1. Introduction

Particulate matter (PM) refers to small solid and liquid matter suspended in the air, and is one of the most serious threat to human health among all the ambient air pollution. High exposure to PM can cause damage to human body including lung (Löndahl *et al.*, 2006), heart (Sun *et al.*, 2010; Brook *et al.*, 2010) and airway (González-Flecha, 2004), depending on the size of the particle. PM is mainly classified into two categories according to their aerodynamic diameter (Kim *et al.*, 2015), namely fine particulate matter ($PM_{2.5}$), which has a diameter smaller than 2.5 μm, and coarse particulate matter (PM_{10}), which has a diameter between 2.5 to 10 μm. The sizes of PMs decide their transport abilities in the atmosphere as well as in the human body. $PM_{2.5}$ tends to travel longer in the atmosphere and penetrate deeper in the human body than PM_{10}. As a result, major health problems related to $PM_{2.5}$ are associated to lungs, Bronchi branches and Bronchioli (Löndahl *et al.*, 2006), while PM_{10} mainly causes damages to respiratory systems (airway) (González-Flecha, 2004). It is estimated that more than two million deaths worldwide each year are directly related to diseases caused by air pollution, most of which by fine particulate matter (Shah *et al.*, 2013). $PM_{2.5}$ is the primary contributor to human health issues relating to ambient air pollution.

The hazard mainly comes from exposure to high concentration of $PM_{2.5}$, and the lower the concentration, the less the danger it exposes to human health. The WHO guideline values for $PM_{2.5}$ is 15 μg/m^3 daily mean and 5 μg/m^3 annual mean (WHO, 2021). This guideline represents the highest possible concentration to which the effect from $PM_{2.5}$ to human health is acceptable, but does not guarantee no damage to health. However, most regions around the world, especially regions in developing countries, have $PM_{2.5}$ levels higher than the WHO guidelines (World Bank, 2017).

The fine particulate matter in the atmosphere comes from both anthropogenic and natural sources. The former include combustion of fossil fuels, industrial and agricultural activities, and erosion of pavement by road traffic (Srimuruganandam and Nagendra, 2012). The natural sources include volcanoes, wildfires, dust storms and sea spray (Anderson *et al.*, 2012). Natural sources contribute only 18% to global $PM_{2.5}$ pollution, with the rest from anthropogenic sources, among which traffic section takes up the highest percentage (Karagulian *et al.*, 2015). Hence, finding a way to mitigate the $PM_{2.5}$ pollution from road transport emissions can greatly reduce the $PM_{2.5}$ level in urban areas.

One proposed approach to this is developing near-road greenspaces. Many researches have examine the effect of greenspaces in reducing regional PM level (Kończak *et al.*, 2021; Song *et al.*, 2015; Lei *et al.*, 2018; Irga *et al.*, 2015; Hofman *et al.*, 2016), which is mainly through two mechanisms - mass removal and transmission block. On one hand, vegetation in greenspaces can help directly remove the PM from the air by capturing and storing them on the leaf surface as well as in the wax layer (Kończak *et al.*, 2021). On the other hand, greenspaces can act as a 'windbreak' that interrupts the dispersion of particulate matter (Morakinyo and Lam, 2016) as well as altering other local meteorological environments including temperature, barometric pressure, relative humidity, etc. which also affect PM level (Hofman *et al.*, 2016).

Based on these theoretical and empirical foundations, near-road greenspaces are believed to have positive effect in lowering PM concentrations. Indeed, there have been studies finding near-road air quality being significantly improved by vegetation (Morakinyo and Lam, 2016), especially in busy roadsides in open areas (Baldauf *et al.*, 2011). However, Vos *et al.* (2013) found that in some cases, instead of reducing $PM_{2.5}$ concentration, roadside vegetation can actually enhance PM pollution nearby by hindering the wind flow and resulting in an accumulation of particulate matter in the area (Abhijith *et al.*, 2017). Such a finding brings uncertainty to the effect of near-road greenspaces on lowering $PM_{2.5}$ level in urban areas, and further investigation is needed.

Previous researches on examining the effect of greenspaces, especially near-road greenspaces, in reducing PM concentration in urban areas can be divided into two streams. The first stream primarily focused on assessing the abilities in capturing particles in the air of greenspaces with different characteristics. Liu *et al.* (2015) found that canopy density, leaf area, mean diameter at breast height, average tree height and grass coverage and height in forests could greatly alter $PM_{2.5}$ concentration. Different vegetation species also have different levels of impacts on PM concentrations. For example, cypress trees reduce PM level more than pine trees (Ji and Zhao, 2014). Variations in the location of vegetation in relation to wind direction can also lead to changes in its ability to reduce PM concentrations (Al-Dabbous and Kumar, 2014). Greenspaces are most effective in reducing PM concentrations when the wind blows from areas of high PM level (e.g. roads) towards them. Lei *et al.* (2018) found that patterns of greenspaces can also influence their ability to reduce PM pollution. Increasing the differences between areas of greenspace patches as well as their edge complexities can significantly lower PM concentrations. These research findings contribute extensively to the academic understandings and policy-making of the urban greenspaces in tackling PM pollutions. However, most of them failed to consider temporal changes. $PM_{2.5}$ concentrations in different seasons can vary greatly, and even within one day the concentrations have highs and lows. In these cases, the influences of greenspaces on PM concentrations could also be changing. Moreover, most of these studies' approach was through field measurements, which, while delivering valuable first-hand data and solid mechanism-level understandings, were not convincing enough if were to be applied to a larger scale.

The other stream that includes this subject used land use regression (LUR) extensively to examine how land use types affect spatial-temporal changes of $PM_{2.5}$ levels. Wu *et al.* (2017) utilized a LUR model with $PM_{2.5}$ concentrations and monthly NDVI (Normalized Difference Vegetation Index) data in Taipei, and found a strong negative correlation between them. Xu *et al.* (2019) also found a relation between forest land type and $PM_{2.5}$ level through LUR. However, the problem with LUR technique is that it always suffers from multicollinearity (Ross *et al.*, 2007), which makes the model output less reliable. To overcome this, Kim (2020) developed a partial least-squares regression model, which minimizes the influence of multicollinearity of the variables, to study the effects of land use on PM levels in different seasons in Seoul, South Korea, and found that the percentage of greenspace area is negatively related to regional PM concentrations. Yet, none of them was able to evaluate the relation between near-road greenspaces and regional $PM_{2.5}$ concentrations.

Therefore, although urban greenspaces have been proven to have significant effect on PM reduction, the influence of near-road greenspaces and its temporal changes are still not clear. Given the fact that road traffic is the largest contribution to $PM_{2.5}$ pollution in most parts of the world (Karagulian *et al.*, 2015), it is important to determine whether near-road greenspaces have a positive or negative effect on reducing PM concentrations. Hence, this study aims to examine the role of near-road greenspaces with regards to

$PM_{2.5}$ concentration, taking London as a case study city. To be more specific, $PM_{2.5}$ data from 21 selected air quality monitoring sites across London were used to examine the relationships between different types of near-road greenspaces and $PM_{2.5}$ concentration as well as the temporal changes in the relationships. It is recognised that greenspaces that are near different types of roads will have different effects in reducing PM concentrations, so the near-roads greenspaces were classified into several categories according to their road types. The result of this study can enrich the understandings of near-road greenspaces' effect in lowering regional $PM_{2.5}$ concentrations and its temporal change, and inform local urban planning.

2. Methods

2.1 Background

London has a population of approximately 9 million and covers a land area of around 1500 km^2. It is the largest city in the UK and has one of the busiest road traffic in the country. It is characterised by a temperate oceanic climate, with warm to hot summer and cool winter, and high precipitation all year.

$PM_{2.5}$ pollution in London

The annual average $PM_{2.5}$ level in London was reported as 13.3 $\mu g/m^3$ in 2016 (Mayor of London, 2019), which was above the WHO guideline for annual mean concentration (5 $\mu g/m^3$). It is estimated that apart from transboundary sources, the largest proportion (30%) of the $PM_{2.5}$ pollution comes from the road transport section (Mayor of London, 2019). In areas with intensive traffic flow (e.g. central London), the $PM_{2.5}$ may be much higher than the annual average level.

Air Quality Monitoring in London

London has one of the largest air quality monitoring networks in the world, with participations from all kinds of organisations and departments. The LAQN (London Air Quality Network) is one of them and is operated by the Environmental Research Group at Imperial College London, in cooperation with TfL (Transport for London), Defra (Department for Environment, Food and Rural Affairs) and local authorities where the monitoring sites are located (London Air, 2022a). It provides the public with open air quality data collected from its monitoring sites all across London. Apart from LAQN, the

AURN (Automatic Rural and Urban Network) is another network that provides nationwide hourly air quality data to the public (Defra, 2022), with several sites in London.

The richness of the air quality data is a very important reason for choosing London as the case study city. The spatial change of $PM_{2.5}$ concentrations across London is a very important dimension of this study, hence it is crucial to gather data from different monitoring sites.

Road classification

The roads in London (and the UK in general) are classified into four categories (GOV.UK, 2012):

1. A roads - major roads aiming to provide transport links within or between areas. This type of roads should have the highest volume of traffic among the four.
2. B roads - a lower class of roads, often with poorer physical standard. Intended to feed traffic between A roads and smaller roads
3. Classified unnumbered - smaller roads connecting A, B roads with unclassified roads. Also known as C roads
4. Unclassified - local roads supporting local traffic. Most roads in the UK fall into this category. This class of roads should have the lowest volume of traffic.

Except for those four categories, motorway is another category of roads that provide high-speed long distance transportation. The number of motorways is much lower than other four types of roads.

Greenspace in London

London is a green city, with roughly 40% of its area being greenspaces. However, the greenspaces are not evenly distributed across the whole city, with a much larger portion in Outer London and a smaller portion in Inner London. The uneven spatial distribution pattern gives an opportunity to study its relationship with regional air quality, and in this case, with regional $PM_{2.5}$ levels.

There are currently two schemes to protect the urban greenspaces in London, with one focusing on protecting undeveloped land around the city called Green Belt and the other aiming to protect greenspaces within the city called Metropolitan Open Land (MOL). The two designations helped develop and maintain extensive urban green areas in London.

22% of London is specified as Green Belt and another 10% is specified as MOL (GiGL, 2018).

2.2 Data sources

$PM_{2.5}$ data

Hourly mean $PM_{2.5}$ concentration data from 21 air quality monitoring sites across London were downloaded from the London Air website (London Air, 2022b), which is the website of the LAQN. Most of the sites are in the LAQN and the others are in the AURN. The 21 selected sites locate mainly in the Inner London, with 2 of them in the Outer London. **Fig 1** shows their locations. Their location information was downloaded from London Datastore (London Datastore, 2019).

The hourly mean $PM_{2.5}$ concentration data is for the year of 2019. This is due to the concern of the impact of COVID-19 pandemic and lockdown since March 2020. During the lockdown most $PM_{2.5}$ sources (road traffic in particular) significantly reduced (Wang and Li, 2021), and therefore the $PM_{2.5}$ level was much lower than normal (pre-COVID level). To minimize the interference, the study period was determined to be the most recent year prior to the pandemic.

It is noteworthy that the $PM_{2.5}$ data used is all provisional (not ratified), so the result of this study should be evaluated and used with caution.

Greenspace

The greenspace information was generated from the OS MasterMap Greenspace Layer (OS, 2021a) provided by the Ordnance Survey, which is the UK's national mapping agency. The MasterMap Greenspace Layer contains all accessible (public park, sports facility, etc.) and non-accessible (private garden) urban greenspaces in the UK. The map is in the form of vector data divided into 5km x 5km grids. 26 grids were downloaded from the EDINA Digimap Ordnance Survey Collection (Digimap, 2021), which is a collection of OS data owned by EDINA at the University of Edinburgh. The MasterMap Greenspace Layer is updated twice a year, in April and October respectively. The dataset used in this study is from October 2019 in order to synchronise with the $PM_{2.5}$ data.

Road

The road information was generated from the OS Open Roads (OS, 2021b) which is also provided by the Ordnance Survey. This dataset contains not only spatial geometry of every road in the UK, but also their information such as classification, name, function, etc. The road dataset is also in the form of vector data with a grid size of 100km x 100km, and is also updated twice a year in April and November. The data used in this study is from November 2019.

2.3 Data pre-processing and EDA

For the investigation of near-road greenspaces' effect on regional $PM_{2.5}$ concentrations, this study focus on examining the relationship between the $PM_{2.5}$ data from each air quality monitoring site and the near-road greenspace conditions in the 1km surrounding area around each site. The 1km buffer was decided based on some previous studies (Lei *et al.*, 2018; Chen *et al.*, 2019; Cai *et al.*, 2020) that investigated the effect of urban greenspaces on $PM_{2.5}$. Before the analysis, some data pre-processing procedures were performed, and explanatory data analysis was then conducted to both the dependent and independent variables.

Data cleaning for $PM_{2.5}$ data

Before the analysis, the $PM_{2.5}$ data was first cleaned. This includes (concrete process in the Appendix):

1. removing unusual values - some of the values that were very abnormal (e.g. negative $PM_{2.5}$ readings) were removed (set to be null).
2. filling missing values - then all the null values were filled using a technique called mean-before-after method (Norazian *et al.*, 2008), which is to replace a missing value with the mean of the data points before and after it. In cases where there were several continuous missing values, the closest non-null data points before and after the missing value were used to generate the replacement using linear regression. If the number of continuous missing values exceeded 12 (i.e. half a day), the 12 missing values were then replaced with the values from the same period of the previous day . This is a method commonly used in dealing with missing values within environmental datasets (Chen and Xiao, 2018).

After removing all unusual values and filling all missing values, an initial observation towards the $PM_{2.5}$ data found an annual mean of 11.8 μg/m^3 with all 21 sites exceeded the WHO guideline of 5 μg/m^3, as shown in **table 1**. However, compared to the reported 13.3 μg/m^3 annual mean in 2016, most of the sites had a lower annual mean, which proved that London's past efforts on reducing the $PM_{2.5}$ pollution have been working, although the pollution level is still significantly harmful to human.

In terms of daily mean, London's $PM_{2.5}$ concentration exceeded the WHO guideline of 15 μg/m^3 on 74 out of 365 days, as illustrated in **Fig 2**. Most of these days were in winter (November to January) and spring (February to April), which revealed a fluctuation in the annual trend with more days of high concentrations and higher monthly means during November to April and fewer days and lower monthly means during May to October. As other studies have shown, there is a very strong seasonal difference in the $PM_{2.5}$ level, and the presence of such difference could have impact on the relationships between near-road greenspace and $PM_{2.5}$ concentration.

Similarly, the fluctuation in the daily trends of London's $PM_{2.5}$ level is also notable. As **Fig 3** shows, there are two peaks in $PM_{2.5}$ concentration throughout a day - one between 7-9 am with a concentration of around 12.5 μg/m^3, and the other around midnight with a concentration over 13 μg/m^3. The lowest concentration is typically reached between 2-3 pm with an average concentration below 10 μg/m^3. This daily pattern also adds uncertainties as well as possibilities to the effect of near-road greenspace on reducing $PM_{2.5}$ pollution.

The summary statistics for the dependent variable are shown down in table 2 together with the explanatory variables.

Spatial geometry manipulation

The 1km-radius buffers around all sites were generated based on site locations using Python package `geopandas`. Then all greenspaces and different types of roads in each site buffer were found using package `shapely`. The classification of roads contains the five types (include motorway) as mentioned above, as well as a sixth class 'Other' which represents all roads that are not assigned a road classification at national or local level (labelled 'Not Classified') or do not have the classification information (labelled

'Unknown') (OS, 2017). **Fig 4** shows an example of the buffer site as well as the roads and greenspaces that are in it.

It is worth mentioning that there were two pairs of sites that were very close to each other (less than 1.5km). However, after performing a Student t-test (citation) on their $PM_{2.5}$ data, it was found that they were significantly different (p-value < 0.05), hence they were kept in the study.

A 50m buffer zone was then generated for each road and used to find all near-road greenspaces. Several studies (Kassomenos *et al.*, 2014; Eeftens *et al.*, 2012; Holguin *et al.*, 2007) on road traffic and $PM_{2.5}$ pollution backed up the choice of 50m buffer. These near-road greenspaces were also classified according to their nearby roads. For an area of greenspace that was close to more than one type of road, it was counted multiple times as near-road greenspace. This means that for each road class there is a set of marked near-road greenspaces, and an area of greenspace can be marked as several different types of near-road greenspaces at the same time.

Generating explanatory variables

In order to investigate the effects of different types of near-road greenspace on reducing $PM_{2.5}$ concentration, it is important to determine proper variables to represent the near-road greenspace conditions in each site buffer. The simplest possible choice would be to use the percentage of near-road greenspace, which is the area of near-road greenspaces divided by the area of all greenspaces in a site buffer. The problem with using the area percentage as an indication is that for places where there are only a small number of roads the percentage will be very small while for places with many roads the percentage will be very large. As a result, instead of being an indication for near-road greenspace condition, it is actually an indication for the number of roads.

One approach to mitigate the influence from the number of roads is to divide the area of near-road greenspaces by the total length of roads. In this way, the division result becomes near-road greenspace area per road length, which only reflects the conditions of near-road sections of the greenspace with regardless of the number of roads in each site buffer.

Therefore, in this study, a greenspace-area-per-road-length number was calculated for each type of road as an indicator for the near-road greenspace conditions in each site buffer. This was accomplished based on the road and greenspace geometries prepared in the previous section. All site buffers with no specific type of roads were assigned zero for their indicator for the specific road type.

The summary statistics for the explanatory variables are shown in **table 2**.

2.4 Multivariate linear regression models

A preliminary analysis on annual mean concentrations for all 21 sites was first performed to evaluate their overall relationship with the near-road greenspace. The global Moran's I of the annual means indicated that there was no obvious spatial auto-correlation in the dependent variable, so a non-spatial multivariate linear regression was performed.

The model performance was evaluated through a LOOCV (LeaveOneOut cross-validation) which is a type of cross-validation method that works well with small sample size data (Scikit-learn, 2013a). A typical cross-validation (k-fold) splits a dataset into k subsets and uses each subset once as a testing set to evaluate the performance of the model trained by all the other subsets (Scikit-learn, 2013b). The result of cross-validation is the average performance of the k models. When the sample size is small, the k-fold cross-validation result can have large variance because how the samples are split will greatly alter the result. A LOOCV, on the other hand, split the samples into training and testing set N times, where N is the sample size, with only one sample as the testing set and all the other N-1 samples as training set. Each time the testing sample is used to evaluate the performance of the model fitted with the training set, and the cross-validation result is the average performance of the N models. The advantage of LOOCV is that the estimation is deterministic, meaning that there is no variance in the estimated performance of the model because every sample is used once to evaluate the model, and that the process can be repeated (Wei *et al.*, 2019). The downside of LOOCV is its high computational cost (Syed, 2011; Wei *et al.*, 2019), although for a small sample size it is neglectable.

The effect of each type of near-road classification was determined according to their corresponding feature importance and model coefficient. The feature importance was computed using permutation feature importance technique from Python package `sklearn`, which calculates the decrease in the model performance when the specific feature (independent variable) is shuffled (Breiman, 2001). A common method is to repeat the shuffle procedure several times (in this case 50 times), and calculate the mean and the standard deviation from all the repeated samples for each feature. The feature importance reflects how much a model depends on a feature, and in the case of this study, how much effect each type of near-road greenspace have on regional $PM_{2.5}$ level.

After the initial investigation on the relationship between near-road greenspace and regional $PM_{2.5}$ level, the temporal changes in it were explored in the further depth. This was accomplished using a series of multivariate linear regression models. The temporal changes were analysed along two time series: 12 months throughout a year and 24 hours throughout a day. The hourly $PM_{2.5}$ concentrations were first used to generate monthly mean concentrations as well as average concentrations at each hour during the year. The two sets of concentrations at different time intervals were then analysed in groups separated by each unit time interval. In other words, 12 groups of monthly mean concentrations and 24 groups of hourly mean concentrations in an average day during the year were analysed independently. Each analysis included an identification of spatial auto-correlation, a fit to a multivariate linear regression model, a LOOCV for model performance, permutation feature importance and a check for residual's normality. None of the variable was transformed or scaled, because the coefficients of the model were to be used as indication of the effect of the near-road greenspace on $PM_{2.5}$ concentration.

3. Results

3.1 Modelling annual mean $PM_{2.5}$ concentration

The preliminary analysis on the annual mean $PM_{2.5}$ concentrations found a global Moran's I of 0.096 using a Gaussian kernel weights matrix, and the multivariate linear regression model as a function of the near-road greenspace conditions had an r-squared value of 0.365 and a LOOCV r-squared of 0.081, and the residuals of the model were normally distributed and not spatially auto-correlated. **Table 3** shows the coefficient and feature importance mean and error estimations for the explanatory variables. The indicator for greenspace near Unclassified road had the highest estimated feature importance, which was even higher than the r-squared value of the model. This means that the performance depends heavily on the variable, and shuffling it would alter the r-squared value to negative. The effect of near-Unclassified-road greenspace, therefore, was the highest among the five types, and the estimated coefficient (-0.108) indicated that the higher the indicator (near-Unclassified-road greenspace area per road length), the lower the $PM_{2.5}$ level.

However, the low performance of the model and the high variations (high standard deviation) in the feature importance estimations made the result less convincing. There might be some spatial-temporal changes in the relationship that were altering the annual mean model performance, and since the influence of spatial auto-correlation had already been excluded, it was necessary to check the temporal changes.

3.2 Temporal changes in an average day

The 24 groups of annual mean $PM_{2.5}$ concentrations for each hour were separately tested for global Moran's I and none of them was found spatial auto-correlated. They were then used to fit a multivariate linear regression model as a function of their near-road greenspace indicators, and their residuals were normally distributed with no spatial auto-correlation spotted. Their performances are shown in **Fig 5**. The models of the annual means for hours between 0am and 3am and between 9am and 12pm had better performance than the others, with r-squared value higher than 0.4 and LOOCV r-squared value higher than 0.1. These hourly intervals were exactly the intervals at which the annual mean $PM_{2.5}$ concentrations were falling (Fig 3). The model with the highest performance was for 9am where the r-squared (0.481) and the LOOCV r-squared value (0.227) were both the highest out of the 24 models. Conversely, the hourly intervals when the corresponding model performance was low coincided with the time periods when the concentrations were rising. The lowest-performance model was for 5pm with an r-squared value of 0.203 and a LOOCV r-squared value of 0.005. The average r-squared value of the 24 models was 0.337 and the average LOOCV r-squared value was 0.065.

The feature importance estimations for models of all hourly intervals are presented in **Fig 6**. In almost all models the indicator for greenspace near Unclassified road had the highest feature importance, especially in the high-performance models where its importance was significantly higher than the other four features. In contrast, A road and Other road greenspace indicators had the two lowest estimated feature importance (between 0.2 and 0.3) in most models except for 0am-4am when the estimation for A road was relatively higher and 5am-8am when that for Other road was around 0.5. The indicators for B road and Classified Unnumbered road had comparatively stable feature importance with a value between 0.3 and 0.6 in most models. The variations in the estimations were still relatively large, with a higher average deviation (0.41) for the Unclassified road indicator and lower for the rest.

The model coefficients were used to determine the effect of different indicators, and hence different types of near-road greenspace, on $PM_{2.5}$ levels. **Fig 7** shows the coefficients of all indicators for every model. In all 24 models, the effects of greenspaces near Unclassified and Other roads on $PM_{2.5}$ levels were negative while the other three types of greenspaces had positive effects. The changing patterns in the effect sizes of the five features as well as the intercept were relatively similar, which was a declining-rising-declining-rising-declining trend.

3.3 Temporal changes in monthly mean

The same routine of analyses was performed to the 12 groups of monthly mean $PM_{2.5}$ concentrations. Since no spatial auto-correlation was spotted in all groups of monthly means, multivariate linear regression models as a function of near-road greenspace conditions were fitted and tested. The residuals for all 12 models were approximately normally distributed, and no spatial auto-correlation was found in the residuals. The model evaluation results are shown in **Fig 8**. The models for the monthly means during summer months (June to August) overall performed better than the others. The June model had the highest r-squared value (0.545) as well as the highest LOOCV r-squared value (0.280). The second highest performing model was the August one with an r-squared value of 0.499 and a LOOCV r-squared value of 0.189. On the other hand, winter and spring month models had lower performance. The model for April had the lowest r-squared value of 0.079 with a LOOCV r-squared value of 0.102. The high and low performance seasons coincided with the high and low seasons of $PM_{2.5}$ as shown in Fig 2. The r-squared mean for the 12 months was 0.323 and the LOOCV r-squared mean was 0.079.

As for the feature importance estimation, Unclassified road indicator had the highest average importance, as shown in **Fig 9**. It was significantly higher than other features during February to July, but was lower during September to November, and almost to the same level as B road in August and during December to January. A road had low feature importance estimations in most months, except for June when it was estimated to be the second most important feature with an estimation of 1.932. Similarly, Other road had relatively low estimations during January to July and November, with high estimations from August to October and December. B road and Classified Unnumbered road both had low feature importance estimations between February and June, while estimations for July, September and December were median. In the models for August, October and November, estimations for B road were relatively high while estimations for Classified Unnumbered road were low.

The variations in the estimated feature importance were overall lower than that in the 24 groups of annual means for each hour. The average standard deviation of the estimations for Unclassified road indicator was the highest (0.361), with the other four indicators having about half the average standard deviation.

The patterns of the coefficients are presented in **Fig 10**. The changes in the intercepts of the 12 models followed a similar pattern to the monthly $PM_{2.5}$ concentrations as shown in Fig 2, with peaked values in February and April. The coefficients of the five features were much more chaotic. On one hand, the effect of Unclassified road indicator remained negative for the entire year. Its size was higher during February to August and peaked (-0.205) in June, while lower during autumn (September to November) and early winter (December and January). On the other hand, the effects of B road and Classified Unnumbered road indicators remained positive, with the effect size of the former peaking in August and the latter during May to July. The rest two features, being the indicators for A road and Other road, had relatively higher variations in their model coefficients. The effect of A road was positive in most months, with the size of the effect reached its maximum in June at 0.137. However, its effect in October and November was negative, although the effect size was not large. Conversely, the effect of Other road was negative except for in February and March, with the highest negative effect size in June at -0.054 and the highest positive effect size in March at 0.020. Overall, the average effect size of the Unclassified road was the highest (-0.109) and that of the Other road was the lowest (-0.025).