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Prediction of Ambient PM_{10} Concentration in Malaysian Cities Using Geostatistical Analyses

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Abstract - Unplanned urbanisation and industrialisation caused deterioration of the atmosphere, hence affecting human health and the environment. Malaysia is one of the Southeast Asian countries that struggle significantly with air pollution. Although some measures have been taken to monitor the air pollutants level in various cities, the limited monitoring stations in the country leave some areas unmonitored. A spatial interpolation technique is a primary method for monitoring unmanned regions to develop a better mitigation strategy towards reducing urban air pollution. Particulate Matter 10 (PM_{10}), one of Malaysia's primary air pollutants, is used to predict and indicate the air pollutant's presence in some unmeasured locations. Spatial interpolation models and geostatistical analysis such as ordinary kriging (OK), universal kriging (UK), and Inverse Distance Weighting (IDW) were used in this study to predict and assess the distribution of PM_{10} to other regions. The PM_{10} thematic map produced by IDW has a maximum and minimum value of 76 $\mu g/m^3$ and 42 $\mu g/m^3$, while the UK predicted a maximum and minimum value of 61 $\mu g/m^3$ and 54 $\mu g/m^3$, respectively. The OK predicted a maximum value of 60 $\mu g/m^3$ and a minimum value of 53 $\mu g/m^3$. The predicted values from the three interpolation methods aligned with the Malaysian air pollution index (API) with good and moderate air pollution levels. Comparatively, the performance of IDW is more reliable considering its non-bias in predicting PM_{10} concentration. Conclusively, the air pollution prediction map from this study could be leveraged to control and monitor air pollution, especially in unmanned areas.

Keywords: PM_{10}, Spatial Interpolation, Air Pollution, Monitoring Stations, Geostatistical Analysis

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1.0 Introduction

In recent years, rapid urbanisation, the industrial revolution, fossil fuel consumption, vehicular emission, anthropogenic activities, and population growth have severely increased air pollution in the world (Suleiman et al., 2019; Choubin et al., 2020; Tella et al., 2021). Air pollution has been documented to have adverse effects on environmental sustainability and human health, particularly the respiratory and cardiovascular systems (Bai et al., 2016; Suleiman et al., 2020).

Malaysia, a Southeast Asian country, has continued to suffer from poor air quality due to rapid urbanisation, population growth, and industrialisation (Abdullah et al., 2016). Particulate matter has been identified as the dominant air pollutant in Peninsular Malaysia, as compared to other contaminants, such as ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) (Rani et al., 2018). Although $PM_{2.5}$ is the primary indicator for determining the air pollution index (Usmani et al., 2020), however, PM_{10} also poses a threat to human health and the environment (Althuwaynee et al., 2020).

Over 4.8 million deaths were attributed to particulate matter in 2017 (Collaborators et al., 2015; Stanaway et al., 2018; Rovira et al., 2020). The PM_{10} refers to atmospheric inhalable particles with a diameter more acceptable than or equal to 10μm. PM_{10} could easily penetrate the respiratory tract and skin, causing severe damages to the immune, cardiovascular, and respiratory systems, as well as linked with a rise in mortality and morbidity rate (Beloconi et al., 2018; Ganguly and Sharma, 2019; Choubin et al., 2020), particularly after prolonged exposure (Carugno et al., 2018; Gondalia et al., 2019; Cen et al., 2020). Hence, its classification as a significant hazardous air pollutant necessitates quick intervention for mitigation strategies.

A mitigation measure is necessary to attain good air quality and reduce the harmful health effects of air pollution. Therefore, having an accurate map of PM_{10} concentration is essential for monitoring and mitigating the effects of ambient pollution. Nevertheless, the map generation is influenced by the limited number of monitoring stations (Hamm et al., 2015). Thus, it is crucial to generate an accurate distribution of air pollution in unmanned regions. Besides, a spatial air pollution map will ensure an adequate assessment of population exposure to ambient air pollution, allowing for the most effective strategy (Chu et al., 2015; Fioravanti et al., 2021).

The spatial interpolation model is the most common method for estimating a particular pollutant's concentration in unmounted regions (Alimissis et al., 2018). This model uses the known locations' point value to determine the value of unknown areas (Tella et al., 2021). Spatial interpolation models are still in use (Jumaah et al., 2019; Bozdağ et al., 2020; Alberdi et al., 2020; Tella et al., 2021; Fioravanti et al., 2021; Zhang et al., 2021). For example, Gómez-Losada et al. (2019) used OK and IDW to estimate the spatial distribution of short- and long-term air pollutants such as NO_2, O_3, SO_2, and PM_{10} in Spain. Meanwhile, Shukla et al. (2020) also used OK and IDW to map the spatial distribution of $PM_{2.5}$ in Iran. Despite the limitations, such as topographical variation, sampling density, and clustering of monitoring stations (Tadić et al., 2015; Gómez-Losada et al., 2019), the spatial interpolation model is widely applied in air pollution study to obtain high-resolution air pollution predictive values (Shukla et al., 2020).

Contrarily, a kriging method is extensively applied for geostatistical distribution of air pollution due to its high performance compared to the other techniques (e.g., IDW, nearest neighbour, land use regression (LUR), and spatial averaging) (Dalmau et al., 2017; Xu et al., 2019; Zhang et al., 2021). Although IDW is more straightforward than the kriging method, previous research showed that the latter outperforms the former (Gorai et al., 2017; Gómez-Losada et al., 2019).

Notably, spatial interpolation models could either be geostatistical, non-geostatistical or combination of the two (Gómez-Losada et al., 2019). Consequently, the geostatistical analyst tool in geographical information system (GIS) software could determine air pollution levels in less monitored areas. To the best of our knowledge, studies that focus on estimating PM_{10} in Malaysia using GIS tools are scarce. Although Jumaah et al. (2019) used the IDW spatial interpolation to analyse the climatic and air quality records in Kuala Lumpur, however, the study was only restricted to the capital city of Malaysia. Therefore, this research focused on the prediction of PM_{10} using IDW with two different types of kriging methods in five major states in Malaysia. The predictive performance of these two models was also investigated to determine the best process for PM_{10} prediction.

2.0 Methodology

2.1. Data Acquisition

The hourly concentration of PM_{10} was obtained from the Malaysian Department of Environment (DoE). The PM_{10} data covered ten monitoring stations in five states from 2012 to 2016 (Table 1). There were some missing data in the acquired dataset. Therefore, a missing value imputation method was used to remove the affected rows and columns. Subsequently, the annual concentration of the PM_{10} data from 2012 to 2016 was calculated. The average concentration of PM_{10} was determined for each state, aligning with a study by Choubin et al. (2020). The data was imported into the GIS interface for further analysis. Figure 1 shows the site location of the monitoring stations as well as the industries that surrounds them. All the stations were strategically placed in suburban and industrial areas.

Table 1. The location of monitoring stations

States	Stations	Latitude (N)	Longitude (E)
Melaka	Sek. Men. Bukit Rambai	2.2585	102.1727
	Sek. Men. Tinggi Melaka, Melaka	2.1368	101.1205
Negeri Sembilan	Tmn. Semarak (Phase II), Nilai	2.8208	101.8170
	Sek. Men. Teknik Tuanku Jaafar, Ampangan, Seremban	2.7231	101.9667
Perak	Sek. Men. Jalan Tasek, Ipoh	4.6297	101.1161
	Sek. Men. Keb. Air Puteh, Taiping	4.8990	100.6797
Selangor	Sek. Men, (P) Raja Zarina, Kelang	3.0100	101.4081
	Sek. Keb. Bandar Utama, Petaling Jaya	3.1102	101.7046
Penang	Sek. Keb. Cederawasih, Taman Inderawasih, Perai	5.3912	100.3869
	Sek. Keb. Seberang Jaya II, Perai	5.3982	100.4039

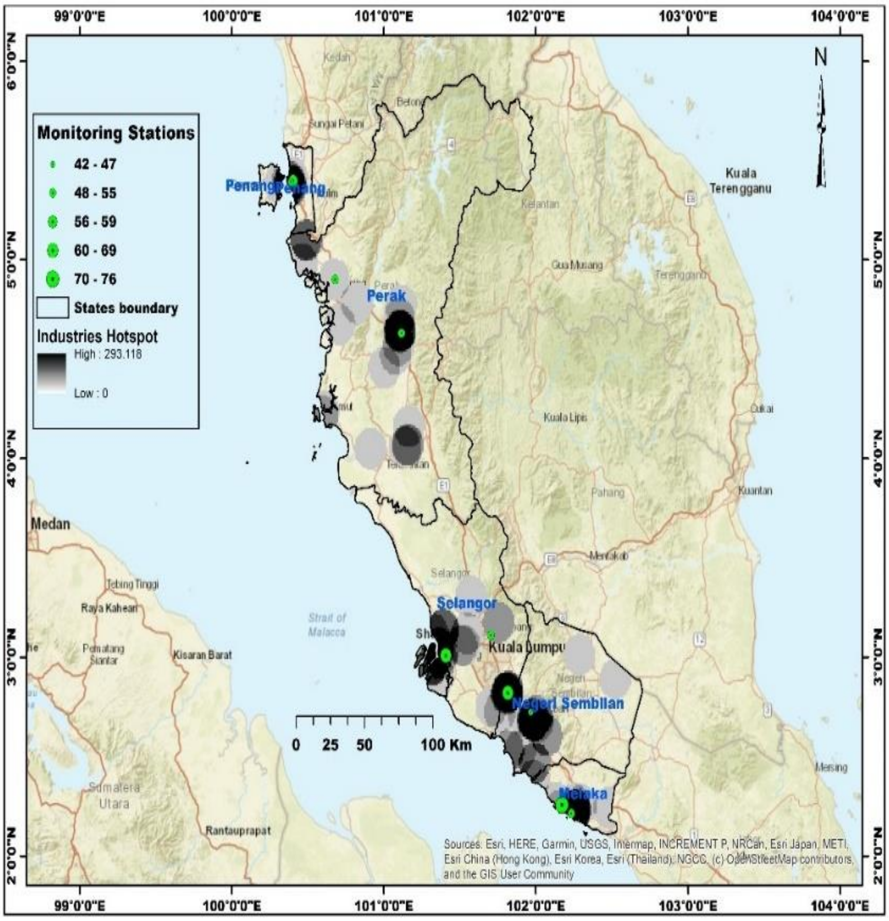


Figure 1. Study area showing the stations with PM_{10} concentration and industries density.

2.2. Geostatistical Analysis using GIS

GIS is a computer-based software for storing, mapping, and analysing earth related data. It is also a spatial phenomenon with the input of geospatial analyst judgment to solve spatial problems (Kumar et al., 2016). GIS is an effective tool for monitoring and studying air quality (Somvanshi et al., 2019). Some notable researches have utilised GIS for spatial and temporal analysis of emitted air pollutants (Maantay, 2007; Kumar et al., 2016; Sohrabinia and Khorshiddoust, 2007). One of the general approaches for mapping air pollution is a spatial interpolation method (Jumaah et al., 2019; Briggs, 1996). Thus, this study used IDW and different types of kriging spatial interpolation methods to estimate air pollution concentration in five states in Peninsular Malaysia. IDW and the kriging interpolation methods are representing the deterministic and stochastic interpolation method that has been extensively utilised in air pollution studies (Gómez-Losada et al., 2019). The IDW, OK, and the UK methods were compared to determine the most suitable interpolation model type in this study.

2.2.1 Kriging Interpolation Method

Kriging is a spatial interpolation method used to predict unmanned locations (Kim et al., 2014). The prediction is based on the features of the variance and the characterised mean. The kriging interpolation gives the most appropriate estimation of a variable Y at an unmanned region X (n-dimensional coordinate vector) from data points around the location (Dalmau et al., 2017). There are two kriging methods, namely ordinary and universal kriging. The OK is the most widely utilised kriging method that predicts a point value at a location by calculating the weighted mean for surrounding data (Wackernagel, 2013; Zhang et al., 2021). The weight derived from the first data estimated could compute all other data (Shukla et al., 2020). The variogram is the function determining the weight in OK, which determines the spatial autocorrelation structure (Gómez-Losada et al., 2019). On the other hand, the UK method, also called the spatial smoothing model (Xu et al., 2019), is mainly utilised for data with a significant spatial trend (Tadić et al., 2015). The UK method also describes the model residuals' spatial autocorrelation.

2.2.2 The IDW

IDW gives preference to data or point value which are closer to each other. The local influence of the measured points is assumed to reduce with distance, and points that are more relative to the target region will have a higher weight (Gómez-Losada et al., 2019; Shukla et al., 2020). The function of the distance is influenced by an exponent (p), which is a positive integer. However, when P = 0, the distance does not diminish, and the unsampled regions are equal to the mean of the measured points. Contrarily, as P increase, the priority of the values closest to the points to be interpolated will be higher. Hence, in this study, the default exponent P = 2 is used, referring to Shukla et al. (2020). At P = 2, the measuring point in determining the predicted point value of unsampled location reduces as a function of a squared distance (Gómez-Losada et al., 2019).

3.0 Results

The study findings were based on the ten monitoring stations mounted around urban and industrial areas. The PM_{10} hourly concentration data used had a minimum of 42 $\mu g/m^3$ and a maximum of 76 $\mu g/m^3$. The mean and standard deviation of the dataset was 57.07 $\mu g/m^3$ and 10.83 $\mu g/m^3$, respectively. Figure 2 shows the normal distribution of the dataset using the quartile-quantile (q-q) plot. The plot shows how well-distributed the points are. Hence, an observable linear formation was observed in the q-q plot. The linear formation indicates that the point features are generally distributed in a straight line.

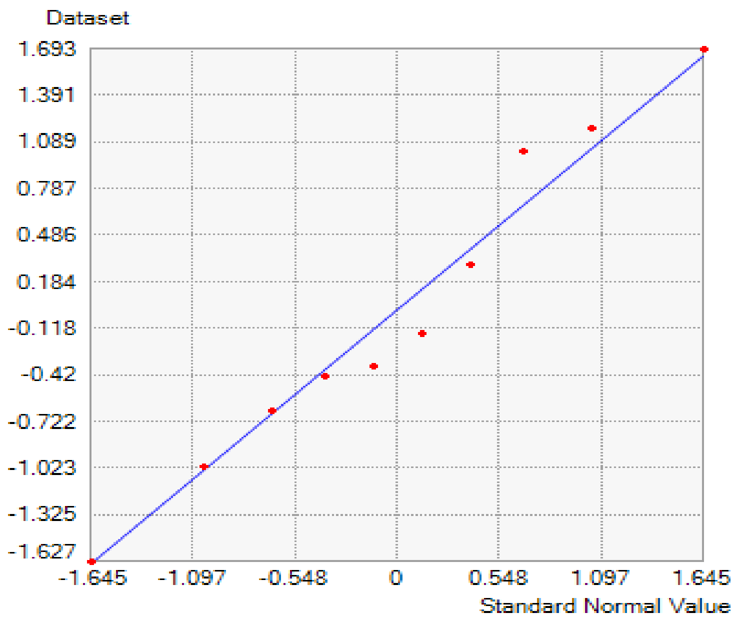
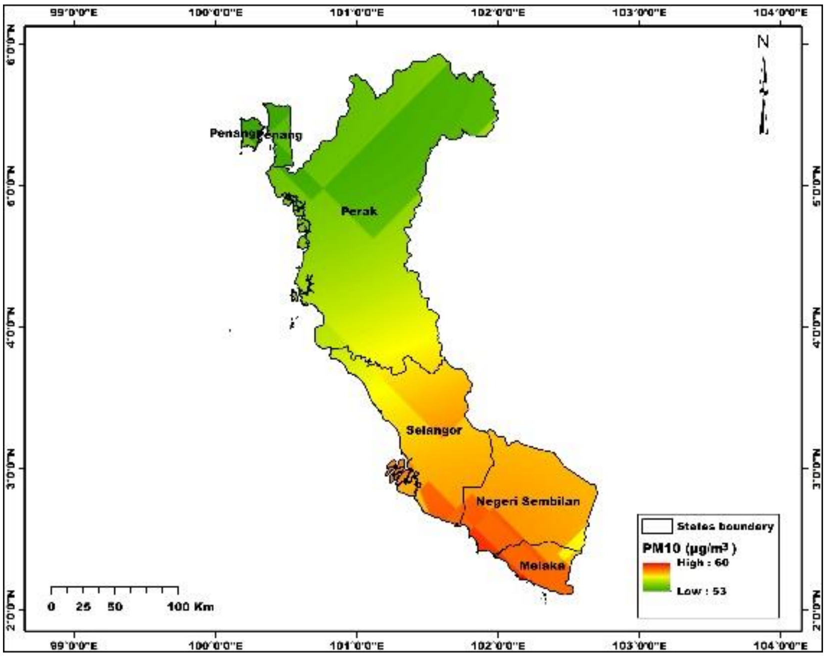


Figure 2. A standard q-q plot of the dataset

The ArcGIS geostatistical analyst tool was used to carry out the three spatial interpolations method; IDW, OK, and the UK. The generated map is shown in Figure 3, which almost follows the same trend. However, there is a virtually biased prediction in the kriging model, excluding the IDW. The model was over or under predicted the original values of the hourly PM_{10} concentration. Figure 3(b) shows that IDW has a lower value of 42 μg/m^3 and the highest value of 76 μg/m^3. For both OK and UK, an over-prediction appears in the minimum value while under-prediction was in the maximum values. The OK exhibits a minimum value of 53 μg/m^3 and a maximum value of 60 μg/m^3, while the UK predicted a low value of 54 μg/m^3 and a high value of 61 μg/m^3 [Figures 3(a) and (c)]. These two types of kriging model underpredicted the values compared to the original maximum value of the dataset (76 μg/m^3). The models also over predicted the values, compared to the minimum value of the dataset (42 μg/m^3). However, for cross-validation, the OK method showed a better prediction with a mean square root of 11.27. The IDW and UK had a mean square root of 15.91 and 11.28, respectively.

In terms of spatial distribution, four out of the five states exhibited a higher PM_{10} concentration. Selangor showed the highest concentration compared to the other states. The finding may be linked to the source emission of the pollutant. Selangor is known for its highly populated state with different commercial and industrial activities (Ahamad et al., 2014).



99°0'0"E
100°0'0"E
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104°0'0"E
N
Penang
Penang
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Negeri Sembilan
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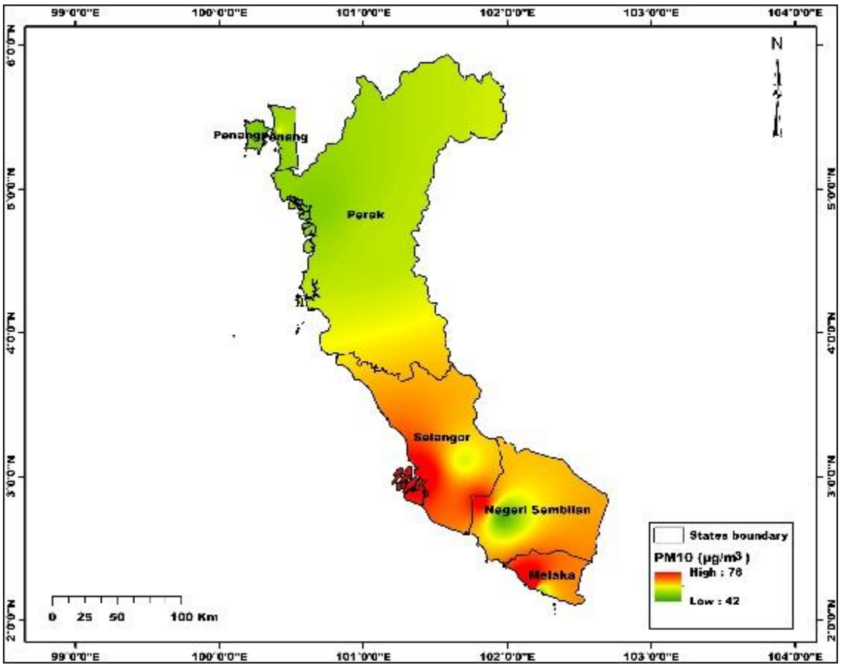
States boundary
PM10 (µg/m3)
High : 60
Low : 53
0 25 50 100 Km

(3a)



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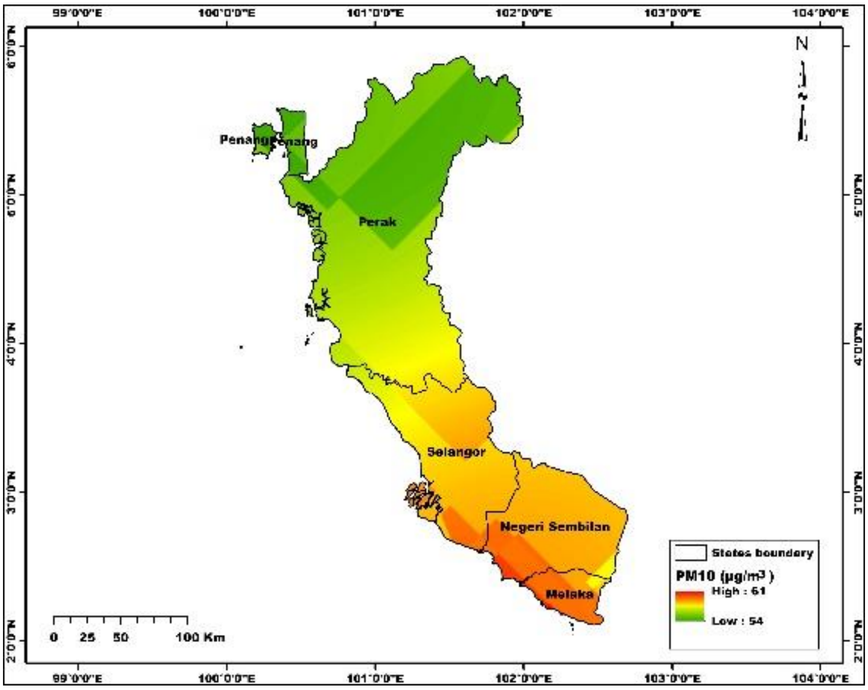
Negeri Sembilan
Melaka
States boundary
PM10 (µg/m3)
High : 76
Low : 42
0 25 50 100 Km

(3b)



(3c)

Figure 3. Spatial interpolation map based on (a) OK, (b) IDW, and (c) UK

4.0 Discussion

The spatial interpolation method is a reliable method for predicting values for areas without data. The dataset's location showed that most monitoring stations are strategically situated around highly populated areas and industries. Notably, the stations proved inadequate in displaying the air pollution concentration for all locations. Thus, this research studied the efficiency of three interpolation models, namely IDW, UK, and OK, predicting the ambient PM_{10} concentration for unmanned regions in five states in Peninsular Malaysia. The maps produced by the three interpolation methods revealed that the air pollution level ranges from good to moderate, which aligns with the Malaysian API (APIMS, 2020). The air pollution level validates the reliability of the prediction maps by the three interpolation methods explored in this study. Compared to the UK and OK, the IDW prediction map had a higher correlation with the dataset's accuracy. However, for the cross-validation study, the OK outperformed both IDW and UK with a lower RMSE. Thus, this study concludes that although all three models are excellent spatial interpolation techniques, the IDW is more appropriate.

Nevertheless, it is hard to conclude which methods exhibited the best performance (Shukla et al., 2020). The under or over prediction of the air pollutant's concentration by the UK and OK interpolation method may be due to the limitation in the kriging method for not interpolating stationary data (Shukla et al., 2020). Further studies that would integrate kriging and regression analysis as a hybrid technique are recommended to improve reliability and accuracy (Yao et al., 2013). Additionally, future studies should include meteorological variables and other influencing factors, as mentioned by Bozdağ et al. (2020), to enhance the performance and accuracy of kriging interpolation techniques.

5.0 Conclusion

This study compared three different spatial interpolation techniques in predicting PM_{10} in five states in Peninsular Malaysia. The acquired PM_{10} data from 2012 to 2016 was used to predict the air pollution concentration across the five states. A q-q plot showed that the dataset is normally distributed. Three different interpolation methods, the IDW, UK, and OK, were used for the prediction. The IDW prediction aligned with the dataset statistics with minimum and maximum values of 42 µg/m^3 and 76 µg/m^3, respectively. Contrarily, the OK showed a low value of 53 µg/m^3 and a high value of 60 µg/m^3. The UK exhibits a minimum value of 54 µg/m^3 with a maximum value of 61 µg/m^3. It is observed that the IDW shows a better performance in the prediction of the PM_{10} concentration level. However, based on the results, it is hard to conclude which models are more dependable and reliable for air pollution prediction. The over or under prediction by the kriging methods may be subjected to these models' inability to interpolate data that are not statistically stationary. Nevertheless, the IDW showed a higher RMSE (15.91) than the kriging methods (11.28). To conclude, the estimated PM_{10} thematic maps could be used as a mean for effective strategies in controlling air pollution.

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