	3.3265	101.2589	65.9391	2.0785	66
W.P Putrajaya	2.9319	101.6818	52.1179	2.7837	44
W.P K. Lumpur (KL)	3.1062	101.7178	60.7715	3.1059	35

SE: Standard error.
n: Number of monthly samples points.

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Table 2. Estimation of long term (2001–2006) monthly mean random error (AOD) for 34 monitoring stations.

Site Location	Latitude	Longitude	Mean Random error	*p*-value
Pasir Gudang	1.4704	103.8940	0.026583	2.23E-17
Teluk Kalung, Kemaman	4.2658	103.4323	0.001716	4.15E-30
Taman Inderawasih, Perai	5.3711	100.3891	−0.03621	1.18E-23
Bukit Rambai, Melaka	2.2586	102.1727	−0.06916	9.48E-10
Jerantut	3.9706	102.3477	0.016756	1.13E-31
Jalan Tasik, Ipoh	4.6294	101.1166	−0.03478	1.77E-25
Perai	5.3982	100.4039	−0.05388	1.36E-14
Nilai	2.8216	101.8114	−0.0166	4.11E-21
Klang	3.0100	101.4085	−0.00907	7.61E-20
Indera Mahkota, Kuantan	3.8193	103.2965	0.052074	3.18E-23
Balok Baru, Kuantan	3.9607	103.3822	−0.02896	1.25E-17
Petaling Jaya (PJ)	3.1092	101.6387	0.017589	1.90E-24
Sg. Petani	5.6315	100.4697	−0.03019	4.59E-23
J.Bahru	1.4974	103.7268	0.023401	7.01E-29
Taiping	4.8987	100.6792	0.004631	7.18E-23
Pangkalan Chepa, Kota Bahru	6.1591	102.2880	0.02165	2.38E-25
Kota Bahru	6.1587	102.2510	0.027273	1.39E-30
Kajang	2.9939	101.7417	0.032397	4.13E-26
Paka-Kertih	4.5980	103.4349	0.027893	1.48E-20
Shah Alam (SA)	3.1047	101.5563	−0.00506	3.64E-26
Langkawi	6.3316	99.8583	−0.02644	1.90E-29
Kangar	6.4240	100.1841	0.005399	1.75E-24
Kuala Terengganu	5.3076	103.1202	−0.06521	5.31E-16
P. Pinang	5.3575	100.2944	0.044279	2.96E-30
Alor Star	6.1372	100.3466	0.028433	8.54E-43
Manjung	4.2003	100.6633	−0.04234	5.15E-28
Bachang	2.2131	102.2343	0.044034	9.49E-26
Muar, Johor	2.0397	102.5769	0.032908	1.21E-30
Tanjung Malim	3.6878	101.5244	0.026456	3.88E-24
Pegoh 4, Ipoh	4.5533	101.0802	−0.02539	3.91E-29
Seremban	2.7236	101.9684	0.021293	1.14E-15
Kuala Selangor	3.3265	101.2589	−0.03693	3.77E-17
W.P Putrajaya	2.9319	101.6818	0.037866	5.01E-13
W.P K. Lumpur (KL)	3.1062	101.7178	0.026865	2.23E-17

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Table 3. Long term comparison on linear regression model and statistical model on PM_{10}-AOD and RMSE ($\mu g\,m^{-3}$) of annual MODIS estimated PM_{10} concentration.

	Linear regression model				Statistical model			
Year	*R*	*n*	RMSE ($\mu g\,m^{-3}$)	*p*	*R*	*n*	RMSE ($\mu g\,m^{-3}$)	*p*
2001	0.60	315	±13.01		0.89	315	±6.25	
2002	0.60	325	±15.36		0.89	325	±8.57	
2003	0.63	322	±14.30		0.90	322	±7.19	
2004	0.62	367	±13.38	$p < 0.0001$	0.90	367	±7.61	$p < 0.0001$
2005	0.60	366	±12.27		0.88	366	±7.42	
2006	0.66	381	±12.52		0.91	381	±6.75	
2001–2006	0.60	2076	+12.90		0.88	2076	±7.32	

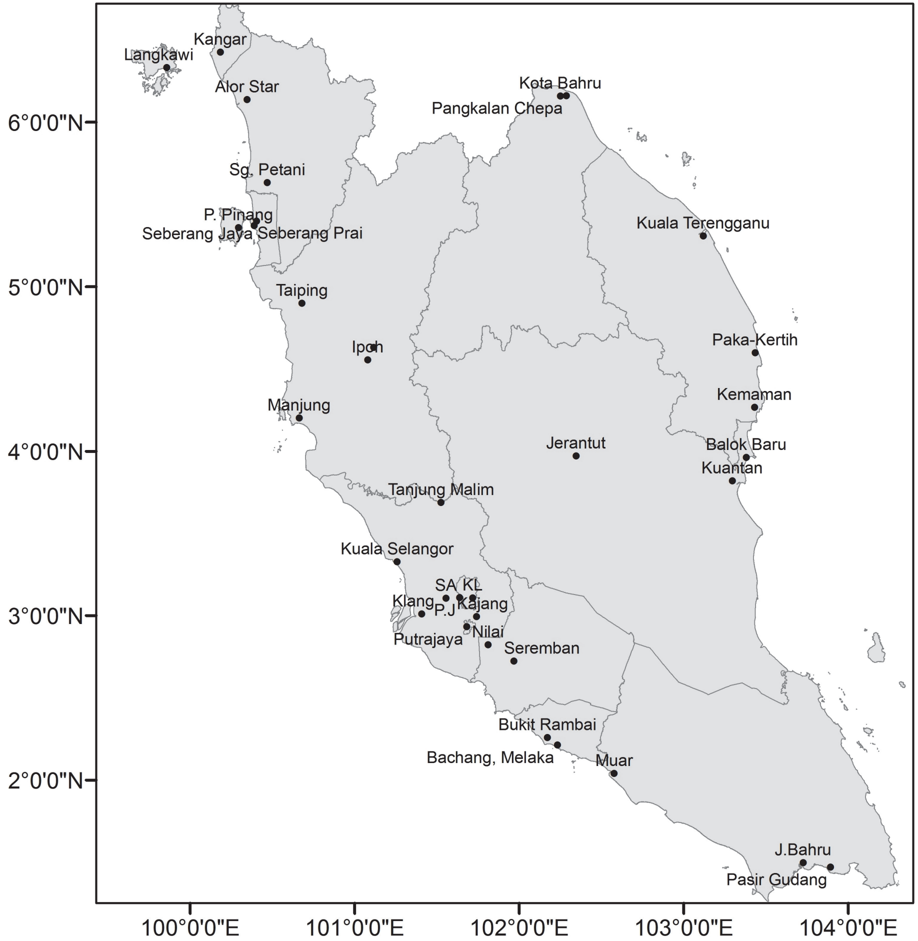

Fig. 1. Spatial distributions of 34 monitoring site to be use in this study. (SA: Shah Alam; KL: Kuala Lumpur; J.Bahru: Johor Bahru; PJ: Petaling Jaya).

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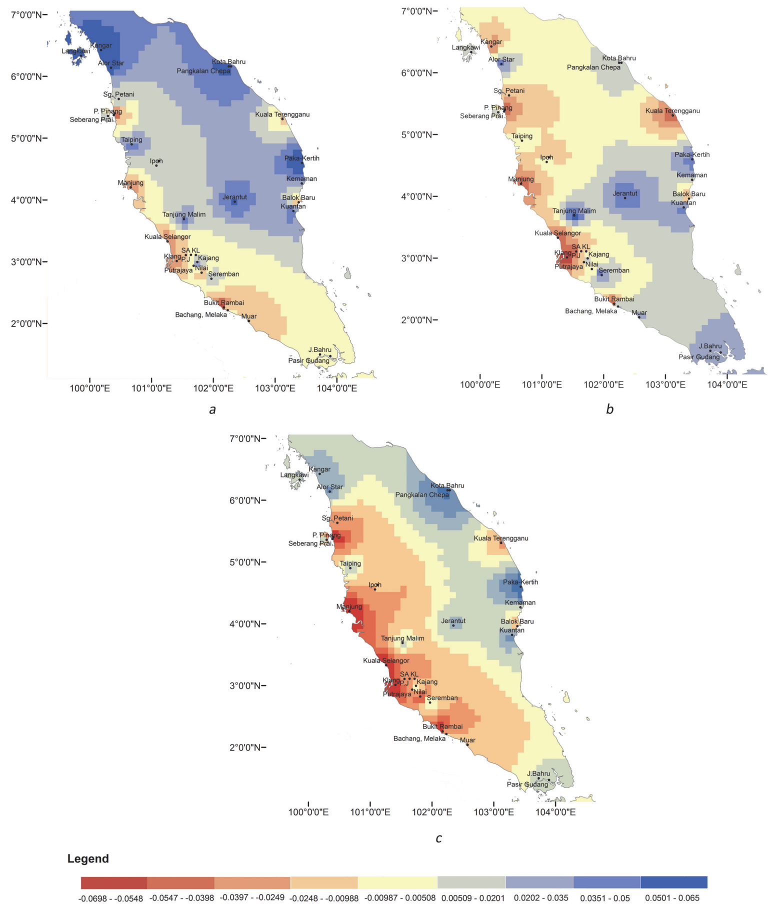

Fig. 2. Seasonal distribution of random error **(a)** intermonsoon, **(b)** northeast monsoon, **(c)** south west monsoon season.

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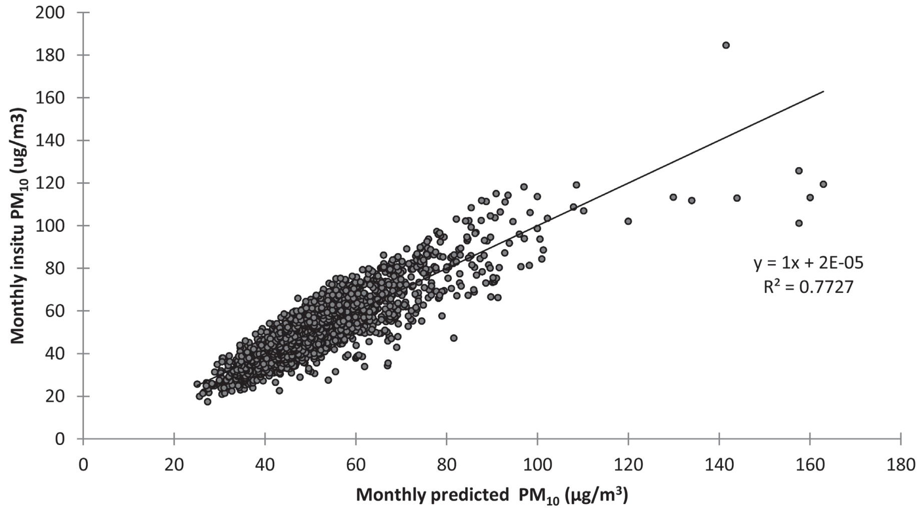

Fig. 3. Assessment of the monthly insitu PM_{10} measurement and monthly predicted PM_{10} by statistical model.

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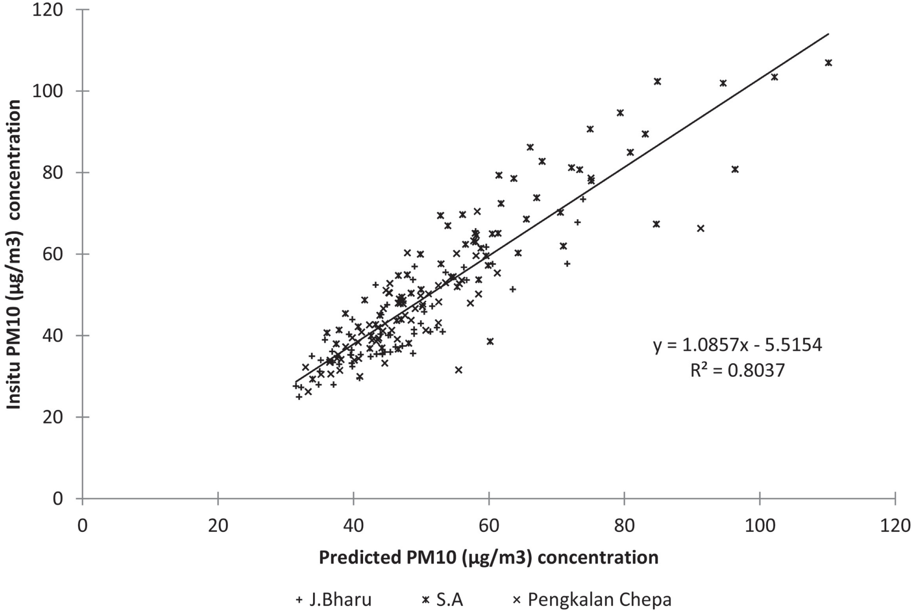

Fig. 4. Assessment of the monthly insitu PM_{10} measurement and monthly predicted PM_{10} from three independent monitoring sites.