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Highly spatially resolved emission inventory of selected air pollutants in Kuala Lumpur's urban environment

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ABSTRACT

Atmospheric pollutant emissions from industry and traffic are causing pressing air quality and climate issues in urban areas. This study aims to estimate the emissions from road transport and small industry in Kuala Lumpur, and to review the spatial distribution of the estimated emissions. The emission data for 2015 from small industries and road traffic for PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x was collated, processed and then aggregated at a 1 km^2 resolution using the Geographic Information System (GIS) and emissions inventory database software tools: ArcGIS and the Emission Inventory Toolkit (EMIT) respectively. The results from this study show that the total emissions for PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x are 8234.4, 3991.7, 2589.3, 5168.8, and 56927 t/y respectively, where close to 99% of the total estimated emissions originated from road traffic sources. On average, Kuala Lumpur population emit 4.55, 2.21, 1.43, 2.86 and 31.5 kg/y/person of PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x respectively which are in range with per capita emission of pollutants in other cities in the world such as Kolkata and Ho Chi Minh City. The spatial resolution of estimated emissions are mainly concentrated in the central grid cells of Kuala Lumpur and in good agreement with road pollution sources. The results show that the majority of the emissions arise from road sources, mainly because emission from other source types have been neglected and data is unavailable.

CRediT author statement

Azliyana Azhari: Conceptualization, Writing-original draft; **Nor Diana Abdul Halim**: Methodology, Writing-original draft; **Murnira Othman**: Data Curation, Investigation; **Mohd Talib Latif**: Writing – reviewing, editing, supervision; **Liew Juneng**: Writing – reviewing and editing, supervision; **Nurzawani Md Sofwan**: Visualisation, Methodology; **Jenny Stocker**: Software, Validation; **Kate Johnson**: Software, Validation.

1. Introduction

Air pollution is one of the main problems in major cities, impacting both human health and specieshabitats. Air pollutants have an adverse effect on the environment, climate, public health and socio-economic aspects, and have been extensively documented (Cole et al., 2005; Gulia et al., 2015; Tonne et al., 2016). The development of industrial and urban areas means that the transportation sector is vital to the economy's infrastructure and plays a crucial role in the daily activities. However, a notable increase in air pollution, arising from anthropogenic activities including industrial activity and traffic emissions, leads to air pollution related issues (Alyuz and Alp, 2014; Cárdenas Rodríguez et al.,

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2016; Luken et al., 2016; Zhang et al., 2010). Industrial activity and road networks grow rapidly to facilitate growing cities and are causing more and more pollutants to be released into the atmosphere, providing a very unhealthy environment for people to live in and leading to discomfort and more serious health conditions (Lee et al., 2011; Lešnik et al., 2019; Mahiyuddin et al., 2013; Zhang and Batterman, 2013). The greatest anthropogenic contributor to air pollution comes from combustion processes (Cole et al., 2005; Norela et al., 2013). The major source of sulphur dioxide (SO_2) is electricity generation by power stations and industry, carbon monoxide (CO) and oxides of nitrogen (NO_x) are mainly sourced from road transport and the emissions of particulate matter with aerodynamic diameter less than 10 μm (PM_{10}) and CO are from transport, industry and power stations (Cole et al., 2005). Identifying and quantifying anthropogenic air pollutant emissions is an essential step in being able to explain measured air pollution levels, develop air pollution forecasting systems and assess pollution control strategies (Huang et al., 2011).

The emission inventory is the record that shows the quantity of air pollutants discharged within a specific period of time and the location of the emission source. It is a key dataset required for air quality studies and is widely used when policy making for pollution-reduction measures (Borge et al., 2014; Permadi et al., 2017; Thunis et al., 2016; Trombetti et al., 2018). An emission inventory is a powerful tool used by environmental government agencies to observe and manage emission sources. There are several uses for emission inventories, for example, total emissions are useful in order to assess increases or decreases in emissions year on year; spatially disaggregated toxic emissions are required as input to atmospheric dispersion models and other applications including air quality forecasting and local air quality management such as pollution-reduction policies (MoEJ, 2012; Trombetti et al., 2018). Emissions inventories commonly comprise emissions from anthropogenic sources and natural sources, whereby anthropogenic sources usually account for mobile and stationary sources. The EMEP/EEA (Environmental Monitoring, Evaluation and Protection/European Environmental Agency) Air Pollution Emission Inventory Guidebook 2019 has listed eleven main source sectors for emissions including: public power; cogeneration and district heating plants; commercial, institutional and residential combustion plants; industrial combustion production processes; extraction and distribution of fossil fuels; solvent use; road transport; other mobile sources and machinery; waste treatment and disposal; agriculture; domestic and residential sector; and nature (EEA, 2019). Production processes and road transport are the two dominant source sectors included within an emissions inventory, although there are approaches to quantify emissions from all sectors (Alyuz and Alp, 2014; Sadavarte and Venkataraman, 2014; Tung et al., 2011). In estimating and validating emissions, two different methods are usually applied, namely the bottom-up approach and the top-down approach. The bottom-up method usually estimates emissions from statistical analyses of activity data, together with specific emission factors, while the top-down method estimates emissions based on observations (Cheewaphongphan et al., 2019; Dios et al., 2012). The top-down method typically estimate emissions using activity data derived from readily available statistics. It utilizes generalized emission measurement variables, such as the total usage of fuel or total population, as pollution indicators (Nguyen and Wooster, 2020; Pulles and Heslinga, 2010; Trombetti et al., 2018). This study uses the bottom-up method to estimate the emission inventory using collated activity data. In the bottom-up approach, the emission estimation were based on the detailed calculation of the emissions from individual sources at a finer scale and aggregated at the required spatial resolution (Dios et al., 2012; López-Aparicio et al., 2017). For each sector, specific information is established based on the particular sectors, housing units and vehicles operating within that sector and the information is used to estimate the emissions for each sector. The bottom-up approach provides more reliable and detailed data specific to the interest by using facility level data (Davis et al., 2015). Calculations of emission estimates are usually undertaken by applying a specific emission factor to a specific activity statistic. Therefore, emission factors are important parameters in developing an emission inventory. An emission factor is a representative value that attempts to relate the quantity of a pollutant released into the atmosphere with an activity associated with the release of that pollutant (EEA, 2019; MoEJ, 2012). Emission factors are usually derived from measurements taken on a number of sources representative of a particular emission sector. Emission factors are the average rate of an emission of a pollutant per unit of activity data for a given vehicle category (Ho and Vu, 2019).

Various researchers have conducted studies on the compilation and establishment of emissions inventories (He et al., 2016; Kim Oanh et al., 2012; Markakis et al., 2012; Pandey et al., 2014; Permadi et al., 2018; Sadavarte and Venkataraman, 2014; Wang et al., 2008). Derivation of a vehicle emissions inventory in Hanoi involved vehicle fleet and driving cycle surveys, and the determination of vehicle emission factors (Tung et al., 2011). Available on-road emission measurement data and activity survey data was used in a bottom-up emission inventory compilation in Beijing (Huo et al., 2009); this work demonstrated that pollutant emissions from mobile sources show temporal and spatial variation trends which are strongly influenced by the characteristics of human activities. More research in Beijing applied a bottom-up approach based on local emission factors, complemented with a Computer Programme to calculate Emissions from a Road Transport (COPERT) model and near real-time traffic data to produce a high resolution vehicle emission inventory on a specific road segment (He et al., 2016). The establishment of a high resolution Geographic Information System (GIS) based spatial and temporal emission inventory involved the collection of various activity information and statistical data including secondary data from local official authorities and experts; measurements from published studies and data from pre-existing databases used in the establishment of mobile sources and the machinery sector (Markakis et al., 2010, 2012). The emission inventory for two major emission sources, including diesel generators for electricity production and light density vehicles from the transport sector in Lebanon, were estimated by assimilating different approaches and data sources (Baayoun et al., 2019). In most developing countries, the collection of various data, including sources and contributions of emissions from limited resources, is the more common approach compared to using the best available techniques and resources with corrective measures as are commonly used in more developed countries (Jamalani et al., 2018).

Developing an emission inventory can help a city elucidate the structure and quantify emissions, thus allowing the assessment of mitigation measures for specific sectors. However, while many previous studies on emissions have focused on emissions totals calculated from inventories, few have investigated the distribution of spatial sources within a city. The spatial distribution of major pollutant emissions within a city reflects the type and intensity of human activity which can, in effect, scale down the distribution of the emissions. This can provide a more accurate analysis of emission sources (Zhang et al., 2018). The development of an emission inventory is crucial for a developing city like Kuala Lumpur. It is not only useful for learning the actual emission volumes but also provides input which can be used in a simulation model of air pollution in the city. This aids the forecasting of air quality and helps facilitate emission reduction strategies which can then be implemented by local government. As such, this paper aims to determine the estimated emissions of the major air pollutants: PM_{10}, particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), SO_2, nitrogen dioxide (NO_2) and NO_x from road transport and small industry in Kuala Lumpur. The estimated emissions will then be used to perform spatial aggregation of the activity data using an emissions inventory tool. This paper also discusses the challenges associated with developing an emissions inventory for the city of Kuala Lumpur.

2. Methodology

2.1. Study area

Kuala Lumpur, the capital city of Malaysia, is located on the west coast of the Malaysian Peninsular lies on the coordinates 3°8′28.3″ N 101°41′11.5″ E (Fig. 1). Kuala Lumpur is located on a flat area of land with an average elevation of 21.95 m above the sea level while the range of elevation in the hilly areas of the city is between 100 and 300 m above sea level. The total land area of Kuala Lumpur is 243 km^2 with a population of 1.78 million living in the urban city of Kuala Lumpur in 2015 (DOSM, 2015). Kuala Lumpur is the most developed, densely-populated and urbanized place in Malaysia. It is the primary economic focus for the entire country as is demonstrated by the increase in Gross Domestic Product (GDP) per capita for Kuala Lumpur which rose from RM 42,414 million in 2005 to RM 94,722 million in 2015 (DOSM, 2016). Kuala

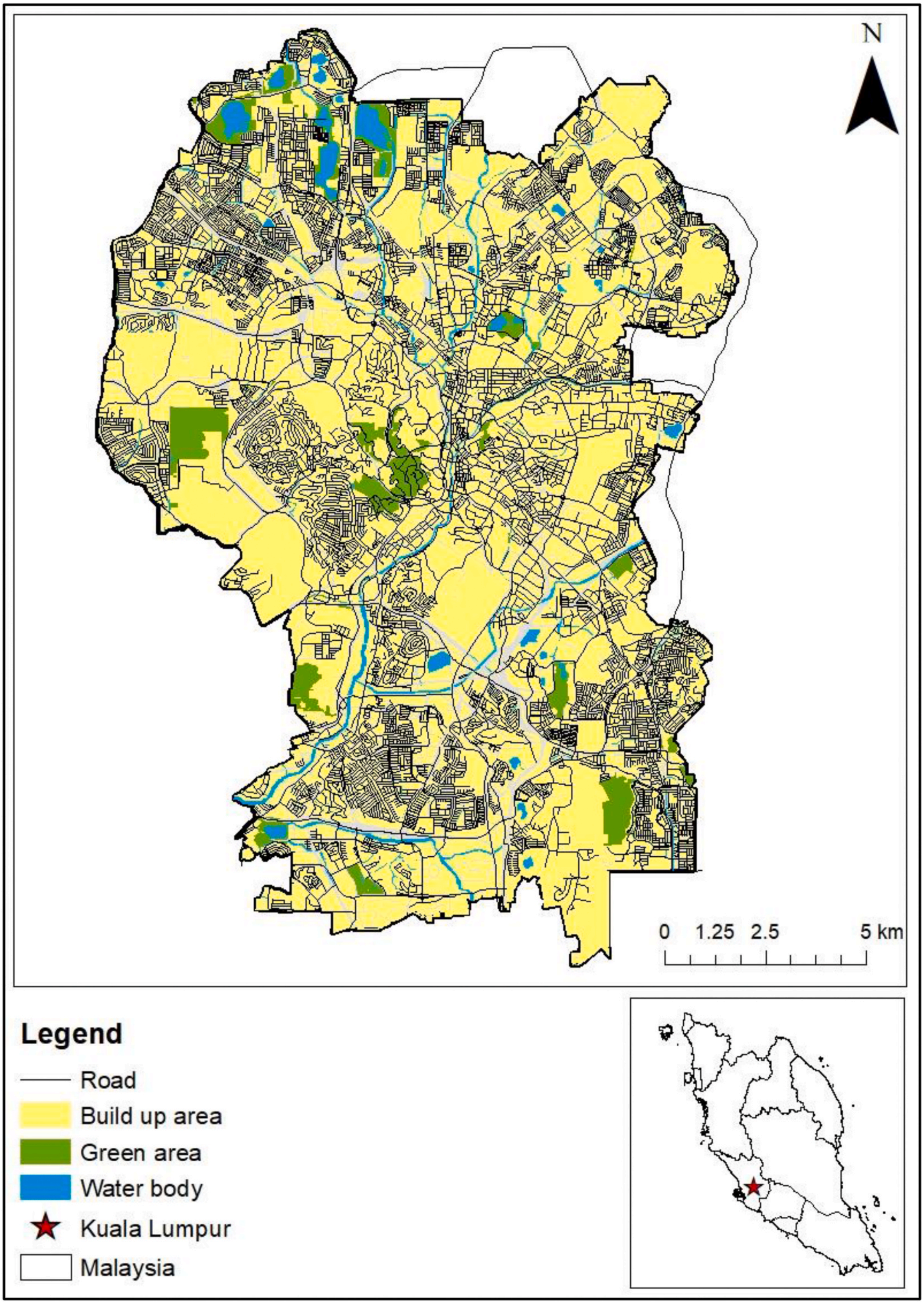

Fig. 1. Location of study area for emission inventory. Red star indicates the location of Kuala Lumpur at the west coast of Peninsular Malaysia, shown on inset. Scale bar relates to Kuala Lumpur city map. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Lumpur's location is strategic and it is seen as the heart of Malaysia. The city is well-connected to the surrounding areas by a highly developed transport network which includes highways, roads and railways (Hadi et al., 2011). Kuala Lumpur has undergone extensive expansion and experienced dramatic growth in the development of activities which has resulted in a continuous change of land use since its establishment (Asnawi et al., 2018). As shown in Fig. 1, the land use area proportions for Kuala Lumpur's city consist of: 90.3% built-up areas, 5.2% green areas and only 4.5% water bodies. The relatively small proportion of green areas and water bodies indicates that Kuala Lumpur city has undergone rapid development, alongside a fast increase in its urban population year-on-year.

2.2. Source of emission data

The air pollutants included in this is study are PM_{10}, SO_2, NO_2 and NO_x. This study used a few types of data in order to calculate the emission rates from road and industrial sources within Kuala Lumpur's Urban Environment for 2015. Table 1 shows the various types of data used to build the emission inventory for Kuala Lumpur.

2.3. Calculation of emission data

2.3.1. Road source

The traffic data provided by the Kuala Lumpur City Hall (DBKL) and the Ministry of Works was used to compile the traffic split needed in Kuala Lumpur's emission inventory. However, although this traffic count data was useful, it was insufficient to generate a complete emissions inventory from road traffic sources because the traffic data was only available on a subset of roads on the network. The fleet split data (i. e. vehicle engine technology, fuel type, engine size, etc.) and speed data were also unavailable. A bottom-up approach was therefore used to calculate the emissions from the available road traffic count data, using approximated fleet and speeds. The fleet was derived from UK fleet data, adjusted to be appropriate for Kuala Lumpur using information provided by the Department of Environment, Malaysia (DOE). The bottom-up approach resulted in representative major road traffic emission rates estimated from the available traffic count and fleet data; specific details are given below. These road traffic emissions were extended to approximate the emissions for the full domain of Kuala Lumpur city on a road-by-road basis. The last step in the emissions inventory process was to spatially aggregate the data into a 1 km gridded format.

2.4. The bottom-up approach

The bottom-up approach used the available road traffic count data with estimated speeds and an estimated fleet, as necessitated by the Emission Inventory Toolkit (EMIT), to estimate the emission rate of the roads. Traffic data for 71 roads was available as a 'road subset' for the calculation of emissions. There are approximately 384 major roads in Kuala Lumpur, so this subset constitutes 18% of all major roads. The estimation of emission rates was calculated using the suitable emission factor, NAEI 2018, that was derived from the UK fleet and based on the activity of the roads (traffic count) using the estimated speed. The supplied roads from the available road traffic count data were classified as either highways or main roads. As speed data was unavailable, highways were estimated to have a speed of 50 km/h while main roads were assumed to have a speed of 30 km/h. The estimated speeds were derived from a traffic survey of Malaysia's vehicles, which consisted of vehicle characteristics (vehicle age, engine size, fuel, and engine technology). The emission rate for subset roads from the bottom-up approach can be estimated using the equation in Eq. (1) below:

$$E_{sub} = \frac{A}{60 \times 60(s)} \times EF_p \quad (1)$$

Where 'E_{sub}' is emission rate of subset roads in the unit g/km/s, 'A' is activity (the number of vehicles per hour, traffic speeds and road width) and 'EF_p' is the emission factor in g/km/vehicle of the air pollutants which change depending on the type of air pollutants arising from the fleet. The fleet used in this study was adjusted from the UK fleet to reflect data available from Malaysia. Fleet data from the UK National Atmospheric Emission Inventory (NAEI) representative of a 2018 urban fleet were used as the base fleet dataset. Fleet adjustments summarized in Table 2 have been applied to the base fleet data, leading to a dataset representative of an older Malaysian fleet. Additional scaling factors have been applied to the sulphur emissions to account for the relatively poor Malaysian fuel quality compared to European fuel (Ramalingam and Fuad, 2015). It was considered that typical fuel sulphur content of Malaysian fuel is 125 ppm for petrol and 350 ppm for diesel, compared to the limit of 10 ppm within the UK. Scaling factors of 12.5 and 35 were therefore applied to the baseline European SO_2 emission factors for petrol and diesel vehicles respectively (Ramalingam and Fuad, 2015). The car fuel use split between petrol and diesel vehicles in Kuala Lumpur was estimated from online secondhand car sales data (Noonwal, 2019). Vehicle count data were only available of a subset of roads in the city (71 roads). These roads were binned into the four road type categories (as listed in Table 2). Then, for each road type, the traffic count data for the subset of roads was assumed to be representative of traffic counts (and hence emission rates) for all roads of this type in the city. The emission

Table 1
Information and source of emission database for generating emission inventory over Kuala Lumpur.

Source	Type of data	Information	Data source
Roads	Road map	Road networks information which consist of major and minor roads	Kuala Lumpur City Hall (DBKL) and ©OpenStreetMap (OSM) contributors
	Traffic data	Traffic data including number of vehicles, vehicle type, vehicle speeds and activity	Road Traffic Volume Malaysia (RTVM) from Ministry of Works and Integrated Transportation Information System (ITIS) from Kuala Lumpur City Hall (DBKL)
Industrial	Point source data	Industrial information which include location of industry, type of industry and emission rate per industry	Department of Environment (DOE)

Table 2
Kuala Lumpur fleet assumptions according to vehicle class for the bottom-up approach.

Vehicle Class	Assumption
Diesel Car	Assume 10% of car fleet are diesel. Use the English Euro split with the fuel restrictions: 94.6% of diesel fuel emits as a Euro 2 vehicle, 5.4% of diesel fuel emits as a Euro 5 vehicle.
Petrol Car	Assume 90% of car fleet are petrol. Use the English Euro split with the fuel restrictions: 89.4% of petrol fuel emits as a Euro 2 vehicle, 10.6% of petrol fuel emits as a Euro 4 vehicle.
Taxi	The English Euro split has been assigned to one Euro category older, and all vehicles assumed to be LPG rather than diesel.
Motorcycle	Same method as petrol cars.
LGV	English diesel light goods vehicle (LGV) split, assigned to one Euro category older and diesel fuel restrictions.
Bus and coach	Assume 50% are compressed natural gas (CNG). For the diesel buses, adjust English split to one Euro category older with diesel fuel restrictions.
Rigid HGV	Rigid heavy goods vehicle (HGV) uses same method as diesel buses.
Articulated HGV	Articulated HGV uses same method as diesel buses.

Note: Additional modifications have been made to account for relatively high sulphur content of Malaysian fuel (Ramalingam and Fuad, 2015).

rates on the 71 roads were calculated by combining: an emissions factor database that includes emissions from a wide range of vehicle types and technologies. The road traffic emissions factor database used is derived from COPERT 4 version 10 (Ntziachristos et al., 2009); the Malaysian fleet data (Table 2); and traffic activity data on each road (traffic counts) using estimated speed data from a traffic survey. The calculated emission rates for the subset of roads were applied to all roads of the same type on the network.

2.5. Extending road traffic emissions estimates to full domain

Since the road layout from the bottom-up approach was incomplete due to the limited availability of the traffic count data on certain roads, OpenStreetMap (2018) data covering the Kuala Lumpur city was downloaded. The road layout emissions were extended to complete the road emissions for the full domain of Kuala Lumpur's urban areas. The term 'major roads' refer to main roads that have an estimated average vehicle speed of more than 30 km/h and a width of more than 10 m while 'minor roads' refers to those roads with an estimated average vehicle speed of less than 30 km/h and a width of 10 m or below. The major roads included were: motorways, trunks, primary, secondary and tertiary roads; while the minor roads consisted of: residential, living streets and unclassified roads. The primary, secondary and tertiary roads were grouped together as the first category, the motorway and trunk roads were grouped together as the second category, the residential and living streets were grouped together as the third category and unclassified roads were the fourth category. For all lane roads in the bottom-up inventory, the calculated emission rate for the subset roads was used to find an average emission rate by road type. The extension to full domain was performed using calculated emissions from the subset to generate emission rates for the 2755 minor roads in Kuala Lumput city and the 15041 minor roads outside of it. These emission rates were then divided by the number of lanes, to give emission rates per lane for each road type. The total road length of all road types in the inventory was calculated and assigned a weighting to each road type in order to estimate the emission rates on these roads. The emission rate for all road types in the minor roads can be estimated using the equation in Eq. (2) below:

$$E_{minor} = \frac{E_{sub}}{N_L \times G} \times 31.536 \tag{2}$$

Where 'E_{minor}' is the emission for a minor road (t/y), 'E_{sub}' is emission rate of the subset roads (g/km/s), 'N_L' is the number of road lanes and 'G' is the length of the road (km) and 31.536 is a constant to convert g/s to t/y. The estimated ratio between emissions on motorways and residential roads was 12:1 and the estimated ratio between motorways and unclassified roads was 6:1.

2.5.1. Emission allocation

Road emission allocation in this study was based on the road type, land use and its spatial characteristics. The road emissions in Kuala Lumpur were spatially allocated into the appropriate grid cells based on their longitude and latitude. The roads (major and minor roads) located within and outside of the Kuala Lumpur boundary were aggregated onto 1 km × 1 km grid sources as shown in Fig. 2. The unit of full road emissions was changed into t/y prior to transformation onto the gridded format.

2.6. Industry

Industrial sources are represented within the emissions inventory as point sources. These point sources are industries that exist in the Kuala Lumpur urban environment, as shown in Fig. 3. There are 248 small industries recorded from the point sources data obtained from the DOE which included production and services processes. Production processes including cement/concrete processing, metal manufacturing, electrical production and so on, are other important emission sources in the industrial sector.

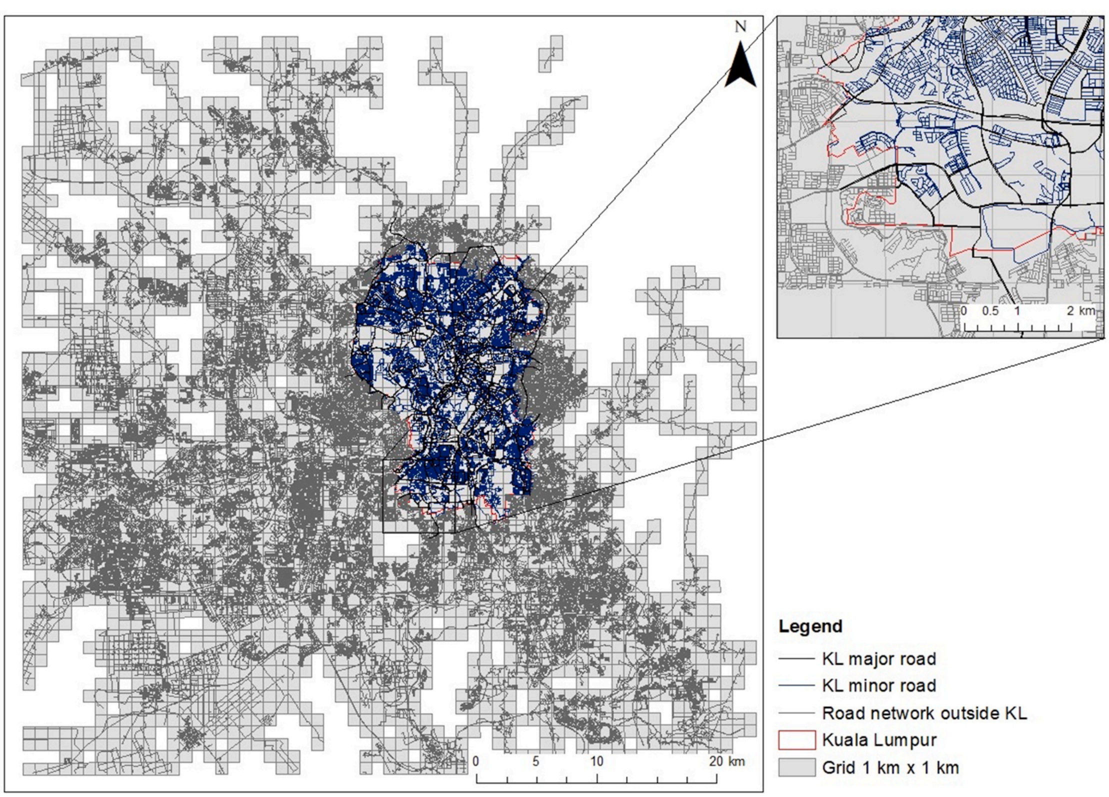

Fig. 2. Emission from major and minor roads aggregated onto 1 km × 1 km grid sources.

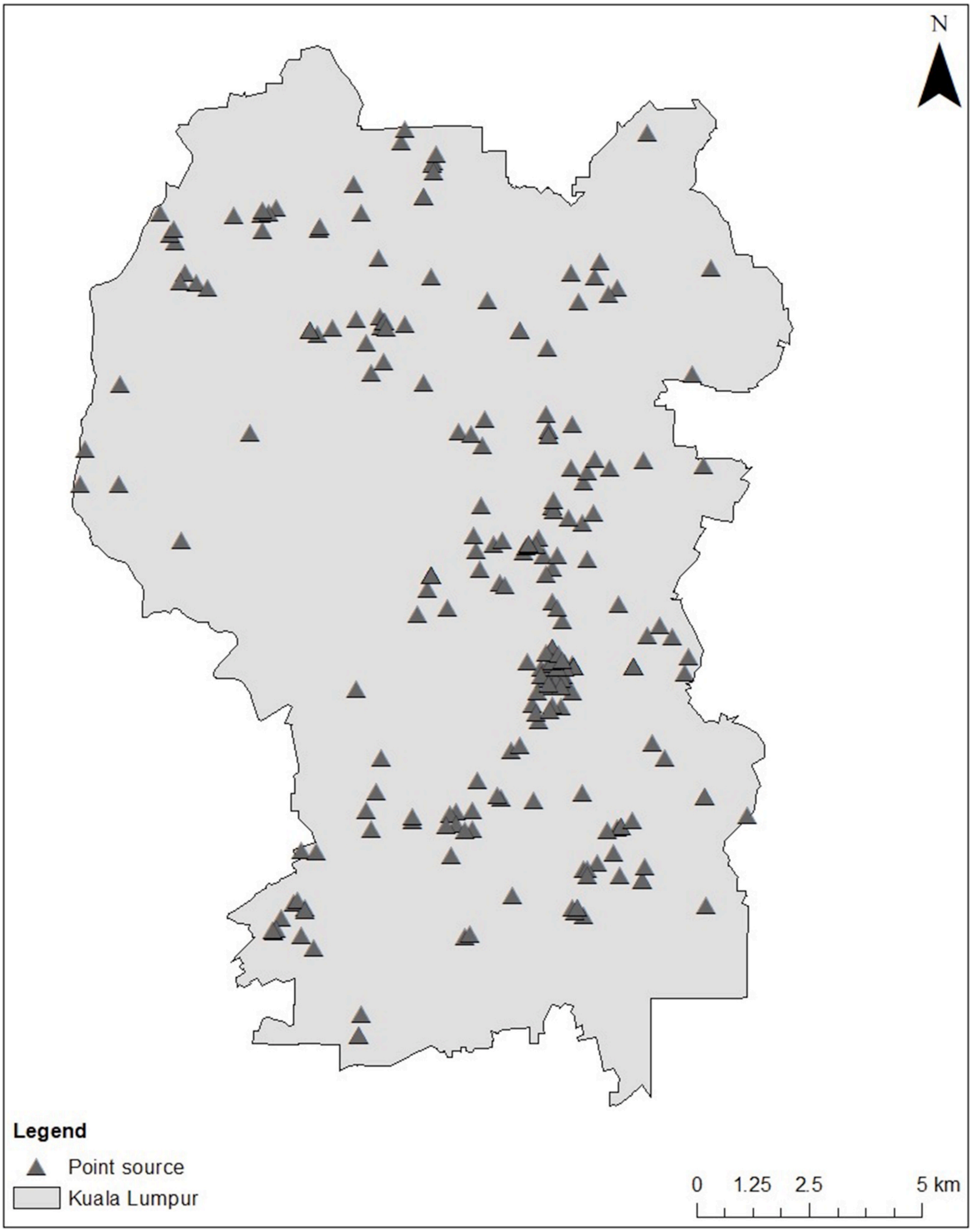

Fig. 3. Emission of point sources within Kuala Lumpur.

This study uses the emission rates provided by the DOE to calculate the estimated emissions of industrial processes. The emission for each pollutant was calculated using the equation in Eq. (3) below:

$$E_{ind} = Er \times fl \tag{3}$$

Where "E_{ind}" is the emission rate of the industry (g/s), "Er" is the emission rate recorded by the industry (g/m^3) and "fl" is the volume flow rate capacity of the stack (m^3/s). The emission rate for industries with limited data is estimated based on the emission rate value for the same type of industry.

2.7. Atmospheric Emission Inventory Toolkit (EMIT)

The atmospheric Emission Inventory Toolkit (EMIT) is a software that functioned to store, manipulate and assess the emissions data from a variety of sources. EMIT is able to hold the emission data from explicit sources from large sources such as major roads and industrial sources to data that is too small to be considered explicitly for which the data will be treated as average emissions on a regular grid. The emissions data can be directly imported or calculated using activity data using in-built emission factor datasets. Once emissions and activity data are imported into EMIT, the total emission rate of the air pollutants can be estimated, completing the emissions inventory.

2.8. Uncertainty analysis

Uncertainty is one of the key concerns in the development of emission inventory. There are several parameters in this analysis which may be influenced by the uncertainties of the overall emission inventory. The emission inventory is developed using UK fleet data with several assumptions to make it more suitable for Kuala Lumpur. No ASEAN emissions factor database was available, so a European database was used. There is a lot of uncertainty in the Kuala Lumpur inventory due to the lack of detailed data including robust traffic fleet, lack of traffic count and lack of other possible sources and some sources might be lacking. This uncertainty, and the fact that there some source sectors have not been included in the inventory (e.g. commercial and domestic emissions), may potentially underestimate the total emissions. The resulting emission inventory can be considered to be a best estimate given data availability.

3. Results and discussion

The estimated average emission rates, per lane, by road type from this study are shown in Table 3. As expected, the estimated average emission rate for all pollutants is the highest for the major road types: motorway and trunk roads, followed by primary, secondary and tertiary roads; the rate for minor road emissions (unclassified roads, residential roads and living streets) is lower. This is consistent with the location of the roads and the number of vehicles utilizing bigger roads (Ho and Clappier, 2011). The NO_x emission was the highest for all road types, compared to other types of pollutants, which shows that NO_x comes from increased fuel consumption, particularly from diesel vehicles (Sadavarte and Venkataraman, 2014). As reported by Kuik et al. (2018), NO_x emissions in urban areas are significantly contributed to by traffic which makes this pollutant important for emission inventory estimations on a city/urban scale.

Estimated road source emissions of $PM_{2.5}$ are depicted in Fig. 4 while the estimated road source emissions of PM_{10}, SO_2, NO_2 and NO_x are depicted via a grid representation in Fig. A1. Within the gridded domain of 1 km × 1 km, the lowest estimated emissions for PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x for any cell are 0.0009, 0.000, 0.0003, 0.0005 and 0.0059 t/y respectively, while the highest estimated emissions are 15.69, 7.649, 4.929, 9.752 and 106.9 t/y respectively. The total estimated emissions from road sources for PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x are 8234.0, 3991.7, 2589.1, 5168.4, and 56920 t/y respectively. As expected, the highest emissions from road sources were NO_2 and NO_x, which significantly denotes contribution from vehicle emissions. As reported by Kuik et al. (2018), NO_x is predominantly emitted as NO and NO_2 by combustion engines where NO_x is emitted as 10% NO_2 and 90% NO (by mass). The estimated emission of primary pollutants is higher in Kuala Lumpur City Centre as depicted by the red grids where the roads have a higher density of traffic and are usually congested.

Table 4 shows the estimated emissions for industrial sources in Kuala Lumpur based on the emission rate data collected by the Department of the Environment, Malaysia. The estimated emissions for industrial point sources considered for this study are relatively small as the industries chosen for estimating emissions are mostly non-combustion industries which include those involved in the production of cement/concrete, electrical/electronic products, electroplating, metal and the production of food and beverages, along with services such as hotels, trading and workshops. Among these industries, the highest estimated emission of all pollutants is NO_x. The NO_x from these industries is expected to be contributed to by domestic processes and combustion, including waste disposal and cooking; with other contributions from sectors such as households and energy conversion (Shahbazi et al., 2016).

The estimated point source emissions of PM_{10}, SO_2, NO_2 and NO_x are represented in Fig. 5. The lowest estimated emission of PM_{10} is 0.00001 t/y while the highest estimated emission is 0.0179 t/y. The lowest estimated emission of SO_2 is 0.00002 t/y while the highest is 0.0091 t/y. The lowest estimated emission of NO_2 is 0.00001 t/y while the highest is 0.0006 t/y. The lowest estimated emission of NO_2 is 0.0020 t/y while the highest is 0.1362 t/y. The total estimated emissions from small point emissions for PM_{10}, SO_2, NO_2 and NO_x are 0.4419, 0.1559, 0.4031 and 7.7240 t/y respectively. The small point sources estimated in this study considered emissions from small industries including production and services.

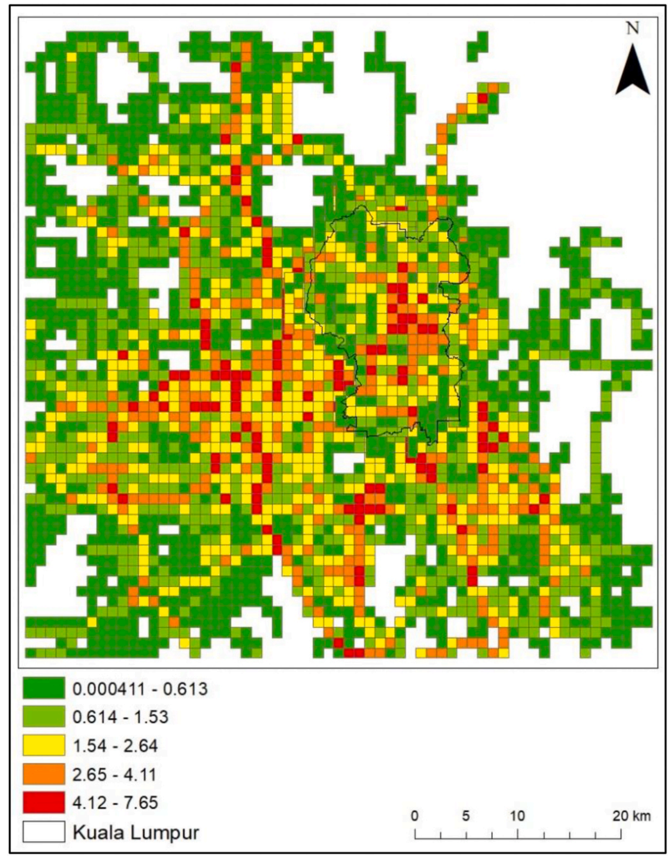

Fig. 4. Road source emission inventory in grid presentation for Kuala Lumpur in t/y for $PM_{2.5}$.

Table 3
The estimated average of emission rates per lane according to road type in Kuala Lumpur.

Type of roads	Road size classification	Emission rate per lane (g/km/s)			
		PM_{10}	SO_2	NO_2	NO_x
Motorway, Trunks	Major	0.0278	0.0087	0.0172	0.1880
Primary, Secondary, Tertiary	Major	0.0200	0.0064	0.0129	0.1420
Unclassified	Minor	0.0046	0.0015	0.0029	0.0313
Residential, Living street	Minor	0.0023	0.0007	0.0014	0.0157

Table 4
The estimated average of emissions of all parameters for industrial sources in Kuala Lumpur.

Type of industry	Activity	PM_{10} (kg/y)	SO_2 (kg/y)	NO_2 (kg/y)	NO_x (kg/y)
Cement/concrete	Production	5.99	0.0252	0.0347	0.694
Electrical/Electronic	Production	0.694	3.18	6.46	129
Electroplating	Production	0.694	3.18	6.46	129
Food & beverages	Production	0.221	0.0252	0.0252	0.504
Hotel	Services	0.274	0.397	4.73	94.6
Metal	Production	0.0631	0.0252	0.662	13.2
Services	Services	0.687	3.18	6.46	129
Trading	Production	0.687	3.18	6.46	129
Workshop (vehicles)	Production	0.195	0.568	2.02	40.4
Paint (vehicles)	Paint used	0.0851	0.0252	0.0252	0.504

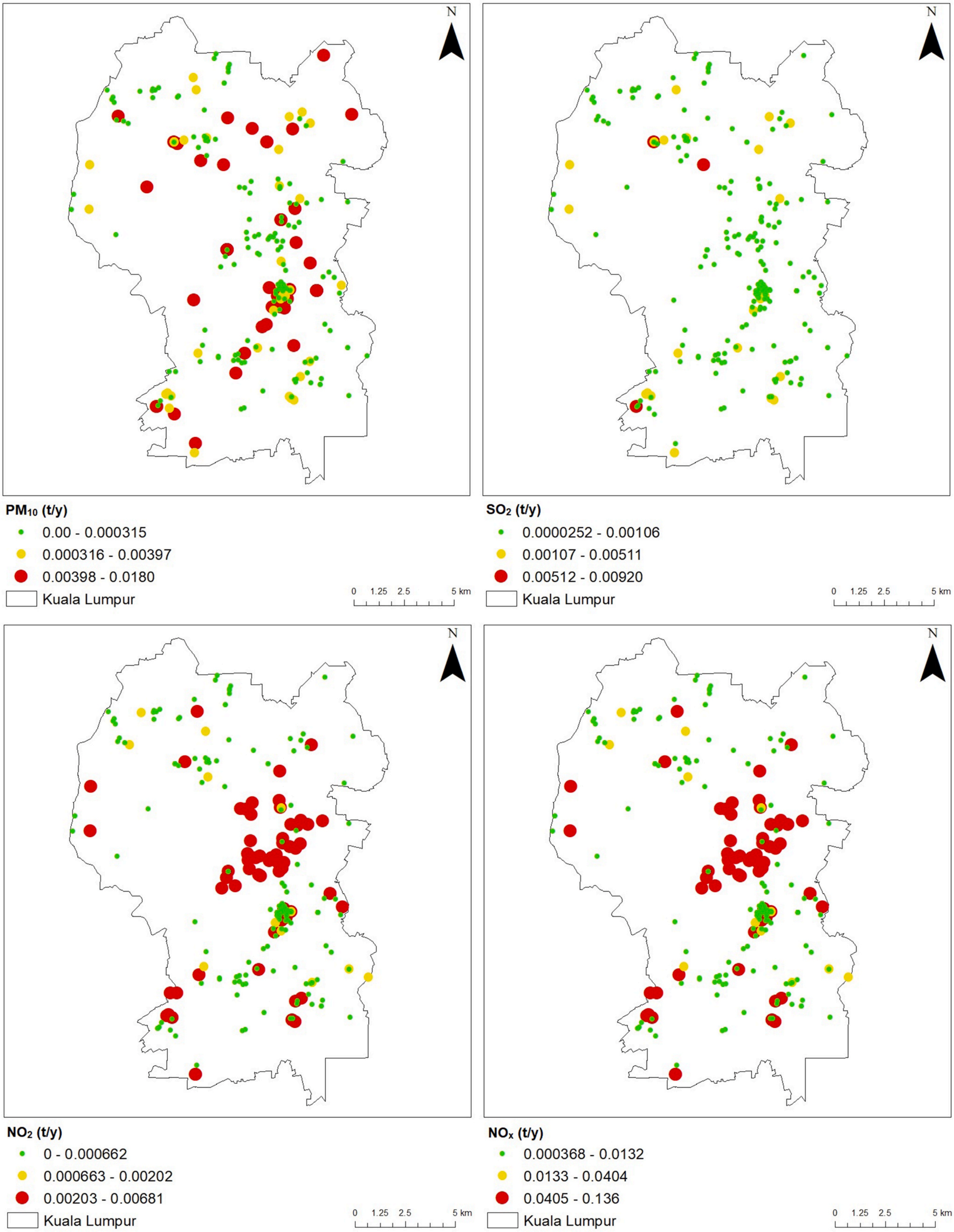

Fig. 5. Point source emission inventory in for Kuala Lumpur in tonne/year for a)PM_{10}, b)SO_2, c)NO_2 and d)NO_x.

Total emissions for PM_{10} is 8234.4 t/y, for $PM_{2.5}$ is 3991.7 t/y, for SO_2 is 2589.3 t/y, for NO_2 is 5168.8 t/y and for NO_x is 56927 t/y. However, the estimated road source emissions accounted for up to 99% of the total emissions estimated for Kuala Lumpur's City Centre due to the absence of other source types such as power generation plants, combustion plants, industrial combustion processes, domestic and residential sources, fossil fuel extraction and distribution, waste treatment and disposal, machinery, agricultural and natural sources. The total estimated emissions for Kuala Lumpur in kg/y/person for road source and point source are summarized in Table 5 alongside the estimated emissions from other studies in the region. Comparing the estimated emissions for Kuala Lumpur with other cities and countries in the world including Izmir, Turkey; Tehran, Iran; Kolkata Metropolitan City, India; Wuxi City, China; Brunei; and Ho Chi Minh City, Vietnam from various studies clearly demonstrated that factors including the method used and the size of sample results in variations of estimated emission values (Dotse et al., 2016; Elbir and Muezzinoglu, 2004; Ho, 2017; Hua et al., 2019; Majumdar et al., 2020; Shahbazi et al., 2016). The estimated emissions are represented in kg/y/person. The estimated emissions for PM_{10}, $PM_{2.5}$ and SO_2 in Kuala Lumpur are comparable with estimates from other countries, especially in the same region. Focusing on the estimated emission of PM_{10}, the estimated emission for Kuala Lumpur in this research is 4.55 kg/y/person which is within range of the lowest estimated emission for Brunei at 0.549 kg/y/person and the highest estimated emission for Wuxi at 19.7 kg/y/person (Dotse et al., 2016; Hua et al., 2019). The estimated emission of NO_x in Kuala Lumpur is 31.5 kg/y/person, the highest compared to other estimated emissions ranging from 5.56 to 20.5 kg/y/person (Dey et al., 2019; Dotse et al., 2016; Hua et al., 2019). There are also high uncertainties in the emission estimates for small industries which were principally from highly uncertain emission factors among the informal industries (Pandey et al., 2014).

Various methods have been utilized to produce an accurate global emission inventory (Shrestha et al., 2013; Trang et al., 2015; Wang et al., 2008), selecting the most suitable method with a limited amount of data has been challenging. Developing an accurate emission inventory in developing countries like Malaysia also poses several challenges and continuous effort should be made to improve the quality of any inventories undertaken. In this particular study, several limitations were encountered which caused the emission inventory to be focused only on road-sourced and small industries' emissions. A reliable emission inventory relies on local representative emissions factors. However, an emission database for the actual vehicle fleets and informal industries in most developing countries does not exist (Kim Oanh et al., 2008; Pandey et al., 2014). Therefore, we had to adapt the UK National Atmospheric Emission Inventory (NAEI) split for 2018 with the additional scalings as is explained in the methodology section. Moreover, it is important to have specific and accurate emission factors. However, there is a lack of city-specific statistics, such as traffic data categorized according to vehicle fleet type and age. The necessity to improve the accuracy of current road network information, particularly in relation to the ongoing road expansion, is also of great importance. Kuik et al. (2018) also suggested that a reasonably good performance model for an emission inventory can be achieved by combining high resolution chemical transport models with other approaches to calculate emissions, this would take into account the realistic diurnal cycle of traffic emissions.

Additionally, there is also limited data available for both traffic and industrial emissions aside from missing sources for biomass burning in the downscaled emissions for urban areas. This paper focuses on principal pollutants such as PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x based on the suitability of the study and availability of information. Emission rates of other key pollutants such as CO, non-methane volatile organic compound (NMVOC) and NO were unable to be estimated by the study due to the lack of information and emission factor of the pollutants. Even though the study was able to calculate the concentration for NO from NO_2 and NO_x emission, the study was however unable to estimate the emission rate of NO due to paucity of NO emission factor. An incomplete database on industries' consumption of biomass or fuels, or other conventional fuels produces a less than accurate estimation of industrial emissions. In such cases, the data was estimated from what related industry data was available and through the use of several assumptions, such as similar production processes or products as adopted in the study. A study by López-Aparicio et al. (2017), found that the assimilation of bottom-up emission estimates along with local activity data obtained from downscaled regional emission inventories may improve the quality of regional inventories; such an approach could be applied to the Kuala Lumpur emissions inventory developed here and may lead to more accurate emissions totals. Over time, emissions and emission factors change for a variety of reasons, including vehicle degradation due to the accumulation of mileage, the introduction of higher emission standards, fuel requirement changes and improvements in emission control technology (Brimblecombe et al., 2015; Carslaw and Rhys-Tyler, 2013). Inventories are the key input for air quality models. To achieve a better representation of concentration on air quality models and to establish a local air quality management system, improvement of inventories is necessary (Elbir et al., 2010; Jimenez-Guerrero et al., 2008). An enhanced emission inventory which includes other pollutant such as CO, NMVOC and NO and which produces a more dynamic representation of emission changes is necessary. Information transfer from different sectors should be particularly enhanced among local authorities, government agencies and industrial players in the city of Kuala Lumpur.

4. Conclusion

Developing emission inventories can be very challenging when source data is sparse, as is the case in Kuala Lumpur, but an important first step in the process is to develop a baseline inventory which can be added to over time. This study focused on estimating emissions from road sources and production and services industry in Kuala Lumpur's Urban Environment. Based on the 1 km^2 gridded emissions created using emission data from various sources, estimated emissions from road sources for PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x were calculated as being

Table 5
Comparison of total estimated emissions in kg/y/person in cities around the world.

City (base year)	Reference	Emission inventory method	Estimated emission (kg/y/person)				
			PM_{10}	$PM_{2.5}$	SO_2	NO_2	NO_x
Kuala Lumpur, Malaysia (2015)	This study	Emission Inventory Toolkit (EMIT)	4.55	2.21	1.43	2.86	31.5
Ho Chi Minh City, Vietnam (2012)	Ho (2017)	EMIssion SENSitivity (EMISENS) model	6.22	n/a	n/a	n/a	n/a
Wuxi City, China (2015)	Hua et al. (2019)	High resolution emission inventory based on a bottom-up approach	19.7	7.08	5.67	1.21	5.67
Kolkata Metropolitan City, India (2015)	Majumdar et al. (2020)	Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS)-city model	4.19	2.10	5.46	n/a	5.56
Tehran, Iran (2013)	Shahbazi et al. (2016)	GIS-based emission inventory	1.04	n/a	n/a	n/a	10.4
Izmir, Turkey (2000)	Elbir and Muezzinoglu (2004)	Activity data based on specific emission factor	7.42	n/a	5.91	n/a	10.5
Brunei (2012)	Dotse et al. (2016)	Sector-wise emission estimates	0.549	n/a	1.27	n/a	20.5

Notes: n/a – not available.

8234, 3991.7, 2589.1, 5168.4, and 56920 t/y respectively. The total estimated emissions from small industries emissions for PM_{10}, SO_2, NO_2 and NO_x were 0.4419, 0.1559, 0.4031 and 7.7240 t/y respectively. The results from this study show that the total emissions for these pollutants were 8234.4, 3991.7, 2589.3, 5168.8, and 56927 t/y respectively. Kuala Lumpur's population emits 4.55, 2.21, 1.43, 2.86 and 31.5 kg/y/person of PM_{10}, $PM_{2.5}$, SO_2, NO_2 and NO_x respectively which are within the range of per capita emissions of pollutants in other cities in the world. The results show that the majority of the emissions arise from road sources, mainly because emissions from other source types such as power generation plants, combustion plants, industrial combustion processes, fossil fuel extraction and distribution, waste treatment and disposal, machinery, agricultural and natural sources have been neglected and data is unavailable. The estimated emissions for small points sources are relatively restricted due to the type and size of the small industries considered in the emission inventory estimations. The estimated emissions described in this paper need to be further improved on in further studies so that the expansion of road networks the inclusion of more industrial activities inside and outside Kuala Lumpur and also missing sources from biomass burning in the downscaled emissions in urban areas are also considered. The database on industries' consumption of biomass or fuels, including other conventional fuels, is also incomplete and needs to be added to so as to increase the quantity of much-needed data available for monitoring and policy-making purposes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apr.2020.10.004.

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