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Modeling emission inventories for key sectors in Ho Chi Minh city, Vietnam
(ベトナム国ホーチミン市を対象とした主要部門からの排出インベントリのモデリング)

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Abstract

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(ベトナム国ホーチミン市を対象とした主要部門からの排出インベントリのモデリング)

By Nguyen Thi Quynh Trang
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In developing countries, air pollution is not improving and in some cases it is getting even worse. The WHO said 98 percent of urban areas in "low- and middle-income countries" with populations of more than 100,000 fall shy of the group's air quality standards. However, to combat with the degradation of air quality, a reliable and official information system about air pollution is crucial and vital. It becomes necessary to make use of all the scientific tools available for the management of the atmospheric environment. One of these tools is emission inventory. This tool can answer the following question: What quantities of air pollutants are emitted and where do they come from? Emission inventories are now regarded as required tools for a wide range of environmental measures such as management of chemicals as well as the prevention of air pollution. In light of this fact it is important to update and compile the local emission inventories using available data so that the scientific background of effective policies and the input data for atmospheric transport and deposition models can be designed.

In this research I focused on compiling local emission inventory for one of two biggest cities in Vietnam – Ho Chi Minh city. I chose Ho Chi Minh city because Hanoi is influenced by the northeast monsoon and strong northeast wind currents in winter that are believed to carry pollutants and dust from the vicinity in the northeast to Hanoi. Meanwhile, the relative independence of situation in HCMC on other adjacent sources facilitates the compiling local emission inventory. Deriving from these facts my research question is to use different data sources like statistics, remote sensing, and air dispersion model to answer these pivotal questions:

- Which emission sectors are the dominating ones influencing air quality in Ho Chi Minh city?
- How did these sectors evolve over time?
- At this moment, how much pollutants are emitted into the atmosphere in Ho Chi Minh city?
- When and where is the pollution the most severe?

To answer these research questions I established three objectives:

i) Estimate the impact of long-range transport biomass burning emission on local air quality in HCMC in pre monsoon season using air quality numerical simulations and remote sensing data,
ii) Model the evolution of main anthropogenic emission sectors in HCMC using remote sensing data and statistical data,
iii) Compile high temporal and spatial resolution vehicle EI in HCMC by modelled traffic flow data.

To achieve above objectives, local statistical data, several remote sensing datasets, global emission inventories, and an air dispersion model were used in this research. Firstly, the impact of biomass burning (BB) emission in the vicinity on air quality in Ho Chi Minh city was assessed using the Weather Research and Forecasting model coupled with Chemistry – WRF Chem and remote sensing data as complementary approach. The simulations showed little influence of BB on local air quality in HCMC. However, when comparing with in situ data and AOD product from MODIS, the uncertainties of WRF Chem output was revealed. So we supported our finding by satellite images analysis, including FRP data, burn area product, AOD, and simulations of HYSPLIT

Trajectory Model. The conclusion of this part is BB is not key emission sector that can strongly impact on air pollution in HCMC.

In chapter 3, basing on the outputs of previous part and literature review, the dominant anthropogenic emission sectors in HCMC were defined: vehicle emission, residential buildings, and manufacturing industrial sector. In terms of Transportation, vehicle fleet in HCMC emitted over 682 Gg CO, 84.8 Gg NOx, 20.4 Gg PM10 and 22000Gg CO2 in 2016, which are were 1.8, 2.6, 2.5 and 2.03 times of the ones in 2009, respectively. This significant increase mainly due to the sharp rise in vehicle population Among five vehicle types, MC contributed around 94% to total CO emission, 14 % to total NOx emission and 50- 60% to CO2 emission. Regarding NOx and PM, truck is claimed as the biggest emission source and the sharing of personal car was considerable in terms of SO2, NMVOC and CO2. The emissions of Manufacturing industry and Residential sectors include both fuel consumption and electricity consumption. Electricity consumption is the most dominated emission source. In 2016, the electricity consumption of Manufacturing industry and Residential sectors in HCMC emitted 6985 Gg and 6691 Gg of CO2, respectively, increasing by 87% and 45% in compare with 2009, respectively. Considering fuel consumption only, both these two sectors account for a very small percentage in compare with Transportation. Regarding spatial allocation of final emission, Transportation is by far the highest emission source, in terms of all species, so the spatial distribution of all pollutions are similar with Transportation emission map. The central business districts like Quan 1, Quan 4 and Quan 7 express the highest emission intensities, which can be over 1900 times of the ones in outskirt area.

In chapter 4, high detailed vehicle emission inventory was compiled based on modelled traffic flow data. The vehicle EI was calculated basing emission factors, vehicle mixing data, road network, and traffic flow. This part take advantages of Google traffic condition maps combined with other traffic parameters provided by previous studies in HCMC to derive hourly traffic flows. The diurnal traffic flow demonstrates clearly the peak hours in study area – 17.00 with traffic densities estimated for Secondary, Primary road, and Tertiary road are over 4000 PCUs and 2600 PCUs respectively. In rush hours, the percentage of congested road increases to 45% from 15% in case of weekdays and rises to 31% from 6% in weekends. The outputs of my model also demonstrate the growth by 130% and 150% of traffic densities in secondary – primary roads and tertiary roads, respectively in the busiest hours on weekdays and the growth by 127% and 145% in secondary – primary roads and tertiary roads in weekend. As a result, the emissions significantly increase by 49 tons of CO (153%), 0.69 tons of NOx (84%) and 0.023 tons of PM2.5 (115%) during traffic jam time, in compare with the "cleanest" time slots. On the whole, because of high traffic flow in peak duration, the total hourly vehicle emission can be double to 2.5 times, in compare with non-busy time slots. It suggests that if traffic densities is reduced by the limitation of personal vehicles or road network expansion, local air quality in HCMC will be improved considerably.

The findings in this study were compared with previous studies conducted in HCMC and Hanoi. And a number of limitations of this work were noted, leaving space for future research to improve and enhance the outputs. Firstly, the simulation of WRF Chem over SEA region in southwest monsoon season is recommended to confirm the influenced area of dominated BB in Kalimantan and Sumatra during those months. Secondly, the changes in VKT, EFs of vehicle fleet and road network should be considered to reduce the uncertainties of annual Transportation emission that is the most dominated sector. Thirdly, regarding Manufacturing and residential sectors, the updated EFs of fuel consumption and electricity consumption. And updated annual fuel and electricity consumption data disaggregated by sectors can improve the estimated emissions for these two sectors. In terms of hourly traffic emission inventory, the fleet composition in weekend is recommended to be estimated to distinguish the difference in traffic situation between weekdays and weekend. Also, the variation of EFs due to a change in speed and acceleration of vehicles should be taken into account to improve the accuracy of estimated emissions. In addition to that, the uncertainties of emission inventory should be estimated in future work.

Lastly, the next important step is the validation of my local emission inventories. The annual EIs of three key sectors can be validated by comparing with other data sources like satellite images or measurements of ground stations, after using air dispersion models. The hourly traffic flow, which directly impacts on hourly vehicle EIs, can be validated by origin-destination matrix data or call detail record data that can be used to calculate the network traffic density.

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List of Abbreviations

BB	Biomass burning
EI	Emission inventory
HCMC	Ho Chi Minh city
LPG	Liquefied petroleum gas
MC	Motorcycle
GHG	Green House Gas
ABCEIM	Atmospheric Brown Cloud - Emission Inventory Manual
SPI-NAMA	Support the Planning and Implementation of Nationally Appropriate Mitigation Actions
MRV	Measurement, Reporting and Verification

Chapter 1
Introduction

1.1 Background

Air pollution in developing countries is not only a major health risk, it also has damaging impacts on the environment and agricultural crop yields. These impacts have significant economic consequences, affecting economic growth as well as welfare. In Southeast (SE) Asia, most countries are now experiencing high levels of air pollution. Not only critical in urban areas, air pollution in this region caused by forest fires and agricultural burning is also of grave concern. With such high levels of polluted emission, the effects of toxic air quality on not only climate change, but also the health of Southeast Asian populations are likely to be significant.

Vietnam is one of the fastest growing economies in SE Asia and, as a result, has undergone rapid urbanization, industrialization and population growth. This has led to the fact that air pollution levels in Vietnam the past few years have reached alarming levels, specifically in metropolitan areas such as Hanoi and Ho Chi Minh City. According to Environmental Performance Index, Yale University, 2016, Vietnam was listed in the most polluted countries in the world, ranked 170th out of 180 countries for air quality. Different factors contribute to the severity of the problem. Crop burning, forest fire from neighboring countries like China, Indonesia, coal power plants with various emission sources within urban area are main drivers of deteriorating air quality. However, the influence level of each emission sources on air quality in each metropolitan areas is still a big question. To improve the worsening air quality in big cities, the thorough understanding about polluted causes are mandatory and crucial.

Nevertheless, inadequate data is a big challenge for local and national governments to tackle the effects of air pollution. The online survey and collected public comments campaign of GreenID, 2016 revealed that although the public is very concerned about air quality because the quality of air has decreased significantly during recent years, people still lack basic knowledge and official information about air quality. 92.2% of respondents were aware that poor air quality is a major factor in their health and wellbeing. The percentage of people who believe that respiratory illnesses has increased over the past three years is 57.2%. Nearly 81.7% of participants thought that the current regulations and measures of the government on air pollution needed to be improved (Air pollution report, 2018, GreenID) Participants of the survey also contributed a number of ideas to help addressing issues related to air pollution. More than a half of total participants believed that it is needed to provide more detail and accurate information about air pollution situation (Fig1.1)

Figure 1.1. The number of ideas to help addressing air pollution issue, according to the opinion of participants in survey organized by GreenID, 2016 in Vietnam

In fact, like other developing countries, the monitoring system, reporting infrastructure and emission inventories (EI) database are insufficient to reflect the updated level of air pollution in Vietnam. EI is an accounting of the amount of pollutants discharged into the atmosphere. It usually contains the total emissions for one or more specific greenhouse gases or air pollutants, originating from all source categories in a certain geographical area and within a specified time span, usually a specific year. It is a crucial tool for identifying the source of pollutants and quantitative expression of pollution load in a defined area at a particular time (G.Beig et al, 2017) In other words, it is the most effective way to help determine significant sources of air pollutants and to target regulatory actions. Additionally, emissions inventory is an essential input to mathematical models that estimate air quality. The effect on air quality of potential regulatory actions can be predicted by applying estimated emissions reductions to emissions inventory data in air quality models (EPA)

In 2006, IPCC released Guidelines for National Greenhouse Gas Inventories (2006 IPCC Guidelines) provide methodologies for estimating national inventories of anthropogenic emissions by sources and removals by sinks of greenhouse gases. This was developed from the 1996 IPCC Guidelines and provided advice on estimation methods at three levels of detail, from tier 1 (the default method) to tier 3 (the most detailed method). 2006 IPCC Guidelines focused on four main sectors: Energy; Industrial Processes and Product Use; Agriculture, Forestry and Other Land Use and Waste. This guideline is applicable to emission factors, activity and uncertainty data collection. According to this, if there are no country-specific peer-reviewed studies available, then the inventory compiler can use IPCC default factors and Tier 1 methods or Tier 2 methods with data from Emission Factor Database. Tier 2 is intermediate and Tier 3 is the most demanding in terms of complexity and data requirements. Tier 2 and 3 are sometimes referred to as higher tier methods and are generally considered to be more accurate on condition that adequate data are available to develop, evaluate and apply a higher tier method. Currently none of the developing countries have the capacity to use Tier 3 method.

Previous air pollution studies in Vietnam applied national or regional emission inventories combining with numerical air dispersion models. EDGAR- HTAP v2 is considered as one of the most updated nationally reported emissions combined with regional scientific inventories in the format of sector-specific grid maps. This global 0.1deg x 0.1deg grid maps are a joint effort from US-EPA, the MICS-Asia group, EMEP/TNO, the REAS and the EDGAR group to serve in the first place the scientific community for hemispheric transport of air pollution. The Regional EI in ASia (REAS) version 2.1 (http://www.nies.go.jp/REAS/) was introduced to cover East, Southeast, South, and Central Asia and Asian part of Russia for period from 2000 to 2008 with monthly interval. This EI includes SO2, NOx, CO, NMVOC, PM10, PM2.5, BC, OC, NH3, CH4, N2O, and CO2. Monthly gridded data with a 0.25° × 0.25° resolution are provided. It includes four main sectors:

- Fuel combustions in power plants, industry, transport, and domestic sectors;
- Industrial process;
- Agricultural activities (fertilizer application and livestock);
- Others (fugitive emissions, solvent use, human, etc.)

These emissions were estimated on district and country levels then spatial allocation was carried out basing on population data; information on the positions of large point sources (LPSs); land cover data sets; land area data sets and road network. The activity data (AT) of this Emission inventory is Fuel consumption data from IEA Energy Balances (IEA, 2004) For non-combustion sources, an industrial activity data set (production of non-ferrous metals, sulfuric acid, iron, and steel) was derived from international statistics. For transportation, AT was based on vehicle numbers, annual distance traveled. Regarding emission factors, default factors from 2006 IPCC Guidelines and other reference data were applied for countries which do not have their own emission factor dataset. The major role of the REAS inventory is to provide emission input data for atmospheric chemistry models (J. Kurokawa et al, 2013)

Tab 1. The growth rate of pollutants species between 2000 and 2008 in Southeast Asia and their main sources according to REAS 2.1 (J. Kurokawa et al, 2013)

Pollutant species	**The growth rate between 2000 to 2008 in Southeast Asia**	**Main emission source in Southeast Asia (SEA)**
SO2	4.2 Tg (+13 %)	Indonesia and Thailand
NOx	5.5 Tg (+56 %)	Indonesia and Thailand. Road transport emissions
CO	48.3 Tg (+34 %)	Biofuel combustion in the domestic sector, and road transport. Indonesia was the largest contributing country (47 %) in 2008, followed by Vietnam.
NMVOC	15.0 Tg (+47 %)	Both domestic and road transport emissions. Nearly half of SEA emissions were from Indonesia, whereas 14 % were from Thailand, and 11 % each were from Malaysia and Vietnam.
NH3	4.2 Tg (+19 %)	Agricultural activities

PM10/PM2.5	3.1/2.3 Tg (+11/+7 %)	The industry and domestic sectors. The largest contributing country was Indonesia, but Vietnam ranked second.
BC	0.37 Tg (+18 %)	Domestic biofuel combustion dominated emissions in Indonesia and Vietnam.
OC	1.42 Tg (+9 %)	Indonesia, and Vietnam
CH_4	29.0 Tg (+18 %)	Agricultural activities
N_2O	0.60 Tg (+13 %)	Agricultural emissions, specifically direct and indirect soil and manure management sources
CO_2	1.5 Pg (+33 %)	Gas and oil combustion

It is apparently seen from Tab 1.1 that the all the pollutions experienced significant increase over 9 years in SEA area. Indonesia and Vietnam were the largest contributors of CO, NMVOC, PM, BC and OC. After 2008, the economic growth of this region has remained robust, so the dramatic rise in emission is expected. This leads to need of updated and accurate emission inventories for pollution hot spots like Indonesia and Vietnam.

Apart from REAS, the national and local EIs developed for Vietnam have not been consistent, comparable and completed. Regarding national scale, Ministry of natural resources and environment of Vietnam carried out three national GHG inventory in 2010 (BUR1- Biennial Update Report), 2013 (BUR2) and 2014 (NC3-National Communications) to submit to the United Nations Framework Convention on Climate Change (UNFCCC) with the financial support from the Global Environment Facility and the United Nations Environment. The findings demonstrated over nine fold growth of Vietnam's total GHG emissions from 1991-2012, averaging 12% annually, while GDP grew by 315%, averaging 7% per year. So, the carbon intensity of Vietnam's economy has been at almost triple the world average. Also, Vietnam's GHG profile is dominated by emissions from energy and agriculture, which combined contribute 89% of total GHG emissions.

Other national EIs were mainly compiled for one type of emission source only, usually a primary sector like Transportation, Agriculture or Industry. For example, in 2007, an EI for Manufacturing sectors in Vietnam was prepared by The International Centre for Environmental Management for The World Bank in partnership with Ministry of Natural Resources and Environment and Ministry of Industry. Pollutants covered in the study were SO_2, NO_2, VOC, TSP and PM10.

A combined top-down and bottom-up EI for thermal power plants and industrial activities in Vietnam for 2010 was conducted using fossil fuel consumption data of thermal power plants and industrial activities collected at the provincial level. Emission factors (EFs) were selected from literature considering the relevancy to the country emission sources.

In 2012, Clean Air Asia published their estimates about road transport emissions and electricity generation - consumption emissions for Asia and individual countries, including Vietnam. This database contains PM, SO_2, NO_x and CO_2 emissions from 2002 to 2010. According to them, the carbon intensity (CO_2 emissions per GDP) and PM emissions of the road transport sector in Vietnam, China and Indonesia had the highest average annual growth rates. In terms of electricity generation, the annual growth rate of CO_2 emissions in Vietnam during 2000-2009 was 15%, the highest rising speed in Asia, because of doubled electricity generation since 2000. These findings implied that Viet Nam's economy is becoming more carbon intensive.

Besides, an emission inventory (EI) with temporal and spatial distributions from forest fires and crop residue open burning in Vietnam for 2010 was developed in a study of N.P.Dong et al, 2014. Satellite data was used to assess temporal and spatial distributions of emissions from forest fires, while statistic data and information from a questionnaire survey were used to assess emissions from this sector.

Apart from these national EIs, a number of local EIs were prepared for two big cities, Hanoi and HCMC.

A study of N.T.K.Oanh et al, 2011 calculated emission from MC fleet in Hanoi in 2008 using International Vehicle Emission (IVE) model. According to this work, motorcycles (MC) contributed 158 Gg CO; 51.5 Gg VOC; 9.5 Gg NOx and 2.4 Gg PM10 to total emission in Hanoi that year.

H.D.Tung et al, 2011 determined emission factors and EIs for two typical types of vehicle in Hanoi - MC and light duty vehicles (LDV) in their research. This data set was output of 2-year emissions monitoring program (2008-2009) launched by the Centre for Environmental Monitoring of the Vietnam Environment Administration and it includes four pollutants: CO, HC, NOx and CO2. Their findings showed that MC and LDVs fleet contributed over 105.7 Gg and 3.862 Gg CO, respectively in 2009.

Another study of T.T.trang et al, 2015 estimated emissions from passenger fleets of cars, taxis and buses in Hanoi in 2010 for 14 species of air pollutant and greenhouse gases (GHGs) Their results showed that the 2010 annual emission from three fleets for CO, volatile organic compounds (VOC), NOx, SOx and particulate matter (PM) were 39.5, 5.9, 3.8, 0.6 and 0.22 Gg, respectively.

In the estimation of V.V.Manh et al, 2011 for traffic emission of Hanoi in 2010, MC was accounted for over 160 Gg CO, LDVs fleet contributed 2.68 Gg CO and total emission of Transportation in Hanoi was 163Gg CO.

N.T.Hung et al, 2014 also compiled a traffic EI for Hanoi using emission model AirQUIS. But different from other studies, their outputs included spatial distribution for traffic EIs.

From these findings, we can see the gap and inconsistency of emissions estimated for traffic sector in Hanoi among previous studies, especially for CO and PM emissions.

In HCMC, a Green House Gases Inventory was prepared with the assistance of the Japan International Cooperation Agency (JICA) under the Project to Support the Planning and Implementation of Nationally Appropriate Mitigation Actions in a Measurement, Reporting and Verification Manner (SPI-NAMA). This is the first comprehensive GHG inventory of HCMC. The compilers used Global Protocol for Community-Scale GHG Emission Inventories (GPC) and the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (2006 IPCC Guidelines) to prepare this inventory. Global Protocol for Community Scale Greenhouse Gas Emission Inventories or GPC is a standard to measure GHG emissions from cities. GPC is promoted by the C40 Cities Climate Leadership Group that is a network of the world's mega cities committed to addressing climate change, including HCMC. This city – level GHG inventory includes five main sectors:

- Stationary energy
- Transportation

- Waste
- Industrial process and product use (IPPU)
- Agriculture, forestry, and other land use (AFOLU)

According to this project report, Transportation and Stationary energy are two most prominent emission sectors in HCMC. Within Stationary energy sector, Manufacturing industries accounts for the highest portion, followed by Residential buildings (Fig. 1.2)

Apart from this GHG EI, a number of on road traffic EIs were compiled for this city. In 2009, Belalcazar, L.C., et al. estimated road traffic emission factors (EFs) for HCMC from a tracer experiment and from roadside pollutants measurements. Their finding was a database of EFs covering NO, PM2.5, propane, butane and 15 additional VOCs. Many later studies applied this database to calculate on road traffic emission in HCMC.

An example is PhD thesis of H.Q.Bang, 2010, that carried out EMISENS model for generating road traffic emissions in HCMC. Main outputs of this study were hourly emissions for NOx, CO, SO2, NMVOC and CH4 and maps of hourly traffic emissions with 1 km resolution. At the same time, this author implied that MC are responsible for the bulk of traffic emissions (contributing 94% of CO, 68% of NMVOC, 61% of SO2 and 99% of CH4) Three years later, this study was upgraded to take into account traffic jams. From a field campaign in HCMC, the author assumed that traffic jam duration accounts for 9.16% of total time and in rush hour, speed of vehicle is in range of 0 ÷ 5 km/h.

Another study of N.T.H.Giang et al, 2014 estimated EFs of gasoline fueled vehicles and diesel fueled vehicles, including PM2.5 and a group of VOCs using inverse modeling for HCMC. Their conclusion was that high PM2.5 levels appeared to associate with diesel fueled vehicles while those of BTEX associated with gasoline fueled vehicles.

A research of N.T.K.Oanh et al, 2015 comparatively analyzed the traffic fleets and on road vehicle emission in 4 Asian cities, namely Bangkok (Thailand), Kathmandu (Nepal), Hanoi and HCMC. According to their conclusion, HCMC had the highest annual transportation emission and the largest MC fleet followed by Hanoi. Large shares of pre-Euro vehicles observed in this city was considered as the main reason leading to high emission level. This study used extensive field data, including parking lot, gasoline stations survey, GPS surveys for driving activities and traffic counting from video camera.

Recently, L.T.P.Linh et al, 2018 quantified road transport sector energy consumption and GHG for 10 cities located in Southern Vietnam, including HCMC using bottom up approach. Similar to study of N.T.K.Oanh et al, 2015, IVE model was applied to estimate GHG emissions from vehicle fleets.

Obviously, these studies have one thing in common: compiling EIs for transportation sector in HCMC. However, the difference in methods, in temporal intervals and input data like EFs, vehicle mixing ratio caused the gap of completeness, comparability and consistency. Furthermore, other primary emission sectors like Manufacturing industry and Residential have not received adequate attention. Therefore, the disparity between estimated emission inventory and real emission level is unavoidable. Besides, among works mentioned above, only study of H.Q.Bang, 2010 provided maps of traffic emission in HCMC that is not only prerequisites for air quality model applications, but also crucial for local authorities to know where and when emission gets elevated.

Deriving from this literature review, I drew a number of conclusions about the needs of local EIs for urban area in Vietnam:

- Local EI needs to be updated, taking advantages of findings and data from previous research conducted in the same study site and open accessed data to ensure the consistency and continuity with predecessor EIs.
- Local EI needs to include other key emission sectors like Manufacturing industry and Residential sources to meet the demand of completeness.
- Local EI needs spatial and temporal allocations, not only the total amount of emissions, to fulfil the requirements of input for atmospheric chemistry transport models and a scientific basis for policy makers to control air pollution in urban area.

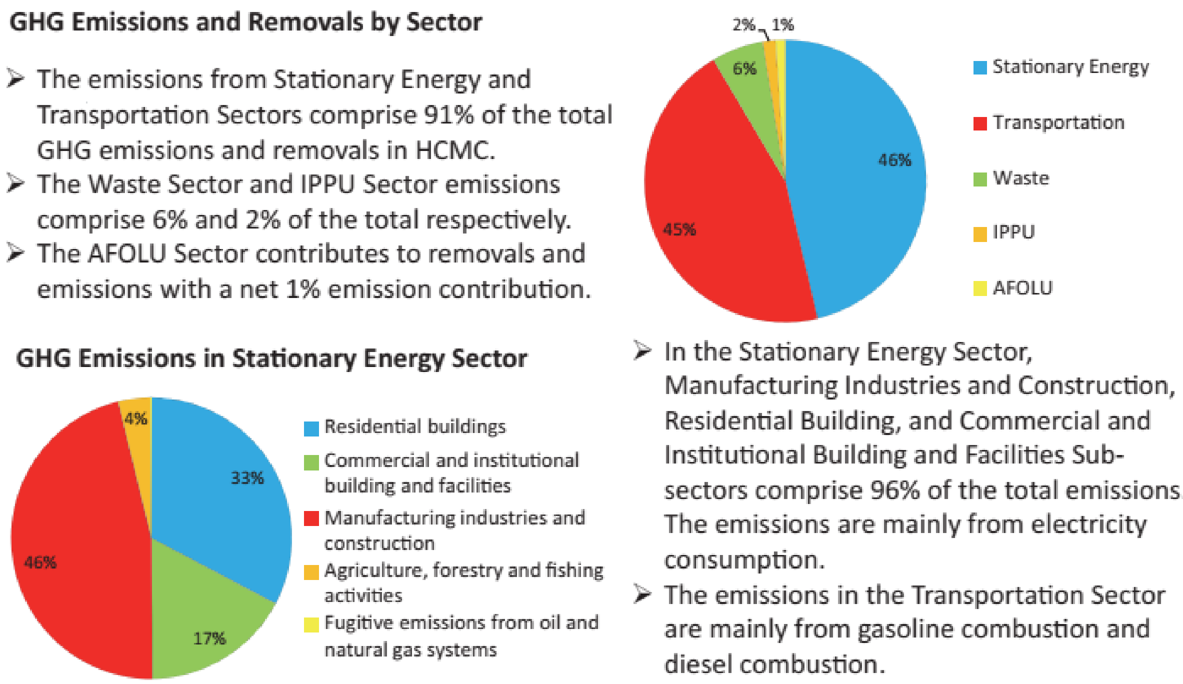


Figure 1.2 GHG emissions by sector in Ho Chi Minh city, 2013 (JICA, 2017)

1.2 Site selection

Meanwhile air pollution level in Hanoi exhibits strong seasonality, and the dependence on meteorological factors, air quality in Ho Chi Minh city expressed relatively little seasonal variation and is mainly caused by the accumulating emissions from vehicles, and industrial facilities within the urban area (Air Quality Report 2018, GreenID). In both two cities, serious air pollution has increased rapidly and becomes now a major concern.

According to data from the US embassy's monitoring station, particulate levels in Hanoi remained high in 2017. Days with the lowest air quality tend to concentrate in the first and fourth quarter of the year (Fig 1.3) Daily average PM2.5 levels was 50.5 µg/m3, which is 2 times higher than Vietnamese regulations and nearly 5 times higher than WHO guidelines. AQI levels were considered unhealthy by international standards, meaning AQI rating exceeded 100, on 209 days. This concentration may be due to the effect of weather conditions during summer and winter on the spread and diffusion of air pollutants. During winter, Hanoi is affected by the northeast monsoon and strong northeast wind currents that are believed to carry pollutants and dust from the vicinity in the northeast to Hanoi. Meanwhile, in Ho Chi Minh City, the annual PM2.5 concentration reached 29.6 µg/m3, exceeding the National Regulation limit of (25 µg/m3 for PM2.5, and 3 times higher than the WHO guideline of 10 µg/m3 (Fig 1.3 and Tab 1.12)

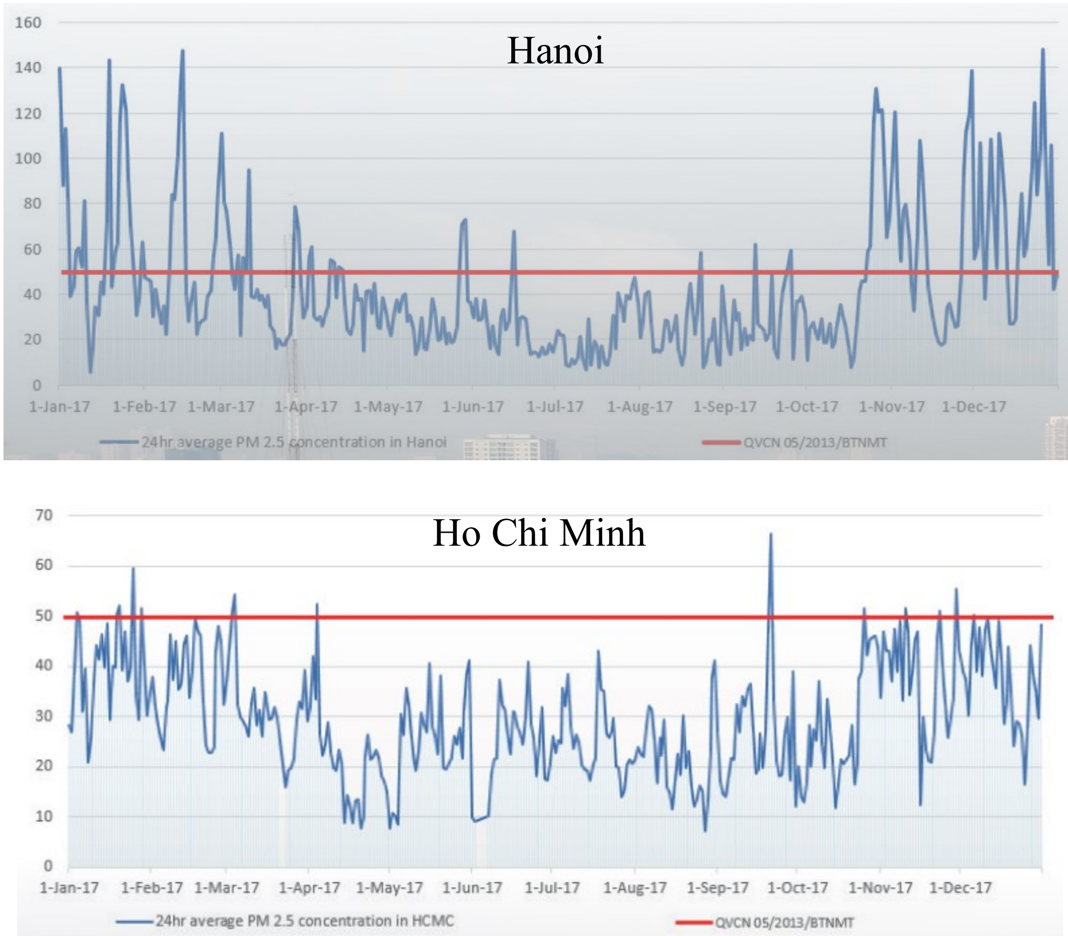


Figure 1.3. Daily average PM2.5 levels from the US embassy's monitoring station in Hanoi (top) and HCMC (bottom), 2017 (Air Quality Report 2018, GreenID)

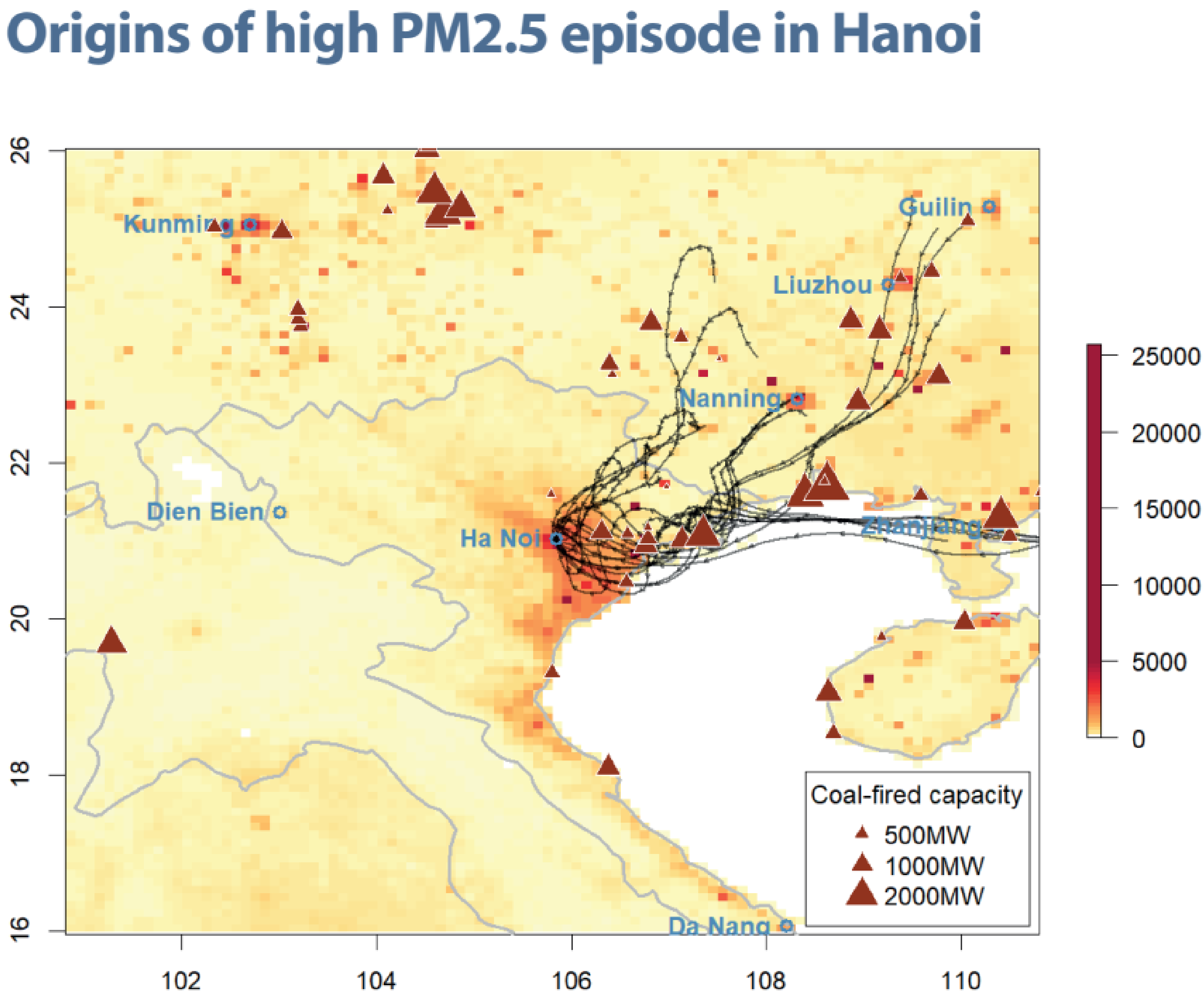
Table 1.2. Overview on air quality in HCMC in 2017 (Air Quality Report 2018, GreenID)

Category	2017	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average AQI	87	108	103	92	68	78	78	79	70	81	84	104	105
Level of AQI	Moderate	Unhealthy for sensitive groups		Moderate								Unhealthy for sensitive groups	
Average PM2.5	29.6	39.4	36.5	31.3	21.5	25.5	25.2	25.2	21.6	26.6	27.7	37.6	37.8
Number of days violating QCVN	14	5	0	2	1	0	0	0	0	1	1	3	1
Number of days violating WHO standard	222	30	23	25	7	17	13	14	9	16	15	26	27
No data	6	0	0	0	0	0	4	0	0	0	0	0	2

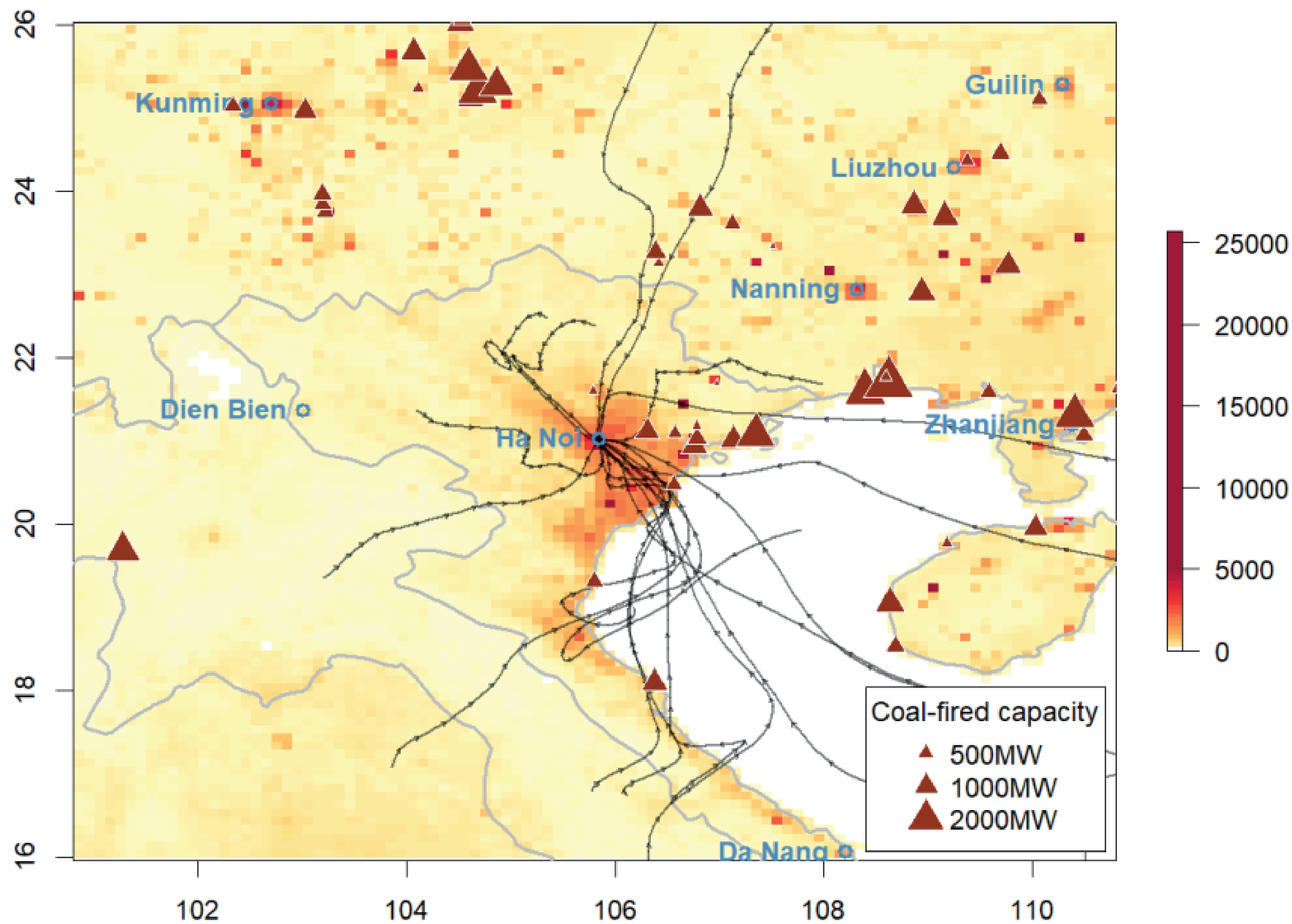
Regarding the sources of air pollution episodes in these two cities, study of GreenID, 2018 applied U.S. NOAA HYSPLIT model to understand the emission sources in the second half of 2017. This model used meteorological data to define the trajectories of air masses. Then the trajectories were overlaid with maps of estimated PM2.5 emissions (in tonnes per year) from the EDGAR emission database (v4.3), and with the locations of operating coal-fired power plants, to identify areas likely to contribute to the episodes (Fig1.5) Their finding suggested that PM2.5 pollution in Hanoi exhibits strong seasonality, with winter months (November-February) being more highly polluted than summer months. In contrast, average pollution levels on different hours of the day showed relatively little variance, indicating that e.g. local transport emissions were not a dominant source of pollution. Hanoi is surrounded by dense rural and urban populations in the southeast, and Vietnam's largest concentration of power plants and industrial facilities lies approximately 100 km to the east of the city. The EDGAR emissions database identified the delta area to the southeast as a major source of residential fuel burning emissions, while both the EDGAR emissions database and analysis of NASA OMI satellite imagery show that the industrial cluster in Quang Ninh is the largest hotspot of NO2 and SO2 emissions in Vietnam, and a major source of PM2.5 emissions. NO2 and SO2 emissions contribute to the formation of secondary PM2.5 (nitrate and sulfate aerosols, respectively), which play an important role in air pollution episodes.

The different pattern was shown in HCMC. PM2.5 levels in Ho Chi Minh City varied widely according to hour of the day, but exhibited relatively little seasonal variation. Besides the HCMC area itself being a significant hotspot of transport and industrial emissions, the coastline to the north is characterized by dense population and significant residential, transport, and small industry emissions. The majority of the analyzed PM2.5 peaks was associated with air masses traveling down the coastline, accumulating pollution from other cities, transportation, power plants, and industrial facilities in the area. The other important source region was the inland region to the south-southwest of HCMC. This analysis emphasizes the importance of controlling pollution inside HCMC itself and the immediate vicinity.

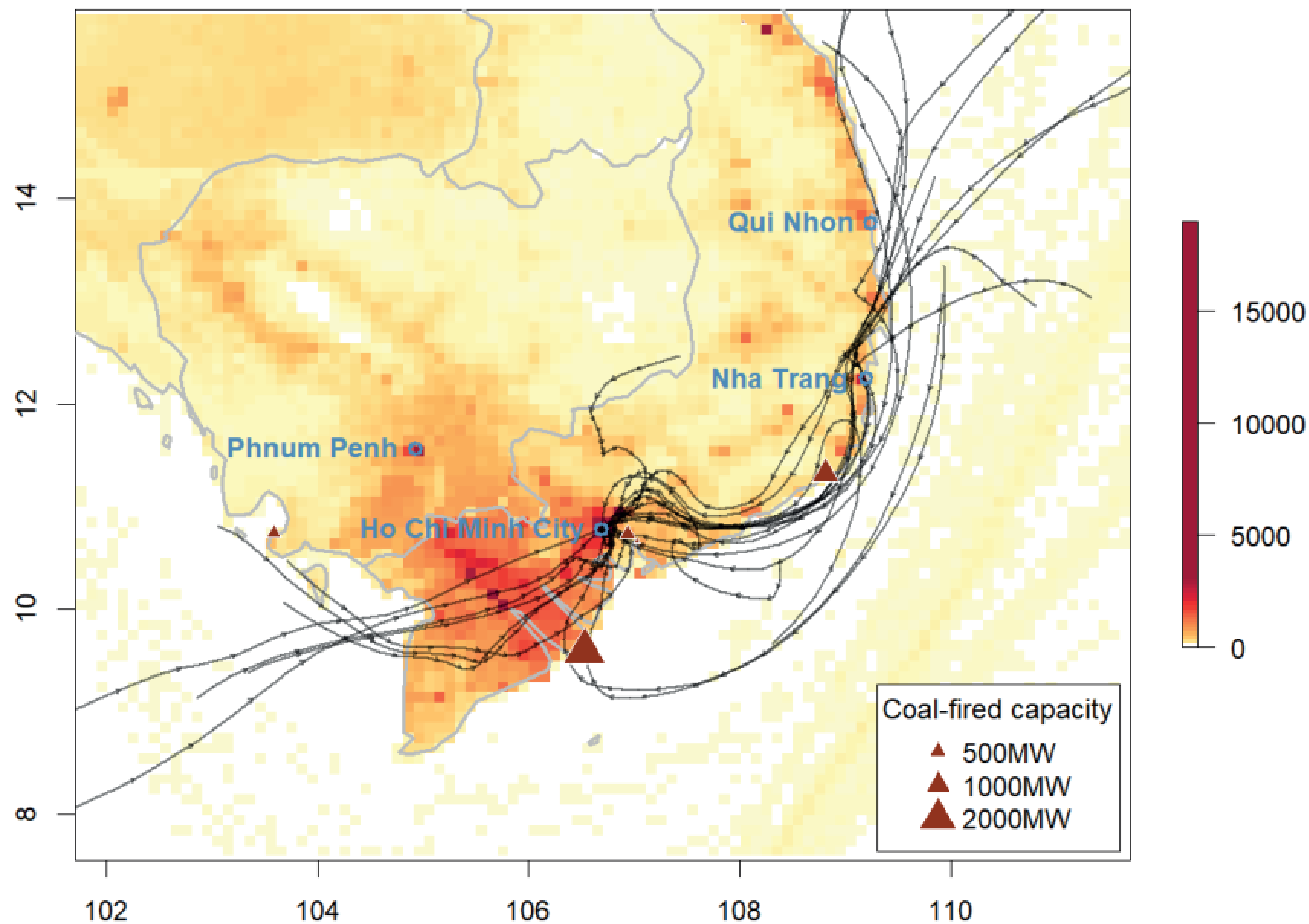
Deriving from this fact, we chose HCMC as study area to prepare EI, although air quality in this city compared favorably to Hanoi. The reason is that the relative independence of situation in HCMC on other adjacent sources facilitates the compiling local EI. Additionally, the updated EI with detail information about urban emission sources will have remarked significance because air quality in HCMC is mainly influenced by anthropogenic emission occurring inside the city.



Origins of clean air masses in Hanoi



Origins of high PM2.5 episode in HCMC



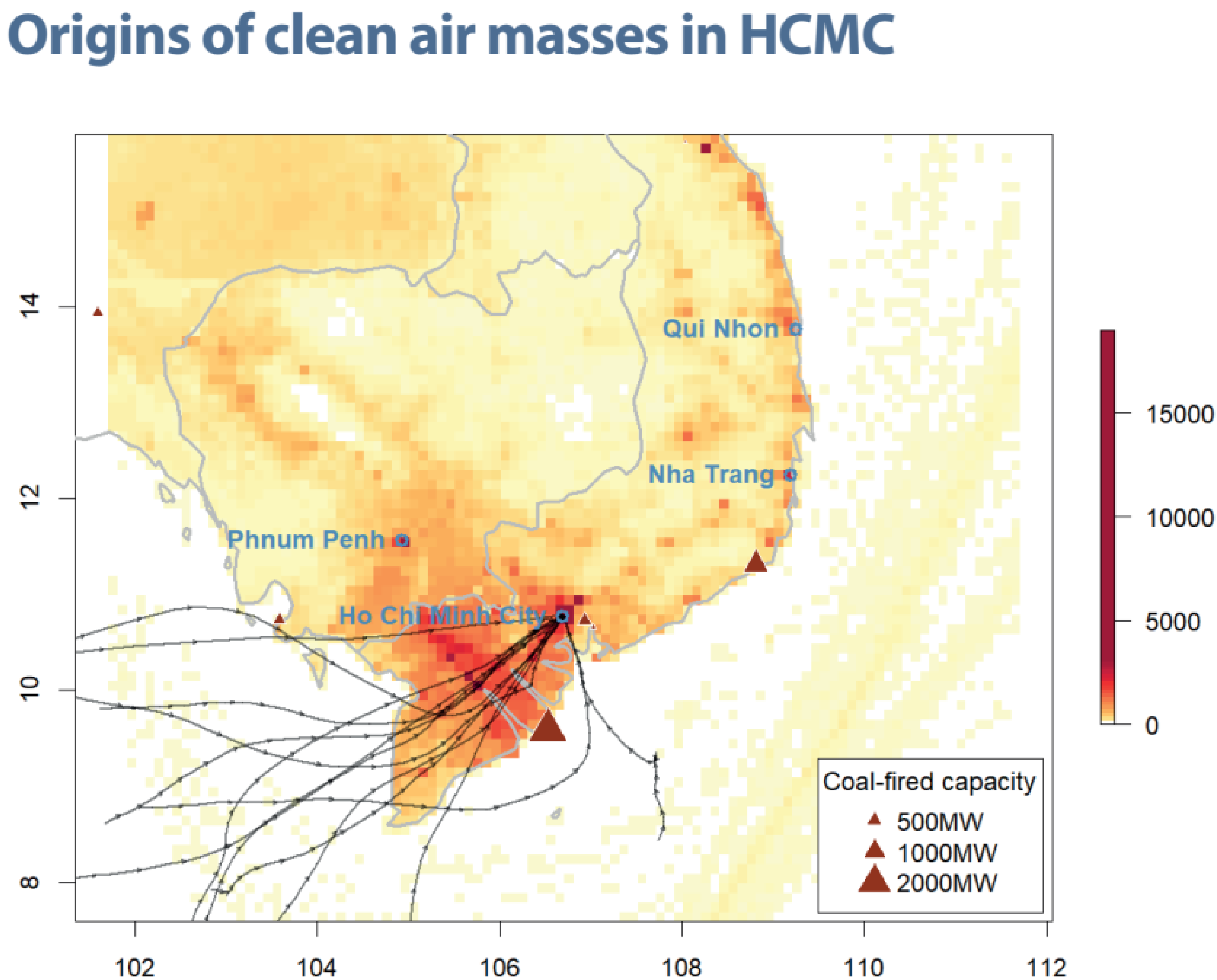


Figure 1.4. The trajectories of air masses in Hanoi and HCMC in the second half of 2017, according to HYSPLIT model and coal-fired power plants location from EDGAR emission database (Air Quality Report 2018, GreenID)

1.3 Objectives of the study

Based on the discussion before, I hypothesize that the synthesis of various data sources, such as inherent EIs, available statistical data and remote sensing data can facilitate the update of local EI. For examining hypothesis, the research objectives are:

- Estimate the impact of long-range transport biomass burning emission on local air quality in HCMC in pre monsoon season using remote sensing data and air quality numerical simulation.
- Model the evolution of key anthropogenic emission sectors in HCMC using inherent EIs, statistical data and remote sensing data.
- Develop high temporal –spatial resolution vehicle EI in HCMC by modelled traffic flow data.

The expected final outputs of this study are:

- Gridded EIs for key anthropogenic emission sectors cover from 2009 to 2016. These EIs has monthly interval and 1 km space resolution and includes 12 species: SO2, NOx, CO, NMVOC, PM10, PM2.5, BC, OC, NH3, CH4, N2O, and CO2, as successor of REAS 2.1. This study considered Scope 1 that is purely territorial source-based GHG accounting and Scope 2 that is consumption accounting separately.
- High temporal and spatial resolution vehicle EI covers one week, including weekdays and weekend. Time resolution of this EI is hourly and space resolution is 0.5 km. Emissions of NOx, CO, PM2.5 are calculated in this detailed EI.

1.4 Originality of the study

Significance of the study

- Update local EI with long term evolution of main emission sources in HCMC.
- Provide a comprehensive method to update and compile local EI using remote sensing data and other open accessed data sources.

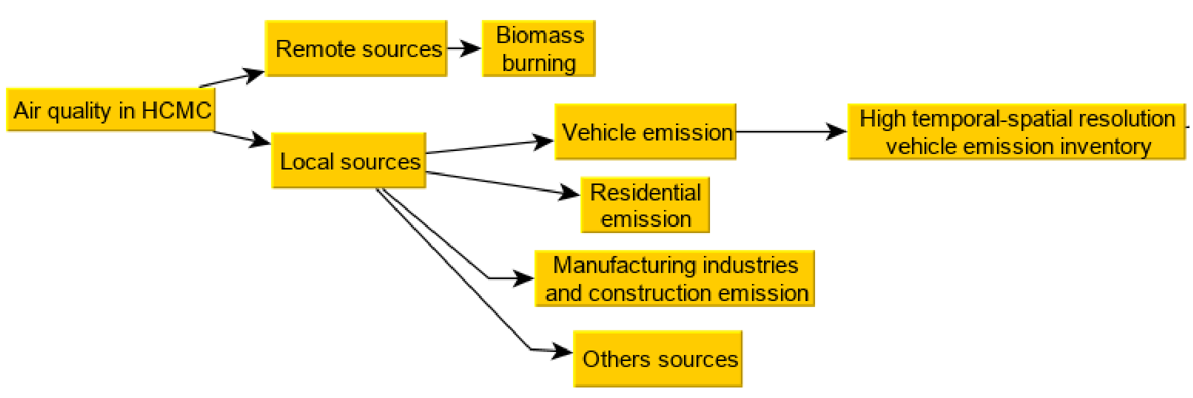
Novelty of the study

- Compile the maps of updated EIs for HCMC with the detail level equivalent with the predecessor – REAS 2.1. These maps are expected to be a significant contribution for user community of atmospheric chemistry transport models and studies of personal exposure, especially for some pollutants, e.g. particulate matter that can cause health effects in the vicinity of the emission site. Besides, this local EI will be comprehensive, consistent, continuous yet comparable with its predecessor and other inherent local EIs.

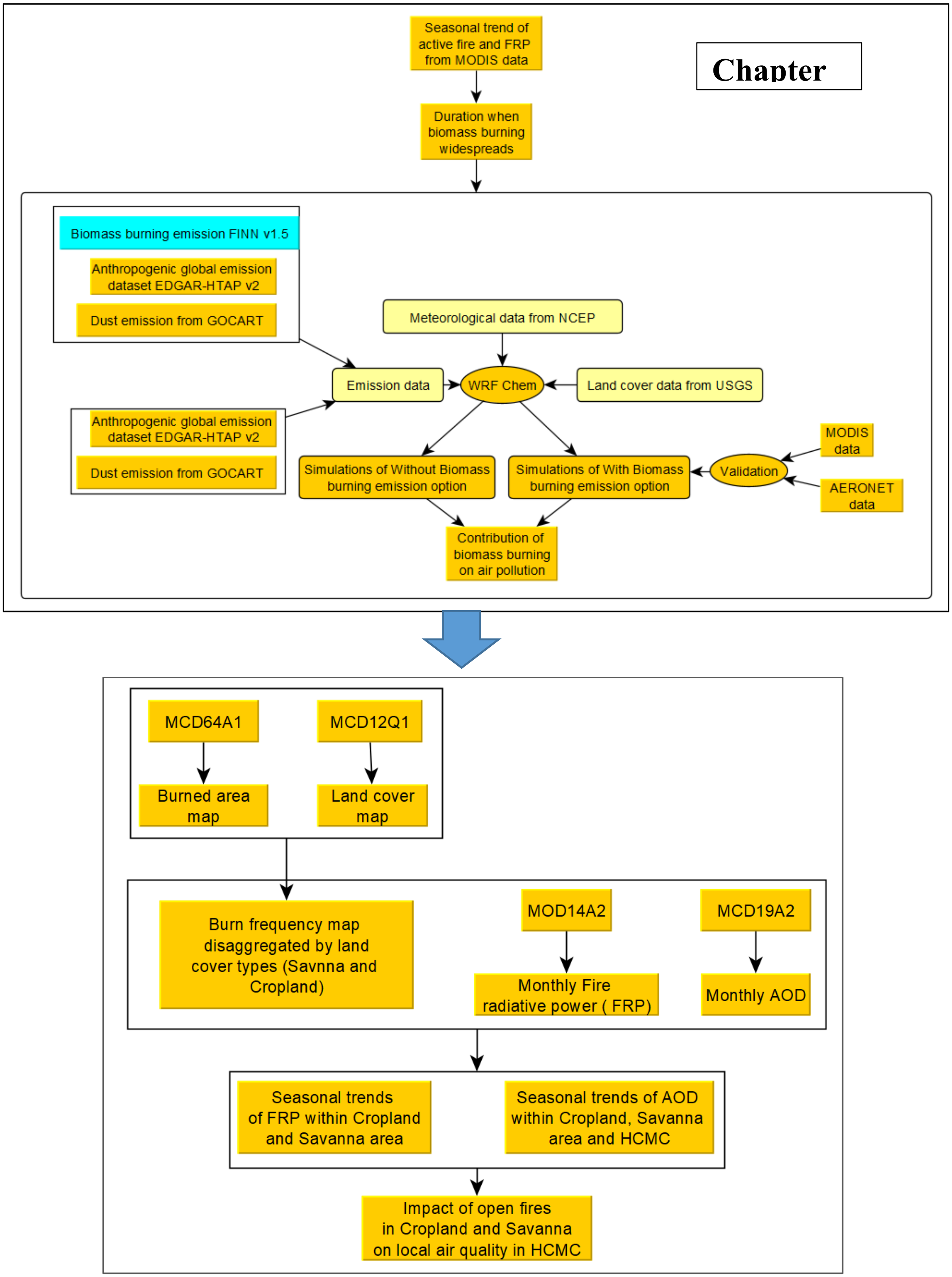
1.5 Thesis outline

This thesis is divided into 5 chapters. In chapter 1, I discussed the importance of compiling local EI in HCMC using available data. The main study is divided into 3 chapters to fulfill the objectives. The first part has the aim to analysis the impact of long-range transport of remote emission sources on local air quality in HCMC. In the next part, I compiled the updated emission inventories for key sectors, including Transportation, Manufacturing industries and construction and Residential sector using statistical data and remote sensing, to fill the gaps among inherent EIs. Among these three chapters, vehicle emission is the most prominent and the most dynamic one so in the next chapter, I generated high resolution vehicle EI, focus on modeling traffic flow in HCMC. Chapter 5 is Conclusion and future work. This layout is shown as flowchart in Figure 1.5.

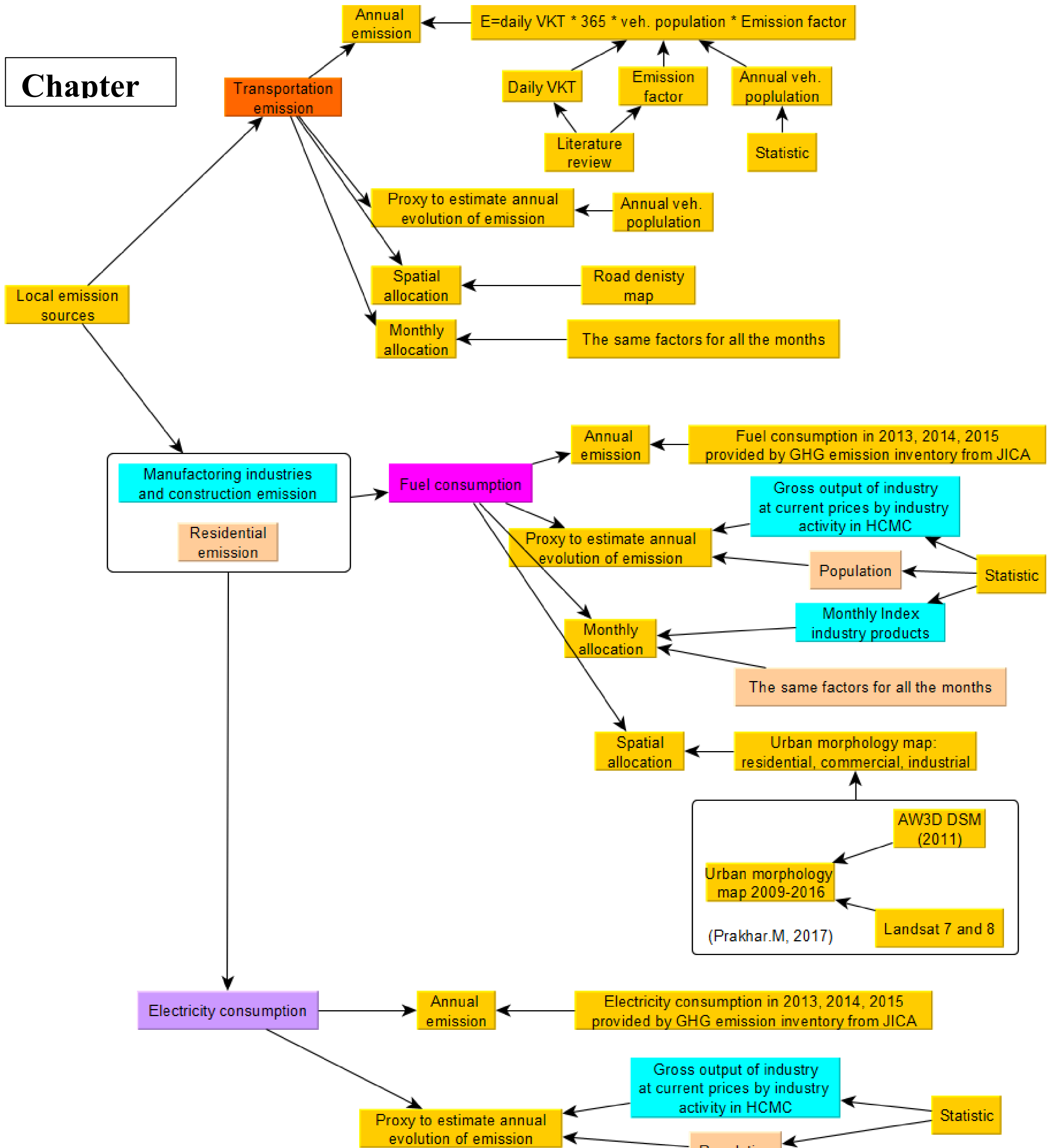
(a)



(b)


Seasonal trend of active fire and FRP from MODIS data
Chapter
Duration when biomass burning widespreads
Biomass burning emission FINN v1.5
Anthropogenic global emission dataset EDGAR-HTAP v2
Dust emission from GOCART
Meteorological data from NCEP
Emission data
WRF Chem
Land cover data from USGS
Anthropogenic global emission dataset EDGAR-HTAP v2
Dust emission from GOCART
MODIS data
Simulations of Without Biomass burning emission option
Simulations of With Biomass burning emission option
Validation
AERONET data
Contribution of biomass burning on air pollution
MCD64A1
MCD12Q1
Burned area map
Land cover map
Burn frequency map disaggregated by land cover types (Savna and Cropland)
MOD14A2
MCD19A2
Monthly Fire radiative power (FRP)
Monthly AOD
Seasonal trends of FRP within Cropland and Savanna area
Seasonal trends of AOD within Cropland, Savanna area and HCMC
Impact of open fires in Cropland and Savanna on local air quality in HCMC

Chapter


Annual emission
E=daily VKT * 365 * veh. population * Emission factor
Transportation emission
Daily VKT
Emission factor
Annual veh. poplulation
Literature review
Statistic
Proxy to estimate annual evolution of emission
Annual veh. poplulation
Spatial allocation
Road denisty map
Local emission sources
Monthly allocation
The same factors for all the months
Annual emission
Fuel consumption in 2013, 2014, 2015 provided by GHG emission inventory from JICA
Manufactoring industries and construction emission
Residential emission
Fuel consumption
Gross output of industry at current prices by industry activity in HCMC
Proxy to estimate annual evolution of emission
Population
Statistic
Monthly Index industry products
Monthly allocation
The same factors for all the months
Spatial allocation
Urban morphology map: residential, commercial, industrial
AW3D DSM (2011)
Urban morphology map 2009-2016
Landsat 7 and 8
(Prakhar.M, 2017)
Electricity consumption
Annual emission
Electricity consumption in 2013, 2014, 2015 provided by GHG emission inventory from JICA
Gross output of industry at current prices by industry activity in HCMC
Statistic
Proxy to estimate annual evolution of emission
Population

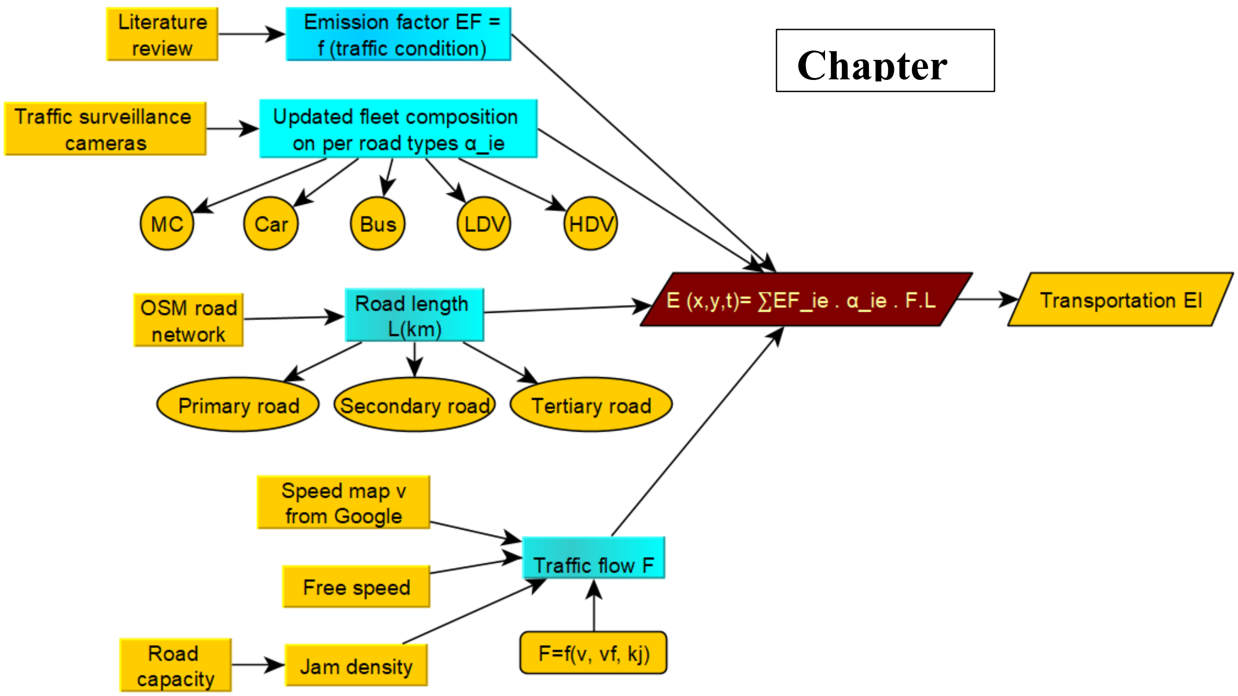


Figure 1.5 Flowchart of the thesis: (a) The connection among chapters; (b) the detailed flowchart of each chapter

Chapter 2.

Impact of biomass burning on air quality in Ho Chi Minh city

2.1. Introduction

Biomass burning (BB) is the combustion of organic matter which derives from natural or manmade fires, such as the human-initiated burning of vegetation for land clearing and natural, lightning-induced fires. Biomass material when burned releases extensive varieties of gases such as CO, CO2, CH4, volatile and semi-volatile organic compounds, aldehyde, organic acid and inorganic elements and particulate matter (PM). The characteristics of biomass burning rely upon the natural condition, types of the fuel burnt, moisture content, weather condition, and particle size and emission factor of the biomass. The flaming of the biomass materials ensures complete combustion, while the smoldering prompts inadequate burning, bringing about the more prominent generation of reactive gases and PM. Both particulate matter and gaseous emission from biomass burning have been perceived to have a serious impact on human health (I.C.Yadav et al, 2019) The global biomass mass can be classified in three major categories (Streets et al., 2003b): such as (1) savanna grassland, (2) forest (tropical, temperate, and boreal), and (3) agricultural land after the harvest (crop residue).

Since fires produce aerosols and chemical oxidants, products of biomass burning have significant impacts not only on local but also on regional air quality, biogeochemical cycles, climate and the hydrological cycle. Emissions from agricultural rice residue burning, forest BB as well as industrial sources, have all been linked to long and medium range transport of air pollution in different regions of the world. For example, high BC concentrations emitted from BB in South Asia and Southeast Asia have significant impact on the melting of snow in the Tibetan Plateau, causing some severe environmental problems (R. Xu et al, 2018) Or arctic ice loss attributed to surface albedo change from pollutant deposition from agricultural fires in Russia (Warneke C. et al, 2010) With rapid economic development and tremendous energy consumption in the past decades, South East Asia, which is located between the Indian Ocean and the Pacific Ocean, has experienced increasingly severe air pollution. In addition, being the original home of the world's most important crops with high coverage level of forest, Southeast Asia is considered as a high BB region. During springtime, there is highest forest and vegetation burnings in this region, causing important effects on air pollutants in the downward regions. The Indochina peninsular regions in Southeast Asia witness intense seasonal biomass burning in the form of wildland forest fires as well as agricultural crop burning and forest conversion fires during the boreal spring (R.Gautam et al, 2012) Aerosol concentrations during the pre monsoon season (March-April) are typically at peak associated with biomass burning activity and contribute significantly to the regional emissions (Carmichael et al., 2003; Janjai et al., 2009; Streets et al., 2009) Therefore, BB has special position in the comprehensive picture of air quality in this area.

In Vietnam, agricultural waste burning has been proved to represent a large contribution to air quality degradation in the rural area (O. B. Popovicheva et al, 2017) Like other developing countries, crop residues have been often field burnt post harvests in a couple of days to prepare for planting the next season's crops. 75.98 Gg of PM2.5 released from rice residue burning accounting for 12.8% of total emissions for Vietnam (K. Lasko et al, 2017) Hanoi is located within the Red River Delta where rice residue burning is prominent. Therefore, during post-harvesting season, rice residue burning is considered as a significant factor in serious air quality in this city (K. Lasko et al, 2018) Usually, there are two concentrated periods of anthropogenic BB: i) rice/wheat straw field burning in spring-summer harvest season in the late of May to the end of June; ii) crop residue burning in October - autumn is the second season rice straw burning. A study of K.Lasko et al, 2018 implied that within the highly-urbanized and cloud covered Hanoi Capital region, autumn has most BB emission trajectories originating in the North, while spring has most originating in the South, suggesting the latter may have bigger impact on air quality.

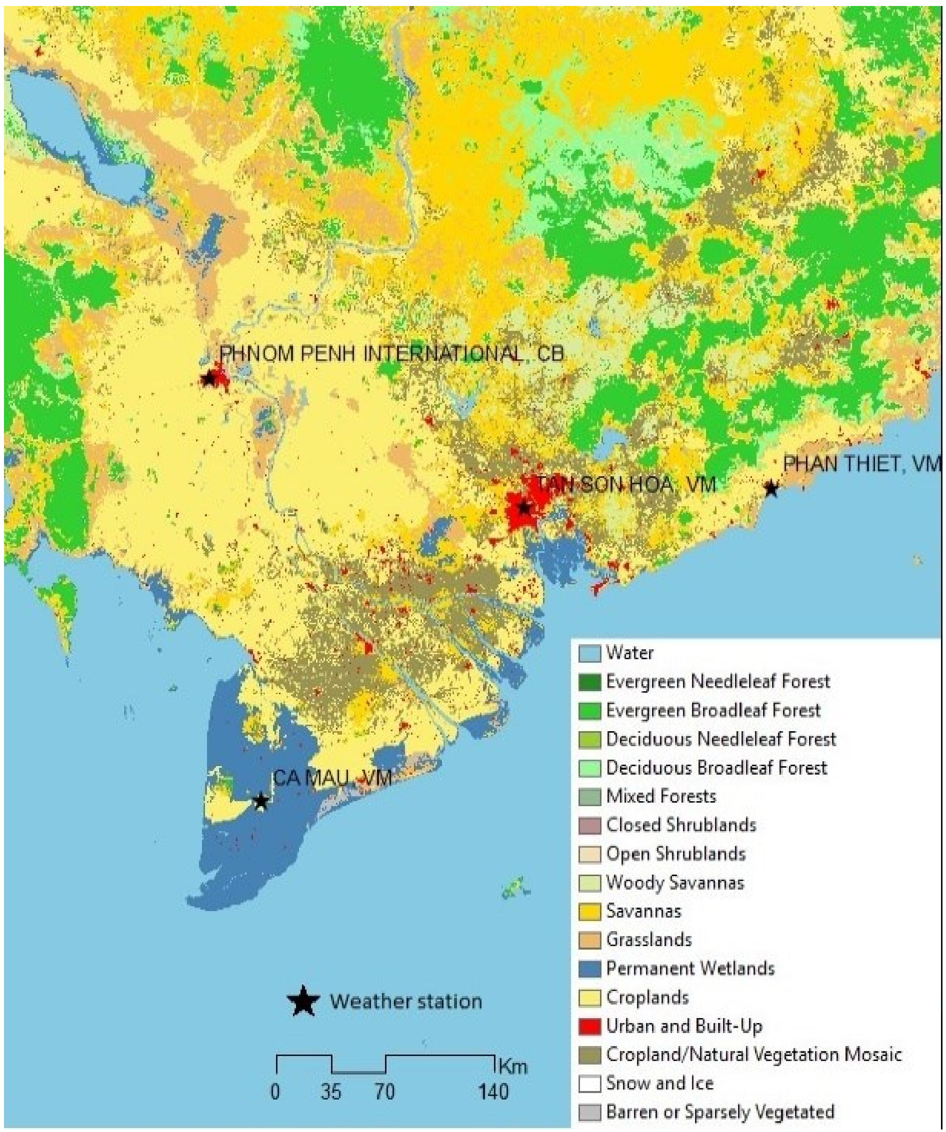


Figure 2.1 Land cover map in the Southern part of Vietnam (from MCD12Q1 product– MODIS) – simulation domain of WRF-Chem model.

Different from Hanoi, the impact of BB on local air quality in Ho Chi Minh city has attracted less attention. Although, this city is surrounded by large area of Savannas and Mekong delta, where BB is likely to occur (Fig 2.1) Besides, during the dry season, from November to April, agricultural biomass burning and forest fires especially from March to late April in mainland Southeast Asian countries of Myanmar, Thailand, Laos and Vietnam frequently cause severe particulate pollution not only in the local areas but also across the whole region and beyond due to the prevailing meteorological conditions (N.D.Hiep et al, 2015) Deriving from that fact, the objective of this part is to examine how much the adjacent BB sources impact on air pollution over the Southern part of Vietnam using the Weather Research and Forecasting model including chemistry and aerosols (WRF-Chem) and satellite images. The findings of this part will decide whether BB emission from adjacent sources will be included in emission inventory of HCMC or not.

2.2 Methodology

This chapter applied two complementary methods: air pollution simulation model and remote sensing data analysis.

2.2.1. WRF Chem

Weather Research and Forecasting model coupled with chemistry (WRF-Chem) is an online mesoscale model capable of simulating meteorological and chemical processes simultaneously (Grell et al., 2005; Fast et al., 2006). WRF-Chem v3.6 was used in this study. A series of experiments parameters were tested for simulations is listed in Tab. 1. CBM-Z (Carbon bond mechanism v. Z) was used for gas phase chemistry schemes. MOSAIC (Model for Simulating Aerosol Interactions and Chemistry) was chosen for aerosol scheme. This scheme predicts size of aerosol particles with 4 sectional aerosol bins and includes some aqueous reactions. Also, it predicts mass of aerosol components: Sulfate, nitrate, ammonium, sea salt, organic carbon, black carbon, dust. MOSAIC can be coupled with atmospheric radiation (direct effect) and coupled with cloud microphysics (indirect effects). This is the most actively developed aerosol module in WRF-Chem. Other physic schemes are listed in Tab. 2.1.

Table 2.1. Physics and chemistry schemes used in the configuration of the WRF-Chem

Parameter	**Option**
Planetary Boundary Layer (PBL) scheme – Surface Layer scheme	Yonsei University (YU) PBL (option 1) (Hong et al., 2006)
Cloud microphysics	Lin et al (option 2) (Lin et al., 1983)
Land-surface model	Noah Land-Surface Model
Radiation scheme (Long wave)	Rapid Radiative Transfer Model (RRTM)
Radiation scheme (Short wave)	Goddard Shortwave scheme
Gas-phase reactions scheme	CBMZ
Aerosol chemistry	MOSAIC using 4 sectional aerosol bins
Photolysis rates	Fast-J
Dust	GOCART (online)

Regarding input data, the land use dataset is incorporated from the US Geological Survey (USGS) based on 24 land use categories. Weather data were downloaded from the National Center for

Environmental Prediction (NCEP) website with the resolution of 0.25 degrees and 6-hour temporal interval. Beside meteorological data and land use data, the most important input of WRF-Chem are various emission data set. They include: anthropogenic global emissions data set EDGAR-HTAP v2 which provides monthly observational data sets with spatial resolution 0.1x0.1 degree; dust emission from GOCART; calculate biogenic emissions online using the Gunther scheme. Biomass burning emission inventory is FINN v1.5 (A daily fire emissions product from NCAR), that will be explained in details in the next part. To see the contribution of BB to air quality in study zone, WRF Chem was run with two options: with and without BB emission data.
Study area comprises the southern part of Vietnam and Eastern part of Cambodia. The model domain (Fig. 1.1) is defined on the Lambert conformal map projection centered at 10.541◦ N, 106.394◦ E at the horizontal resolution of 10 km × 10 km, including 27 vertical layers. This area has the dominant climatic feature – the southwest monsoon from mid-May to October, which generates a distinctly biseasonal pattern of wet and dry periods. FINNv1.5 emission files were updated till 2016, FINNv1.6 - emissions for 2017 and 2018 is not available yet. Therefore, the simulation in this study have been conducted from January to April in 2016 at the time step of one day. Because BB emission gets peak from March to late April in mainland Southeast Asia as mentioned above and that is dry season in our study site.

2.2.2. FINN v 1.5 emission inventory

Fire INventory from NCAR (FINN) is a daily fire emissions product for atmospheric chemistry models (Wiedinmyer et al., 2006; 2011) FINN uses satellite observations of active fires and land cover, together with emission factors and estimated fuel loadings to provide daily, highly-resolved (1 km) open burning emissions estimates for use in regional and global chemical transport models. Basically, there are two distinct methods to estimate biomass burning emission: Burned area (BA) based and Fire radiative power (FRP)-based. Regarding FRP based one, their emissions are directly related to FRP, with a weaker dependency on land cover type. However, FINN applied BA based approach:

$M^{[\epsilon]} = A * B * \beta * EF^{[\epsilon]}$ (1)

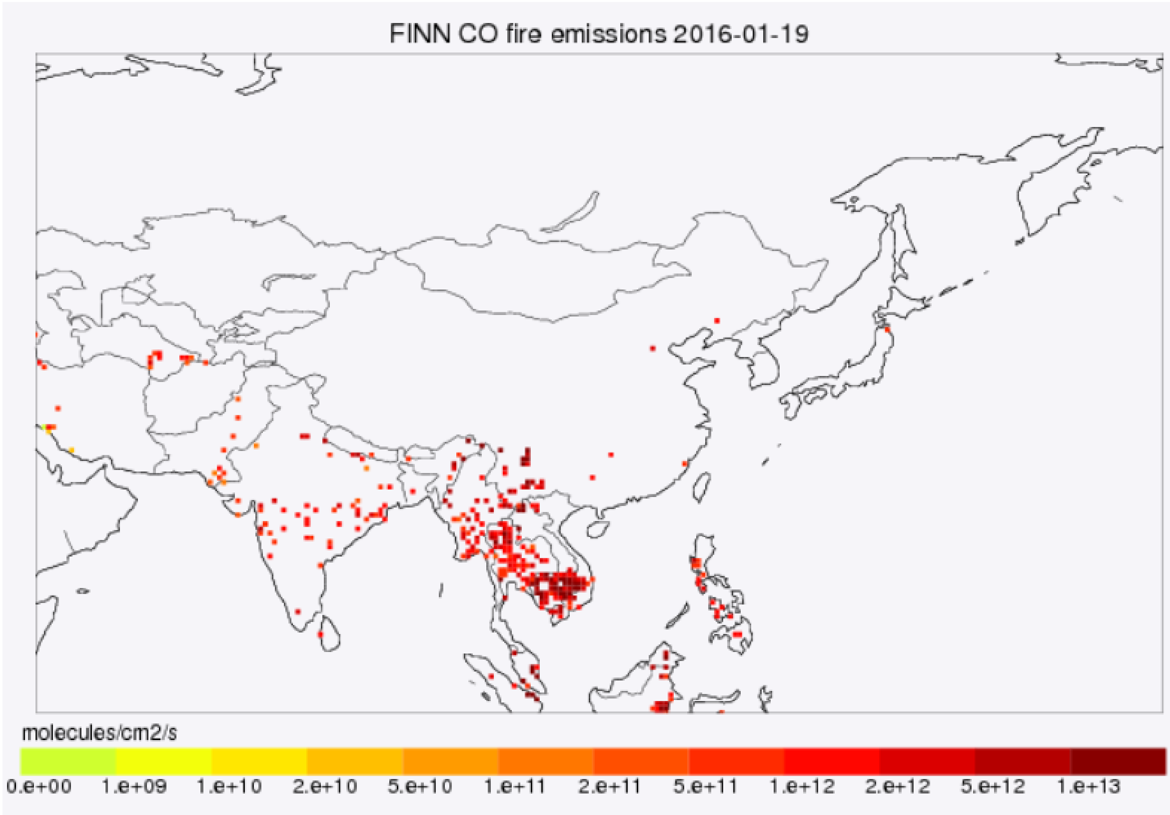
Where M is the emission load of species ϵ (g), A is the BA (km2), B is the fuel load (kg/km2), β is the combustion completeness (unitless) and EF is the emission factor released species ϵ (g/kg). Instead of using direct burned area products from satellite, FINN applied BA products basing on active fire detection is that observational gaps due to cloud cover and satellite revisit time can be filled due to the persistence of the burn scar. However area burned may be underestimated since a substantial part of the grid cell has to be burned in order to be counted.

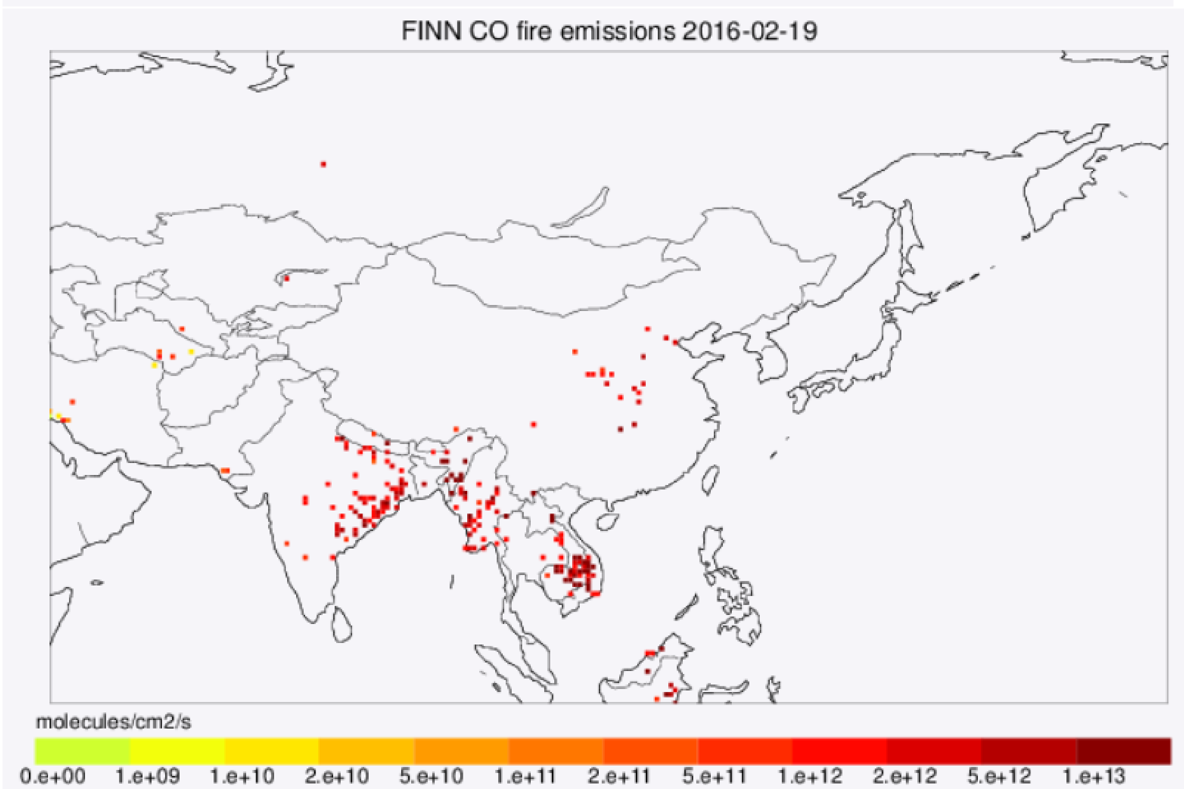
The location and timing for the fires are identified globally by the MODIS Thermal Anomalies Product. This product provides detections of active fires based on observations from the MODIS instruments onboard the NASA Terra and Aqua. For each 1 km2 hot spot, there can be only one fire per day. The type of vegetation burned at each fire pixel is determined by the MODIS Collection 5 Land Cover Type (LCT) product for 2005 (Friedl et al., 2010). Additionally, at each fire point, the MODIS Vegetation Continuous Fields (VCF) product (Collection 3 for 2001) is used to identify the density of the vegetation at each active fire location.

In compare with other BB emission inventories like GFED (Global Fire Emissions Database), FINN captures more small fire activity (Reddington et al., 2016). FINN may capture more emissions in places with a high density of small fires, in compare with GFED4. Additionally, the daily frequency and higher spatial resolution of FINN compared to GFED4s may allow for more realistic representation of pollution from individual fire events.

Conversely, FINN underestimates the intensity of large fires in some environments, due at least in part to the sensitivity of the FINN approach to day-to-day variability in cloud cover (Paton-Walsh et al., 2012) Classification of agricultural fires is difficult due to the tendency of these fires to be small and on privately-owned land. Besides, the assumed burned area estimated by the FINN methods is highly uncertain. Global burned area products are unsuitable to estimate the burned area of small fires due to the limitations of their algorithms. As a simple first approach, a maximum burn area is assumed for each fire pixel detected. Small fires tend to be underestimated. The relationship between fire detections and area burned is highly uncertain also. The land use/land cover (LULC) classifications assigned to the fires introduces some uncertainty to the emission estimates.

In recent years, FINN emissions have been used in many various modeling studies that simulate the chemical and climate impacts from fires. By using FINN emissions within the WRF-Chem model, Jiang et al. (2012) explored the impacts of fire plumes on ozone chemistry during a wildfire event in Idaho and Montana during August 2007. WRF-Chem simulated the immediate addition fire emissions combined with the changes in photolysis rates, boundary layer height, and biogenic emissions. The results highlighted the importance of including the radiative impacts of fire plumes. Val Martin et al. (2013) used FINN emissions in conjunction with satellite observations to explore the importance of fire smoke or air quality and regional climate in Colorado.


FINN CO fire emissions 2016-01-19
molecules/cm2/s
0.e+00 1.e+09 1.e+10 2.e+10 5.e+10 1.e+11 2.e+11 5.e+11 1.e+12 2.e+12 5.e+12 1.e+13


FINN CO fire emissions 2016-02-19
molecules/cm2/s
0.e+00 1.e+09 1.e+10 2.e+10 5.e+10 1.e+11 2.e+11 5.e+11 1.e+12 2.e+12 5.e+12 1.e+13

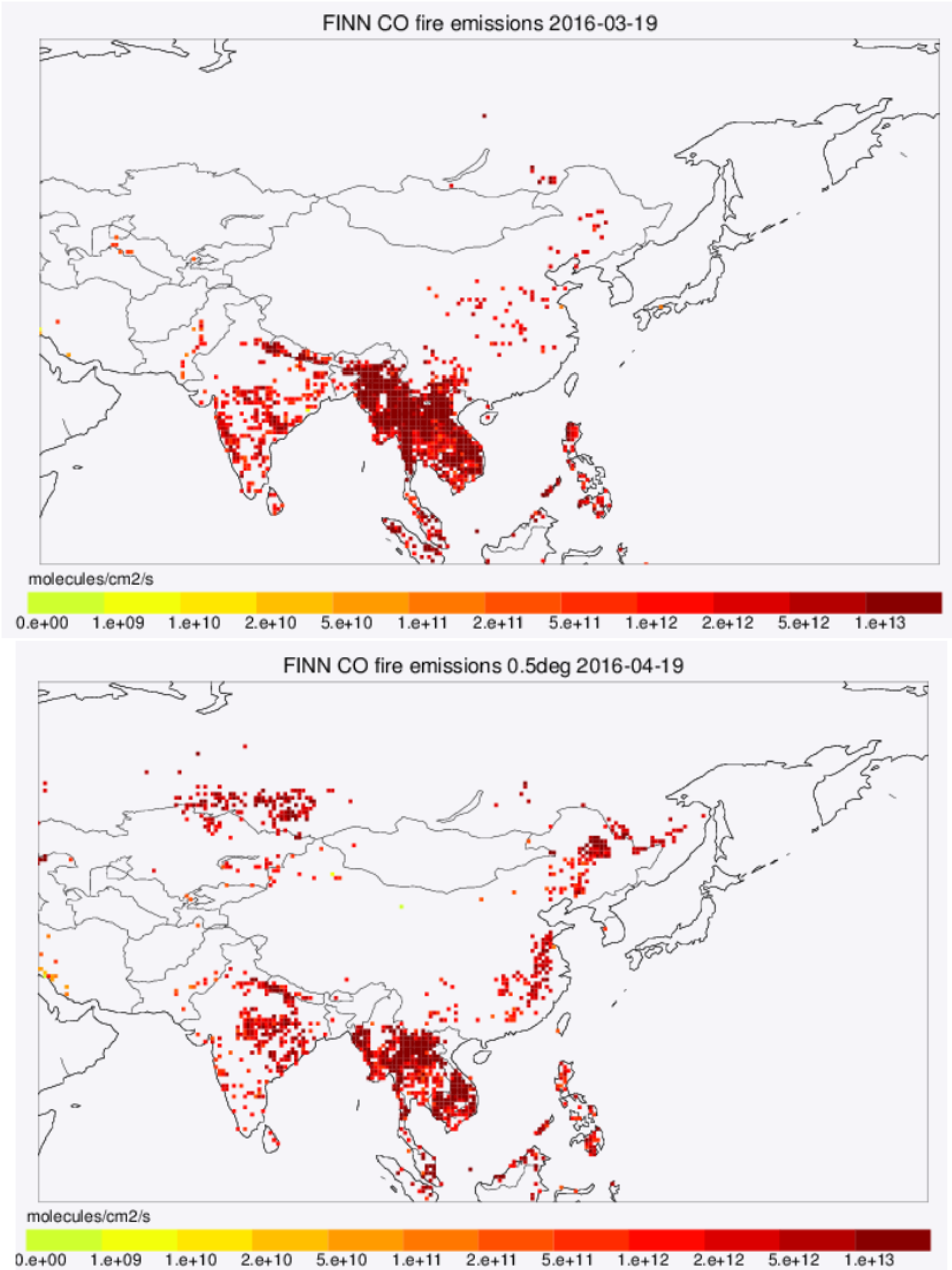


Figure 2.2 FINN emission inventory for Southeast Asia from 2016 Jan to 2016 April

2.2.3. Satellite images

This study applied remote sensing data as a complementary approach for the simulations of WRF Chem. Firstly, the monthly burned area maps from 2001 – 2018 within the buffer around HCMC 400km were derived from MCD64A1 product of MODIS, to create frequent burn area map during 18 years. MCD64A1 Version 6 Burned Area data product is a monthly, global gridded 500 meter (m) product containing per-pixel burned-area and quality information (L.Giglio et al, 2015) This is an upgraded one of the standard MODIS burned area product – MCD45A1, so it includes significantly better detection of small burns (L.Giglio et al, 2015).

In the next step, the frequent burned area map was compared with Land Cover map provided by MCD12Q1 product of MODIS. It is annual global land cover data with 500 m resolution. The primary land cover scheme identifies 17 classes defined by the International Geosphere-Biosphere Programme (IGBP), including 11 natural vegetation classes, three human-altered classes, and three non-vegetated classes (Friedl, M., 2019) The aim of this step is to understand on which land cover type that open fires mainly occur.

After the frequent burned area was disaggregated by land cover types, the monthly averages of fire radiative power (FRP) and aerosol optical depth (AOD) during 2001- 2018 were extracted for each burned regions to see their seasonal trend. FRP is defined as the rate of energy released per unit time and is measured in megawatts (Wooster, 2004). AOD is a measure of the columnar extinction of solar radiation by aerosols and an important optical parameter in estimation of aerosol concentration, evaluation of the level of atmospheric pollution. These inter annual patterns of FRP and AOD were compared with the monthly variation of AOD in HCMC to see how open fires from remote sources impact on local air quality in this city.

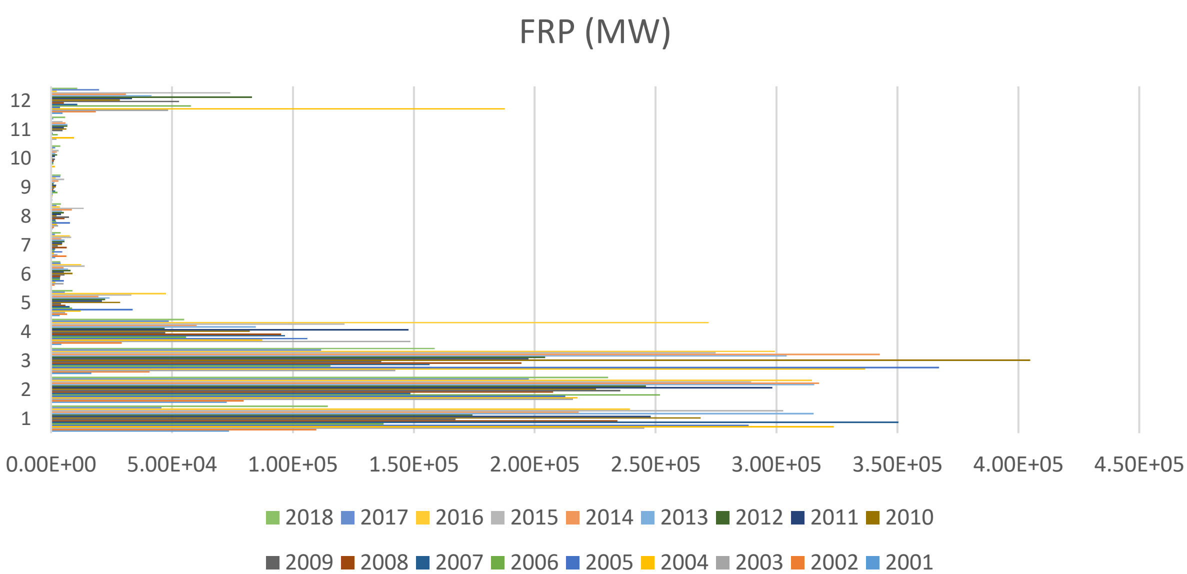
Monthly composite of FRP was derived from MOD14A2.006 from MODIS. Thermal Anomalies and Fire 8-Day (MOD14A2) Version 6 data are generated at 1 kilometer (km) spatial resolution as a Level 3 product. The MOD14A2 gridded composite contains the maximum value of the individual fire pixel classes detected during the eight days of acquisition (Giglio et al., 2003)

Monthly AOD was calculated from MCD19A2 product_MODIS. It applied Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm to create daily gridded Level 2 product with 1 kilometer (km) pixel resolution (Lyapustin, A., 2018). This provides blue band AOD at 0.47 µm, green band AOD at 0.55 µm, AOD model at 1km, AOD uncertainty and other layers.

2.3 Results and discussion

2.3.1 The contribution of biomass burning to air quality over study area according to WRF Chem simulations

Firstly, the seasonal trends of total active fires and FRP within buffer around HCMC 400km were achieved from MOD14A2 to define the time domain of WRF Chem simulation. According to Fig 2.3, it is apparently to see the strong monthly variation of BB in the region. FRP was highest during January-March months, pre monsoon season, during which 80.38% of total fires are recorded with the peak during March with 33.76% of fires, followed by February (24.1%), January (22.52%) and so on (Fig. 2.3). Further, averaged across the six years, February had the highest average FRP (226 487 MW) followed by January (214 271 MW), and March (211 379 MW), with the lowest FRP during October (1396 MW) This strong seasonal variation was related to the climate and weather events and human activities in the region. Our output is in line with other studies about BB in East Asia and South East Asia which implied during March and April, widespread agro-residue burning occurs across farmlands in Indochina (W.R.Huang et al, 2016) Being modeled by satellite images, BB emissions by FINN EI shows the similar pattern. As shown in Fig 2.2, CO emission from open fires, that estimated by FINN, gets intense and spreads out over Indochina peninsula and Thailand in Mar. Its magnitude drops significantly in Apr.



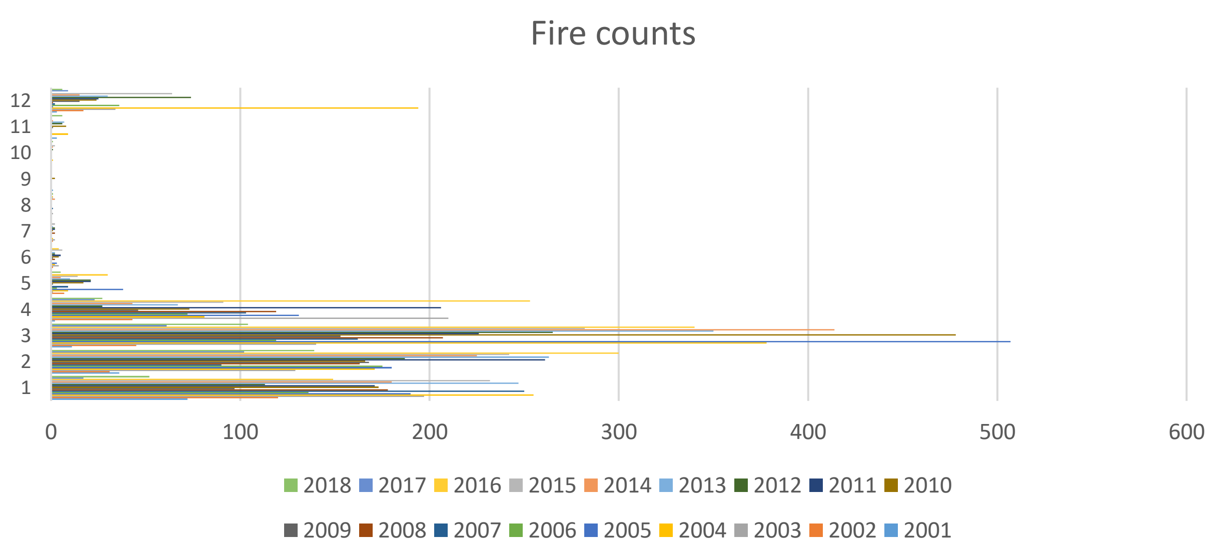
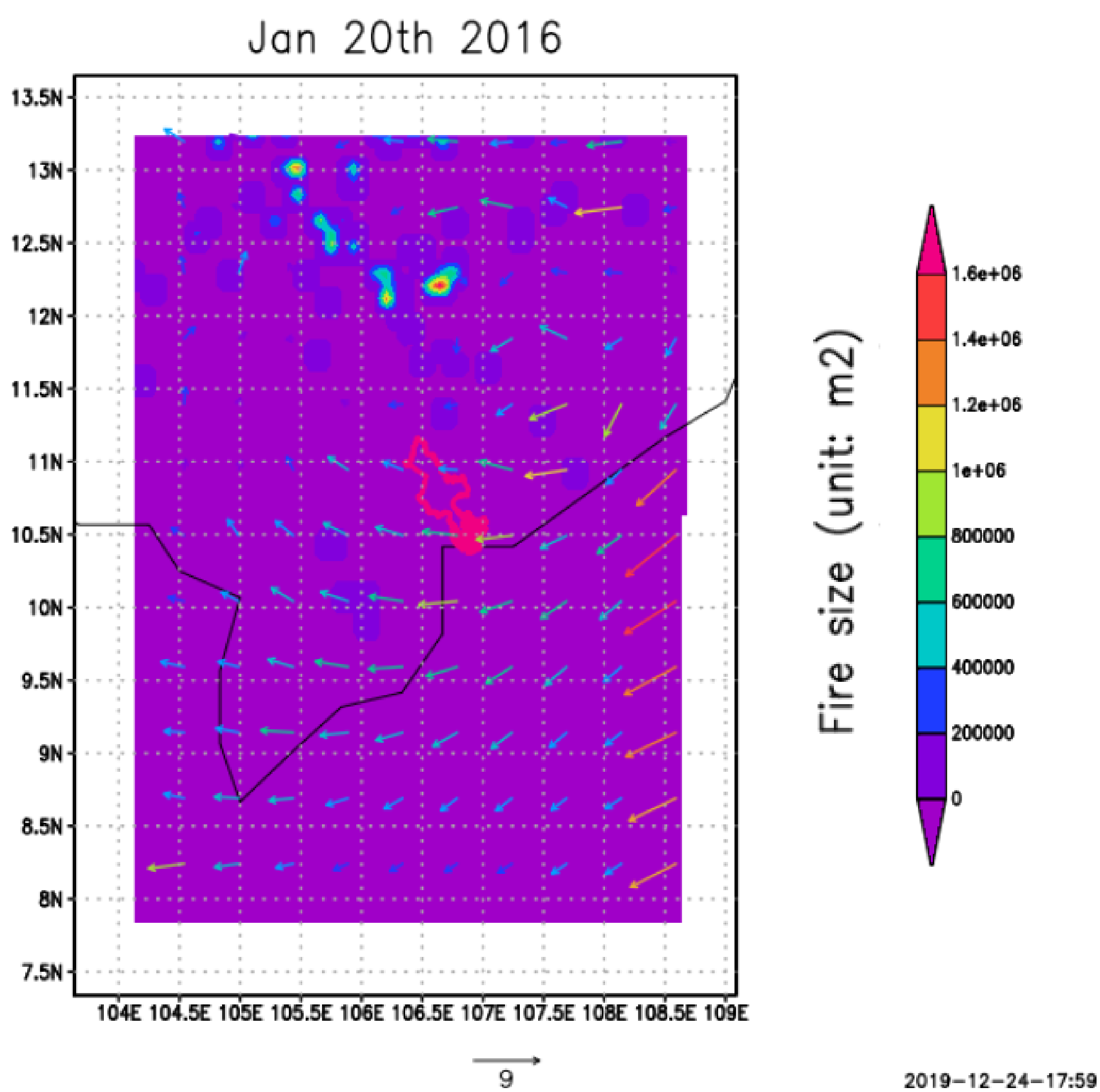
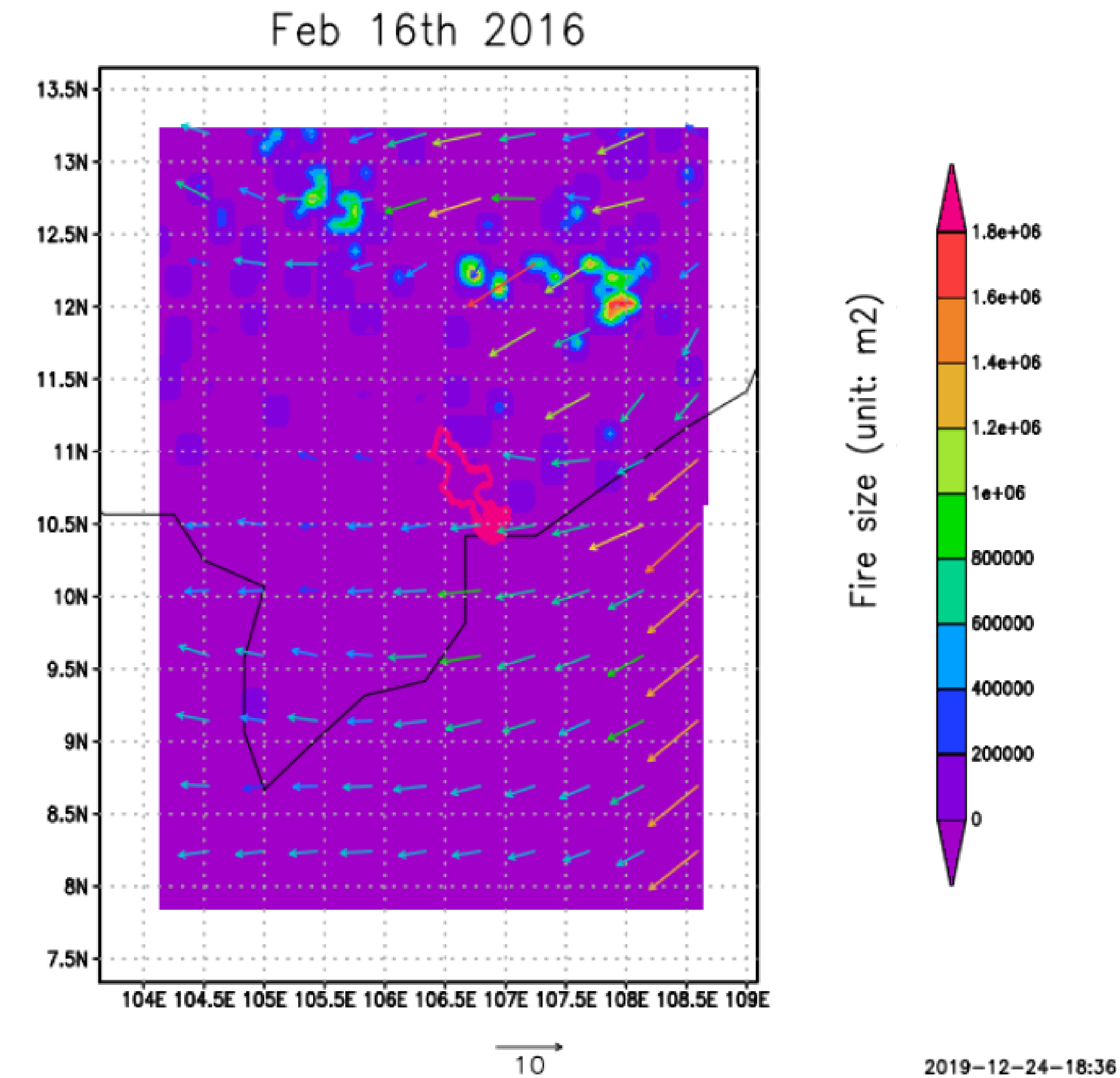


Figure 2.3. FRP and fire counts were highest during March-February months

Based on above MODIS data analysis, BB dominates in study area in pre monsoon season so we run WRF Chem from 2016 January to 2016 April with 1 day interval to see how BB contributes to air quality in this region. The long range transport of BB emission is mainly driven by meteorological factors like wind direction and Fig. 2.4 shows two opposite pictures of wind trajectory in this area. According to wind simulations of WRF Chem, Northeast winds (northeast monsoon) lasts until February, then it changes to Southeast winds from March to April. Therefore, open fire from the North only has change to contribute to air pollution in downwind region until February. As a result, hereafter we analysis the pollutant estimated by WRF Chem in January and February only. To see the impact of BB on HCMC air quality better, we used two points in our domain. A test point locates among open fires and a location point of meteorological station in HCMC (Fig 2.5) This station named Tan Son.




Feb 16th 2016
13.5N
13N
12.5N
12N
11.5N
11N
10.5N
10N
9.5N
9N
8.5N
8N
7.5N
104E 104.5E 105E 105.5E 106E 106.5E 107E 107.5E 108E 108.5E 109E
10
Fire size (unit: m2)
1.8e+06
1.6e+06
1.4e+06
1.2e+06
1e+06
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600000
400000
200000
0
2019-12-24-18:36

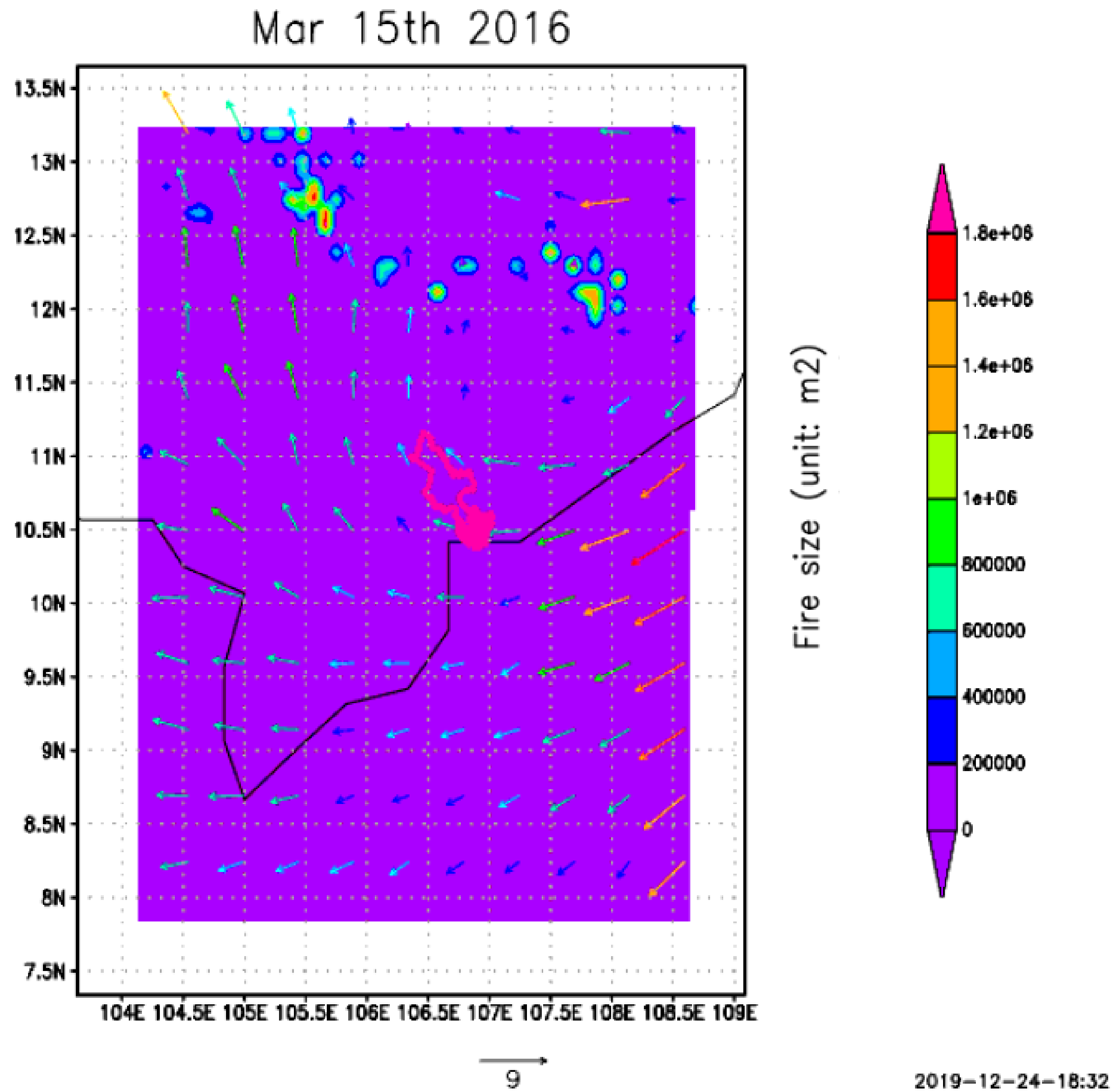


Figure 2.4 Prevailing wind speed simulated by WRF Chem in January, February and March

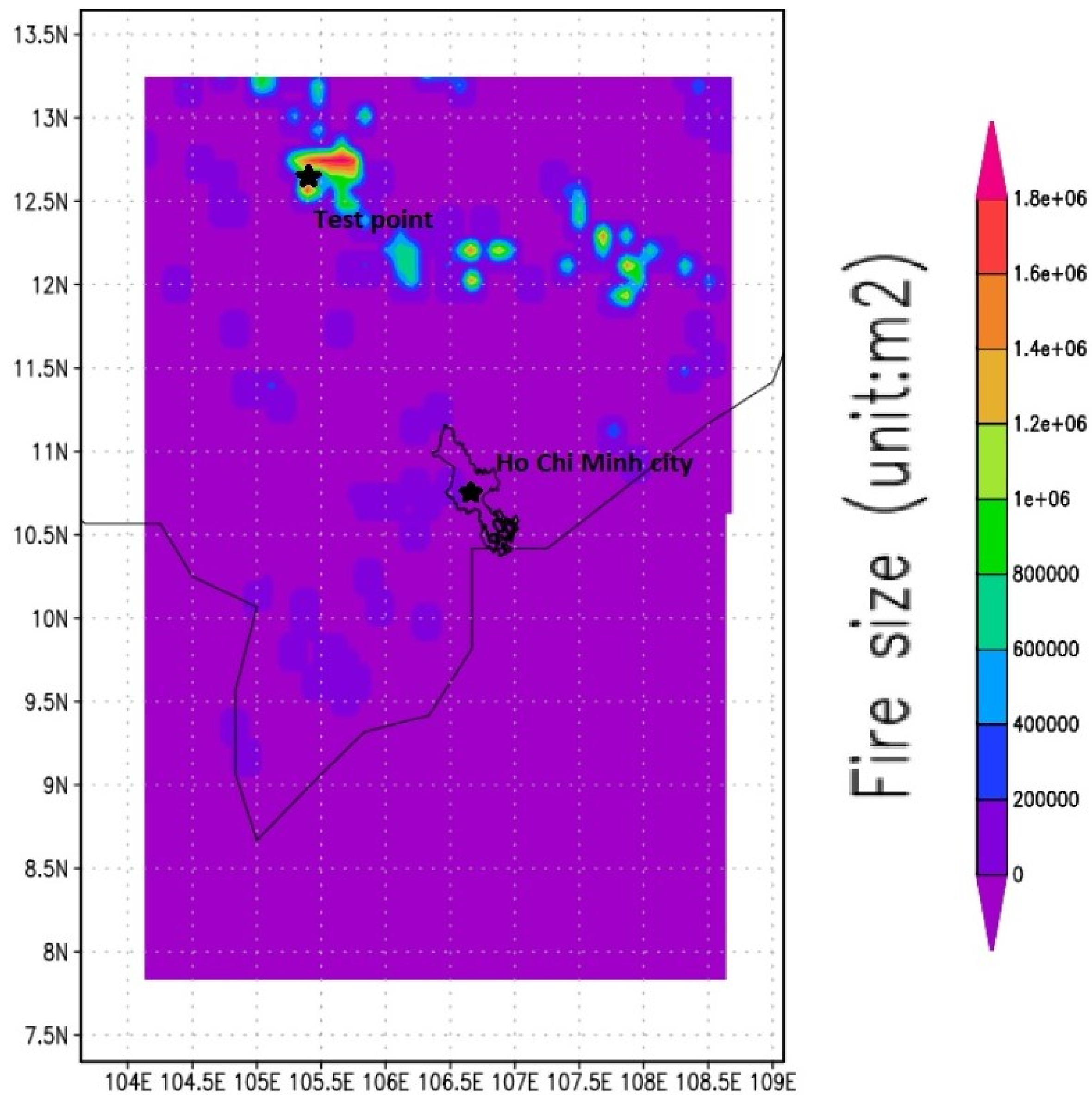
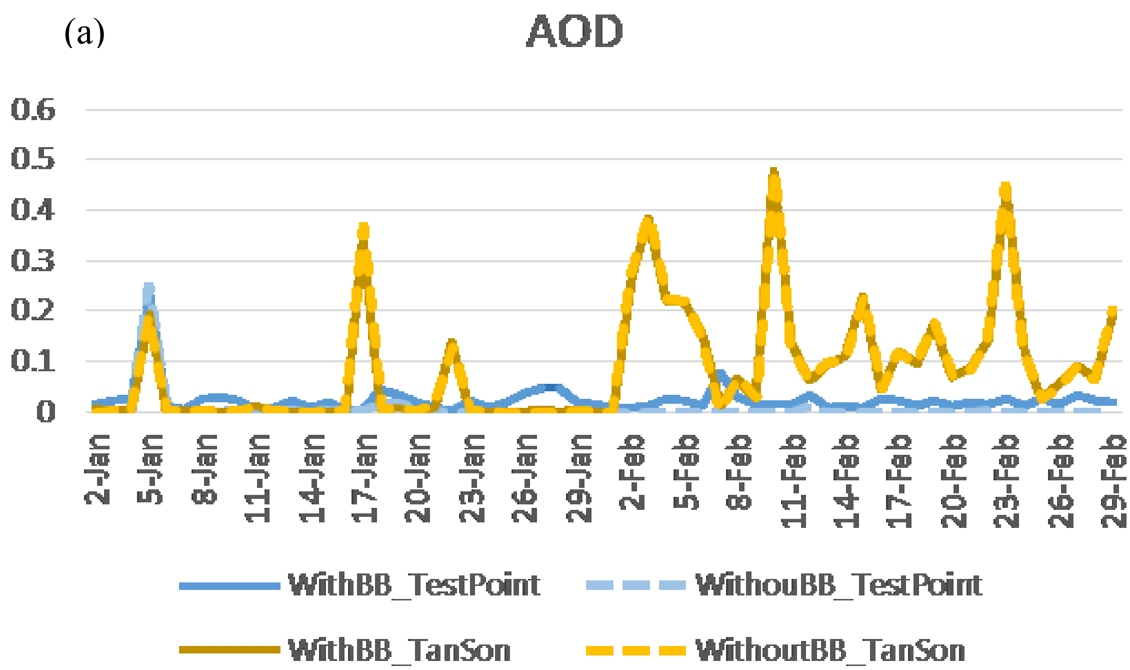


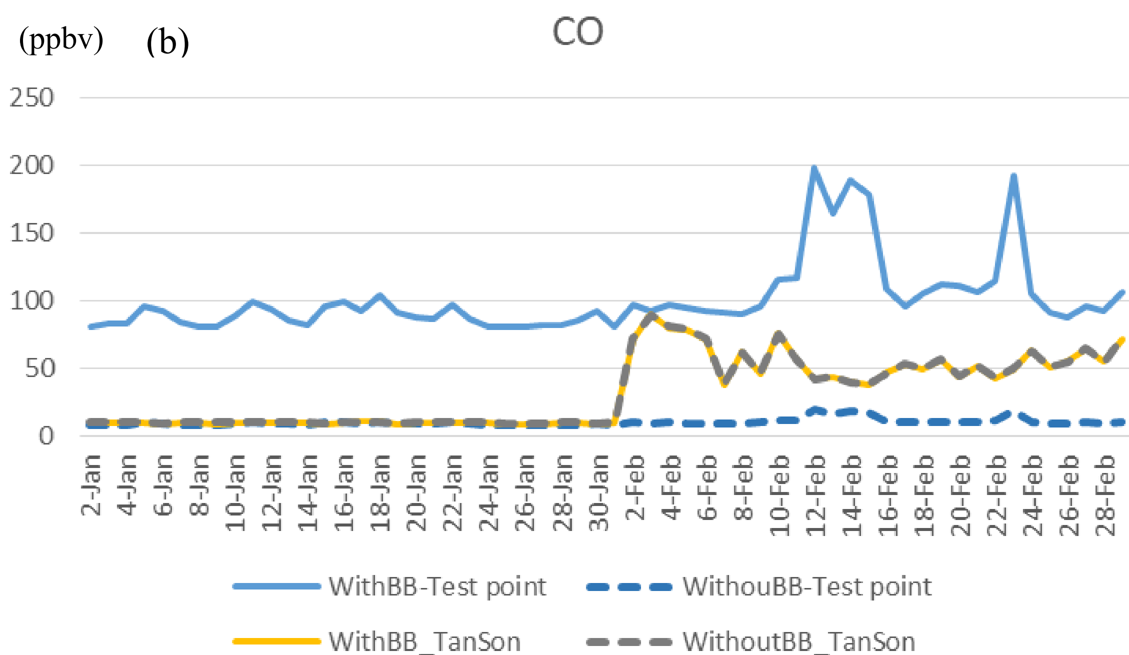
Figure 2.5 Locations of test point and Tan Son station that were used to analysis the impact of BB emission

Fig 2.6 shows the simulated daily AOD, CO, NO2 and SO2 concentrations at two chosen points, equivalent with two running options of WRF Chem. As can be seen, there is virtually no contribution of open fire to NO2 and SO2 concentrations in both survey points. The significant discrepancy between With and Without BB option is only seen for CO, in test point. In February, quite high level of CO (almost 200 ppb) was recorded at test point, revealing the big gap with CO concentration in TanSon station (the peak value around 10 ppb) Also, very small impact on AOD value in test point was shown. It makes sense because among 4 pollution species, CO is directly emitted from incomplete combustion such as biomass burning and fossil fuel use. With a lifetime of several months, CO can be used to track local and regional air pollution, biomass burning and oxidation processes (Weinstock, 1969; Edwards et al., 2006). Besides, the difference in pollution levels between two locations can be seen also. The urban point – TanSon expresses much higher and fluctuated AOD, SO_2 and NO_2 concentration, implying that it located in pollution hot spot.

(a)



(ppbv) (b)



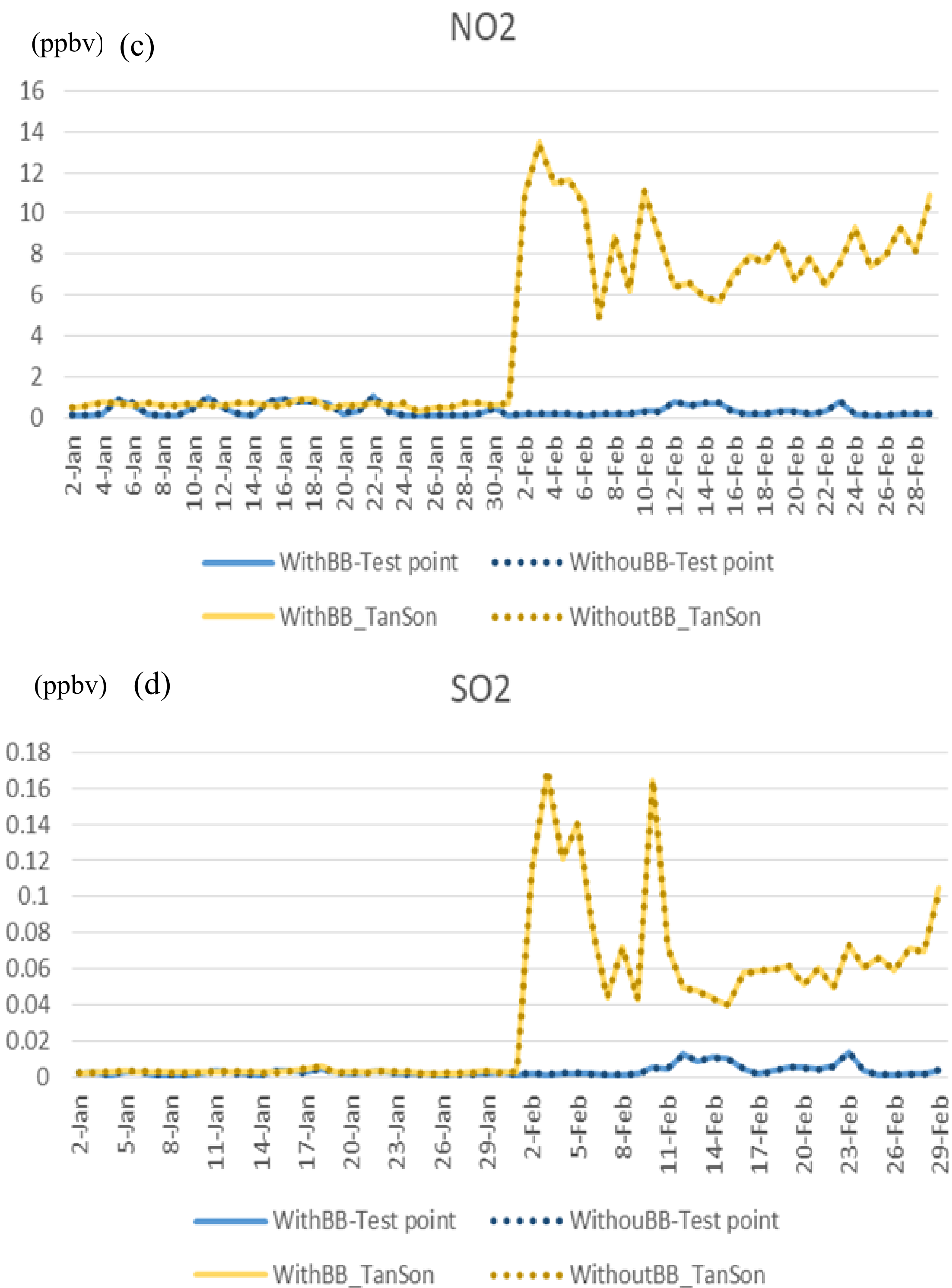


Figure 2.6 Simulated daily (a) AOD, (b) CO, (c) NO2, (d) SO2 concentrations at test point and Tan Son station in January and February, with two options: With BB (with Biomass burning emission) and Without BB (without Biomass burning emission)

To validate the outputs of WRF-Chem, the simulated AOD value is compared with AOD provided by a AERONET station that is located in our domain (Fig. 2.7). The model mainly underestimated the ground truth observations and missed the high values of AOD observed on Feb 4th and Feb 24th. In addition to that, the temporal variation of AOD estimated by WRF Chem does not show the agreement with trend of AOD values provided by AERONET station.

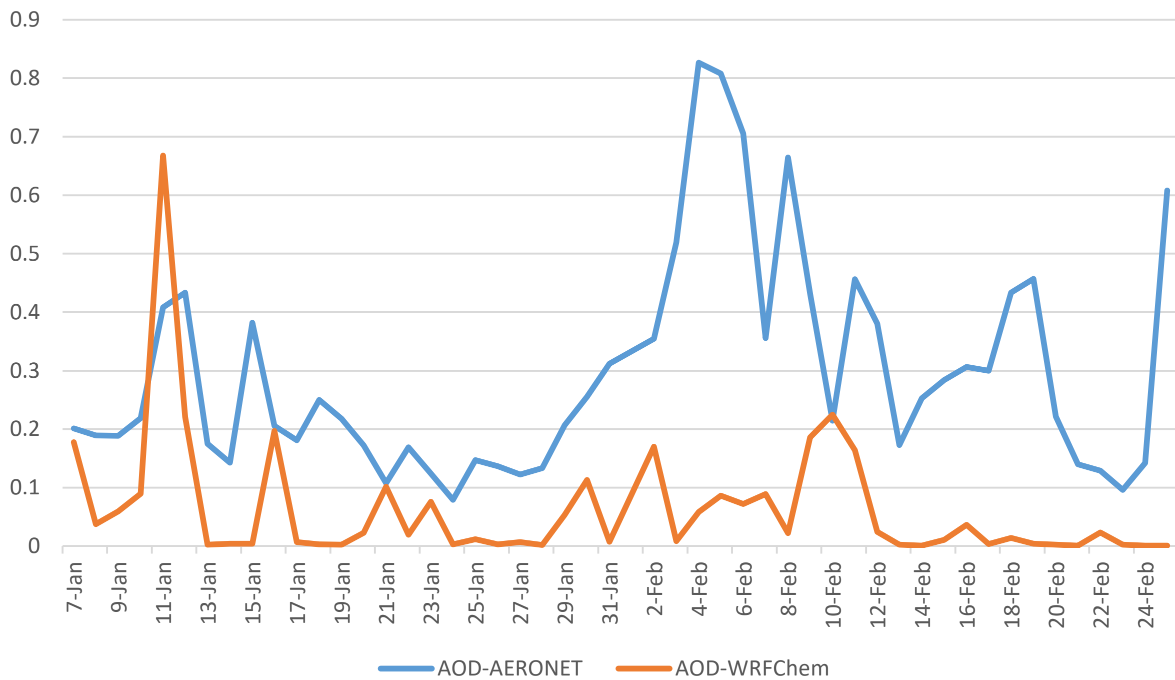


Figure 2.7 Simulated AOD from WRF Chem, in compare with AOD from AERONET and MODIS data

Regarding the spatial distribution of AOD, Fig 2.8 depicts the comparison between WRF Chem modeled AOD and AOD-product of MODIS at the 550 nm wavelength. According to the mean composite of AOD in Feb, 2016 from MCD19A2-MODIS, high levels of aerosol optical thickness were recorded in HCMC, the Southwestern area – cropland and area around Phnom Penh, Cambodia. However, AOD simulations of WRF Chem in both two options: With and Without BB emission were not able to capture the spatially concentrated high level of AOD. The hot spot of pollution was shifted to the South, cropland area, and spread around. The elevated values of aerosol load in urban areas like HCMC or Phnom Penh were missed.

To find the root of these shortcomings, the underestimation of AOD in compare with AERONET measurements and the spatial mismatch with MODIS data, the input data of WRF Chem was checked. As mentioned before, apart from BB emission inventory – FINN, my simulation applied EDGAR-HTAP v2 as global anthropogenic emission inventory. HTAP_V2 dataset consists of 0.1degx0.1deg grid maps (left bottom corner centered) of CH4, CO, SO2, NOx, NMVOC, NH3, PM10, PM2.5, BC and OC for the years 2008 and 2010 (G. Janssens-Maenhout et al, 2015) Fig 2.9 reveals the spatial distribution of PM2.5 emission extracted from HTAP. It is clear to see that the spreading polluted area is coincident with AOD simulations from WRF Chem shown in Fig

2.8. In fact, HTAPv2 applied population data map from Gridded Population of the World (GPW) v3 for its spatial allocation (Fig 2.9 bottom). GPW map could not distinguish HCMC as a densely populated area, so it is likely to be the reason of poor performance of WRF Chem AOD simulations. Besides, the lower AOD level estimated by WRF Chem can be originated from the shortcoming of emission inventories, also. HTAP inventory was modeled with global scale, and updated till 2010. Over 6 year duration (from 2010 to 2016), the increasing trend of anthropogenic activities definitely caused the remarked change in emission. Consequently, the inaccuracy and shortage of its emission calculated for my domain is expected. In fact, when applied in chemical transport modeling, the uncertainties in emission estimation would inevitably lead to gaps in air quality simulation, besides the errors of meteorological field modeling and deficiencies of built-in atmospheric chemical mechanisms. Once again, it proved that, as the key input of chemical transport modeling, improved emission inventories, particularly at regional or local scales, become important for both scientific air quality simulation and effective policy-making, especially for dynamic area like HCMC.

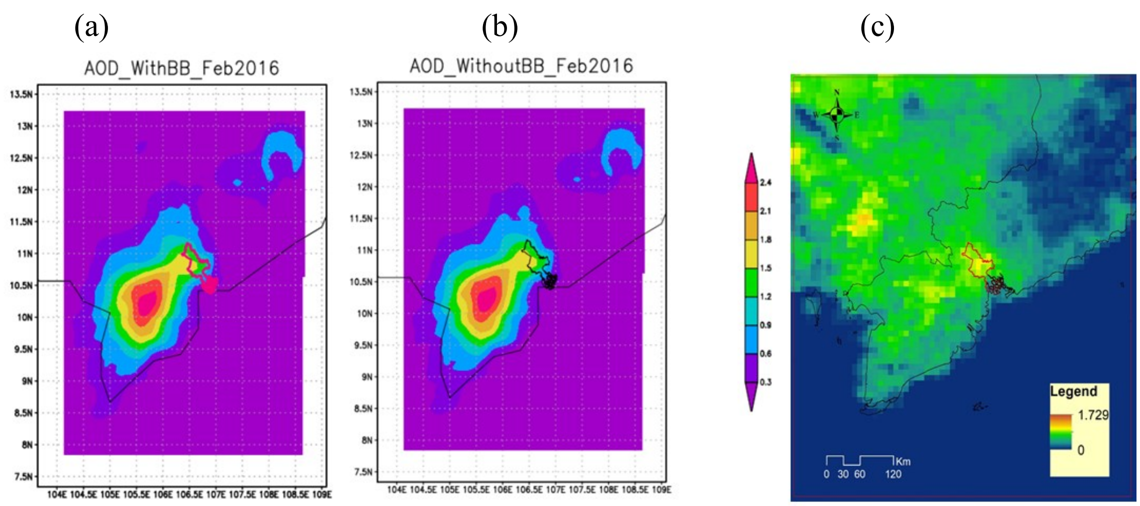
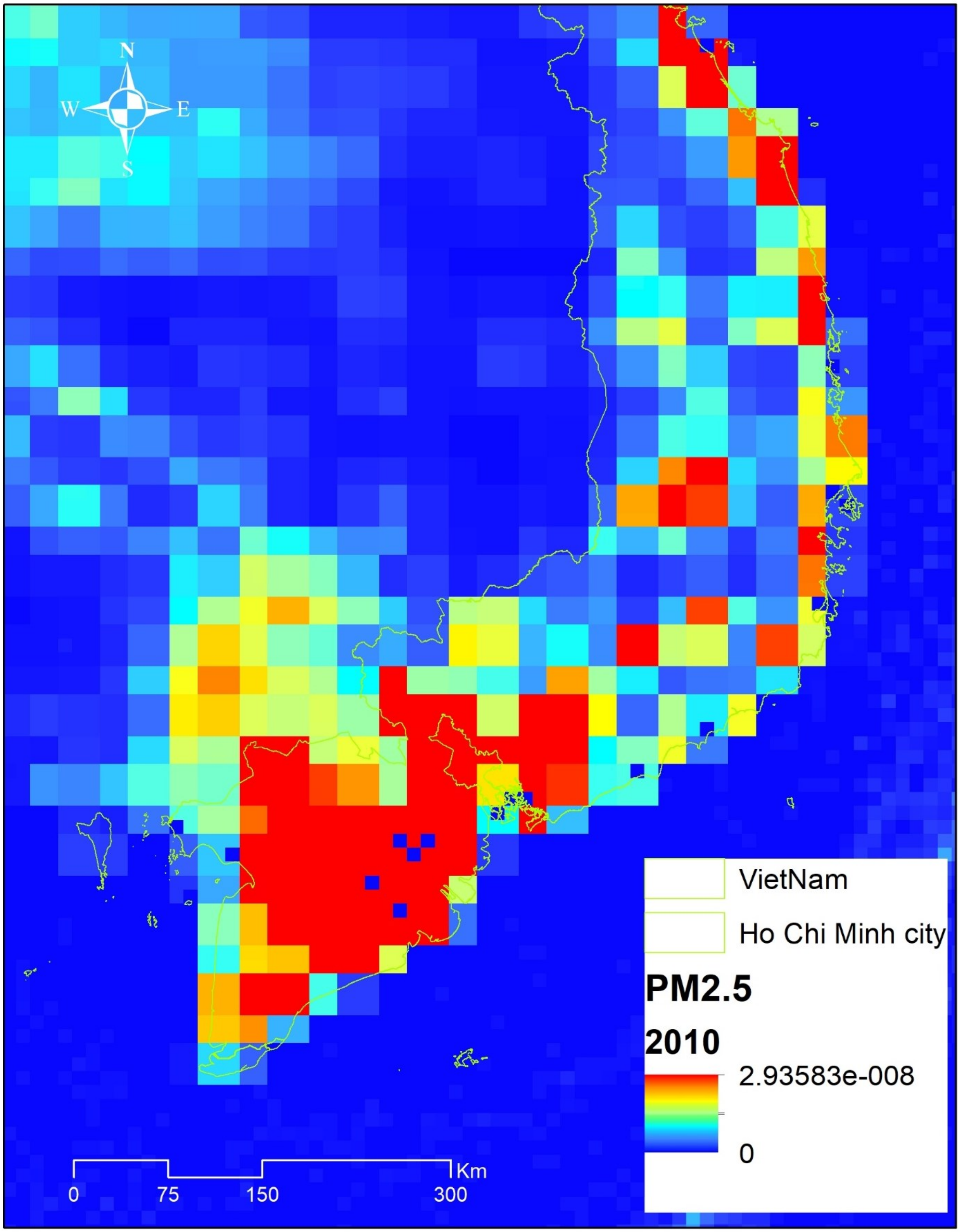


Figure 2.8 Average aerosol optical depth (AOD) at 550 nm deduced from (a) simulated with biomass-burning emission (b) without biomass-burning emission and (c) the MODIS satellite data in February, 2016.


N
W
E
S
VietNam
Ho Chi Minh city
PM2.5
2010
2.93583e-008
0
0
75
150
300
Km

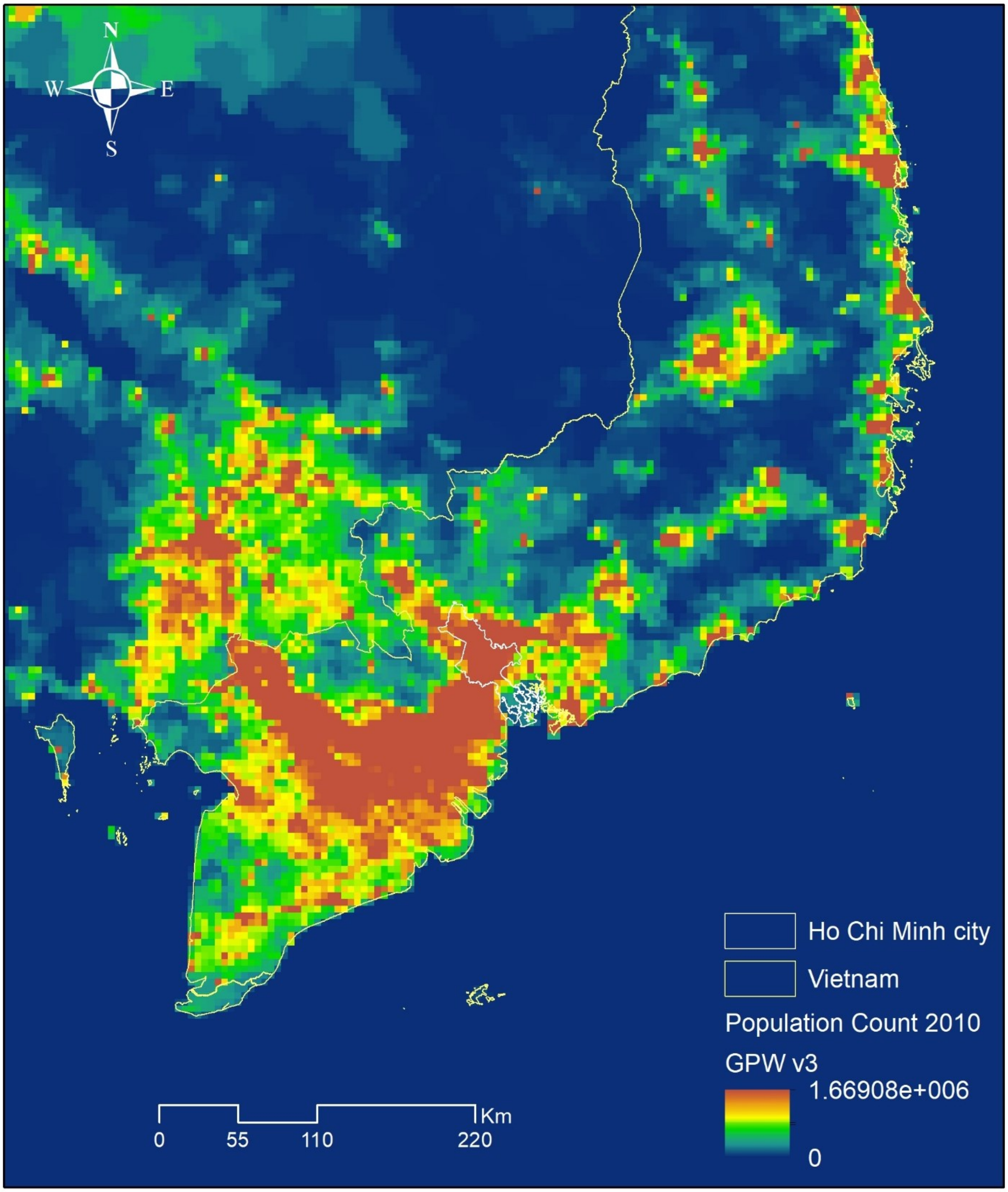


Figure 2.9 PM2.5 emission in 2010 from HTAP v2 emission inventory (top) and Population data in 2010 from GPW v3 data that was applied for spatial allocation of emission in HTAP (bottom)

2.3.2. The contribution of biomass burning to air quality over study area according to satellite images analysis

Because of the shortcoming of WRF Chem simulations, the satellite images analysis was considered as a complementary approach. Firstly, the question where the open fires have come from should be addressed. Fig 2.10 shows the frequent burned area around HCMC within 18 years. Comparing with Land cover map from MODIS MCD12Q1, we can see that active fires mainly occur on Savanna and Crop land area. The Savanna region belongs to Cambodia. The Cropland region is Mekong delta, located in the South of HCMC. In compare with Fire size maps provided by FINN emission inventory (Fig 2.4), it is obvious that FINN omitted the BB in cropland area. As mentioned before, the classification of agricultural fires is difficult for satellite images due to the tendency of these fires to be small and their intensity is lower than natural fire. Therefore, it explained for the drawback of WRF Chem simulation that applied FINN emission inventory as input.

MODIS fire counts were aggregated based on Land use/land cover types from MODIS MCD12Q1, yearly L3 Global 500m product, supporting the statement about fire activities occurring primarily on savannas and crop land (Fig 2.11) On average, savannas open fires are associated with 25 to 80% of total fire counts, followed by crop land. However, the fire events in cropland are likely to be underestimated by MODIS. Because this satellite has the potential to miss a significant number of smaller fires (e.g. Hawbaker et al., 2008, Burling et al, 2011, Yokelson et al., 2011), as well as to miss fires obstructed by clouds and those located in the gaps between MODIS swaths in the tropics (Hyer et al., 2009; Wang et al., 2018)

In the following part, the FRP and AOD trends will be analyzed for burned area – Savanna and burned area – Crop land separately. From Fig 2.12, it is conspicuous that BB starts from Dec to Mar of next year in Savanna area. The mean FRP sharply increases to over 200 MW in Jan then drops quickly by around 150 MW afterward. However, the seasonal variation of AOD within this area shows revert trend. Mar is when the peaks of AOD (about 0.35 in terms of mean value) was often observed every year. From Apr, the air quality here gets better gradually then AOD substantially falls in Dec and Jan. According to this, BB emission shows quite little impact on pollution level in this region. The elevated aerosol optical thickness must be caused by other sources.

The FRP recorded by MODIS within Cropland shows much lower intensity and quite different trend from the ones in Savanna (Fig 2.13) The highest FRP values are found in Mar and Apr, around 20MW, almost 10 times smaller than FRP peak in Savanna. Moreover, monthly AOD values expresses the clear bimodal trend. One peak happens in Mar, Apr, coincident with FRP, another slumped months are Aug, Sept. Dec and Jan are when AOD drops significantly. Meanwhile, the monthly mean of AOD in HCMC demonstrates not so clear seasonal trend (Fig. 2.14) AOD in all 12 months are over 0.28, the maximum values are around 0.35 in Mar and Sept. This AOD shows quite poor correlations with FRP in both Savanna and Cropland, implying the modest contribution of open fires in these two areas on local air quality (Fig 2.15) On the other hand, AOD in HCMC seems to follow the bimodal trend with AOD in cropland area (Fig 2.16) So, the situations in these two regions can be driven by the same emission source. The peak of

FRP in Cropland in Mar and Apr is likely to be a rationale of high AOD level during these two months, but how is about the second peak of AOD in Aug and Sept?

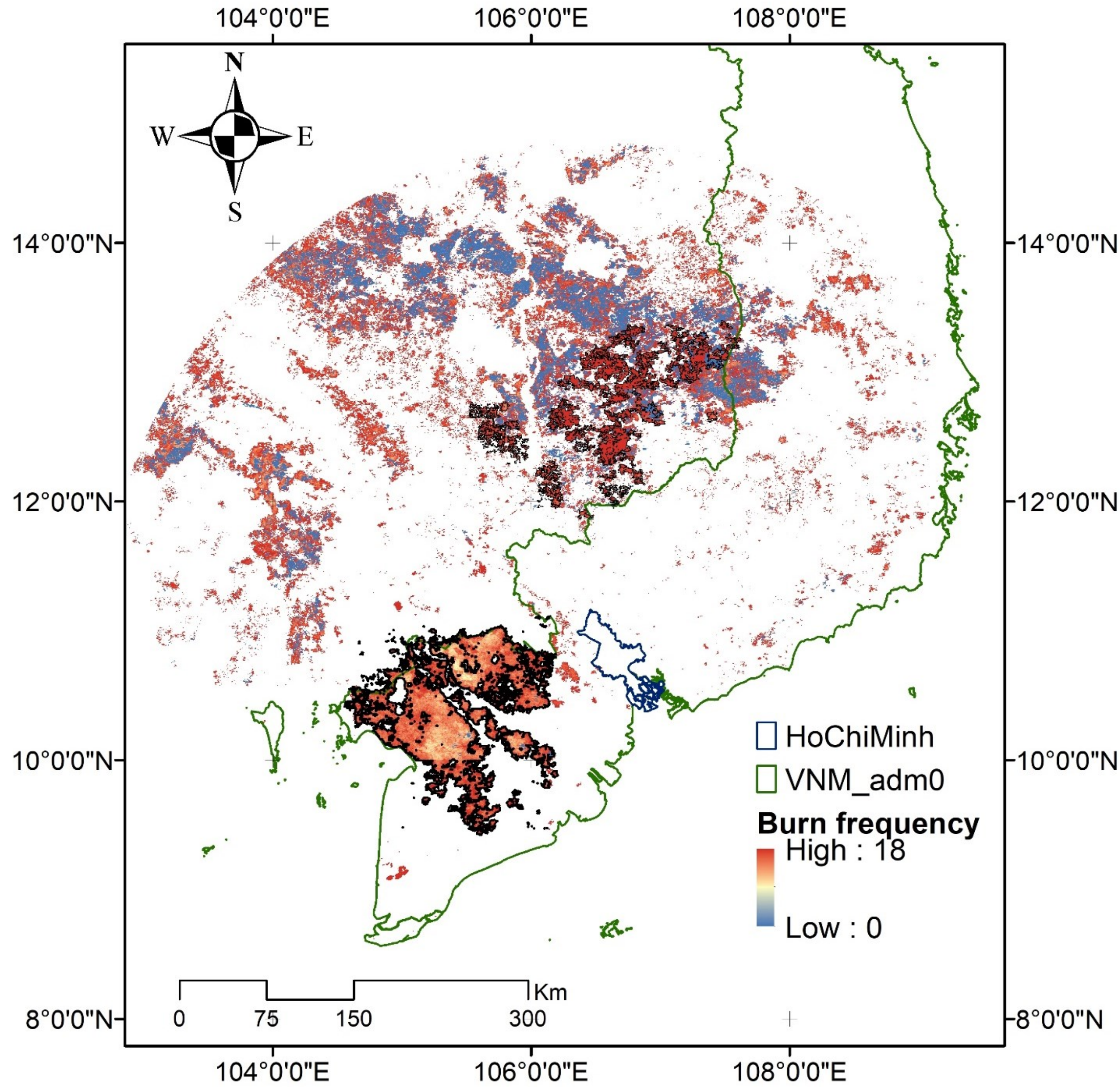


Figure 2.10 Burn frequency map from MCD64A1, MODIS.

Firstly, the bimodal trend is clearer in Cropland area and the source must be located in this area or closer to this area than HCMC. Aug and Sept are southwest monsoon season in Southeast Asia (SEA) area. During these months, biomass burning gets dominated in Kalimantan and Sumatra, Indonesia (Makiko Nakata et al, 2018) So one extreme fire event occurred in this area was chosen to check the impact on air quality of the Southern part of Vietnam. Fig 2.17 shows the dispersion of plume from severe forest fires in October, 2015 in Indonesia. These maps provided by https://worldview.earthdata.nasa.gov/ showed the locations of fires quite clear. At the same time, the CO image from Aqua/AIRS satellite that day and monthly AOT image from MERRA-2 reveals the impacted region of this peak event. The haze did not cover my study domain. To support this statement, the wind trajectory frequencies that originated from this area (forward trajectories) (Fig 2.18 top) and the wind direction was likely to transport pollution to HCMC (backward trajectories) (Fig 2.18 bottom) were checked by NOAA HYSPLIT model. It is obvious that the wind reaching the south of Vietnam originated from the Southeastern China, passing by South China Sea. Meanwhile, prevailing wind from forest fire hot spots in Indonesia did not pass by Vietnam, making BB smoke becomes unfavorable for the transport to my study area. So the impact of BB in Sumatra and Kalimantan in southwest monsoon season on the elevated AOD level in Cropland area and HCMC rarely happens.

The second cause can be the omitting agricultural burns of MODIS satellite in rainy season. According to Justice et al., 2002, monitoring small-holder agricultural fires and resulting emissions is difficult mainly due to the ephemeral nature of agricultural fires, combined with timing of satellite overpass, small flaming fire size, and cloud cover obstructing observations. Fig 2.19 demonstrates the monthly composite of cloud coverage for MOD14A2 (from 2001-2018) over my study area. Because of rainy season, the cloud cover percentage is quite high from Jul to Sept, making the obstruction the small fires from agriculture. And FRP data from MODIS can underestimate the BB emission during these months. This is in line with pervious study of K.Lasko, 2018 (Fig 2.20) Cloud fraction is 25-30% higher than dry season during two harvest seasons in Mekong River Delta (May and Aug).

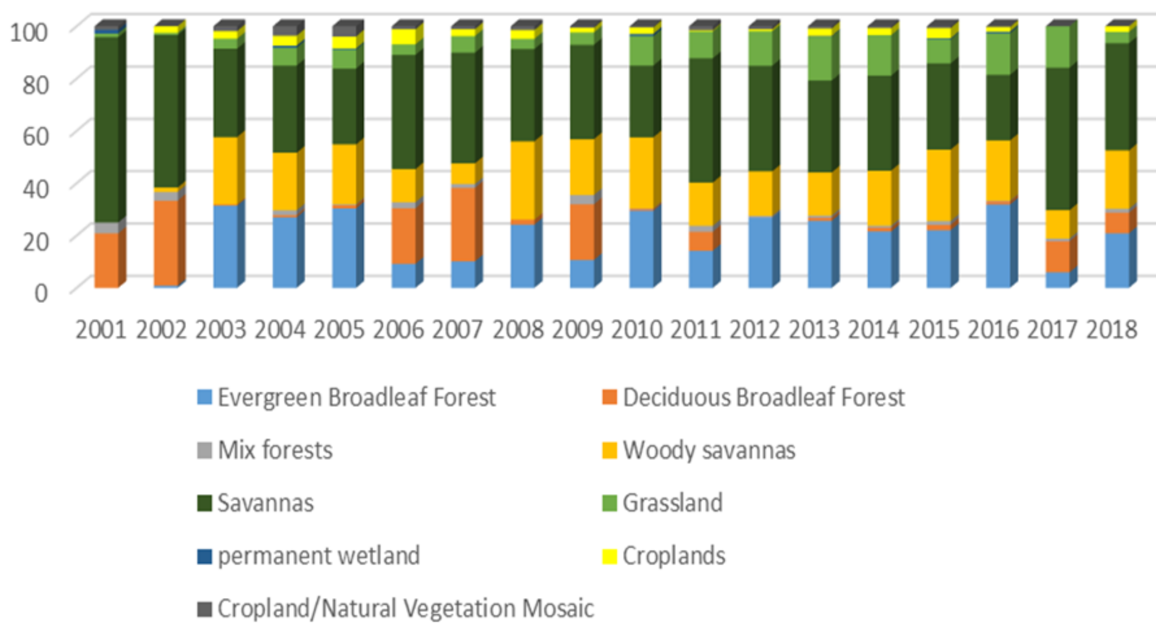
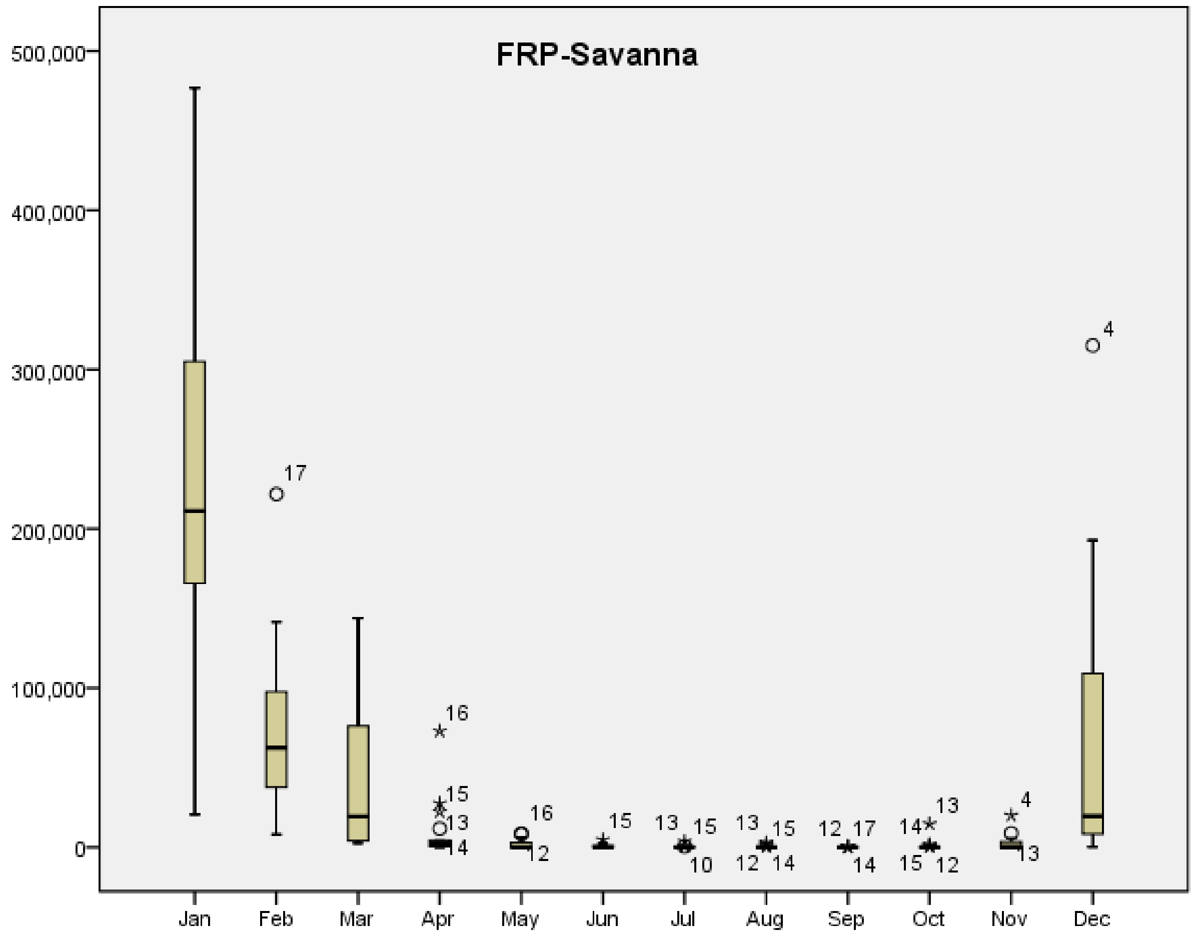


Figure 2.11. MODIS fire counts aggregated based on Land use/land cover types (provided by MCD12Q1) from 2001 to 2018.


FRP-Savanna
500,000
400,000
300,000
200,000
100,000
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
17
16
15
13
4
16
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15
12
4
13
4

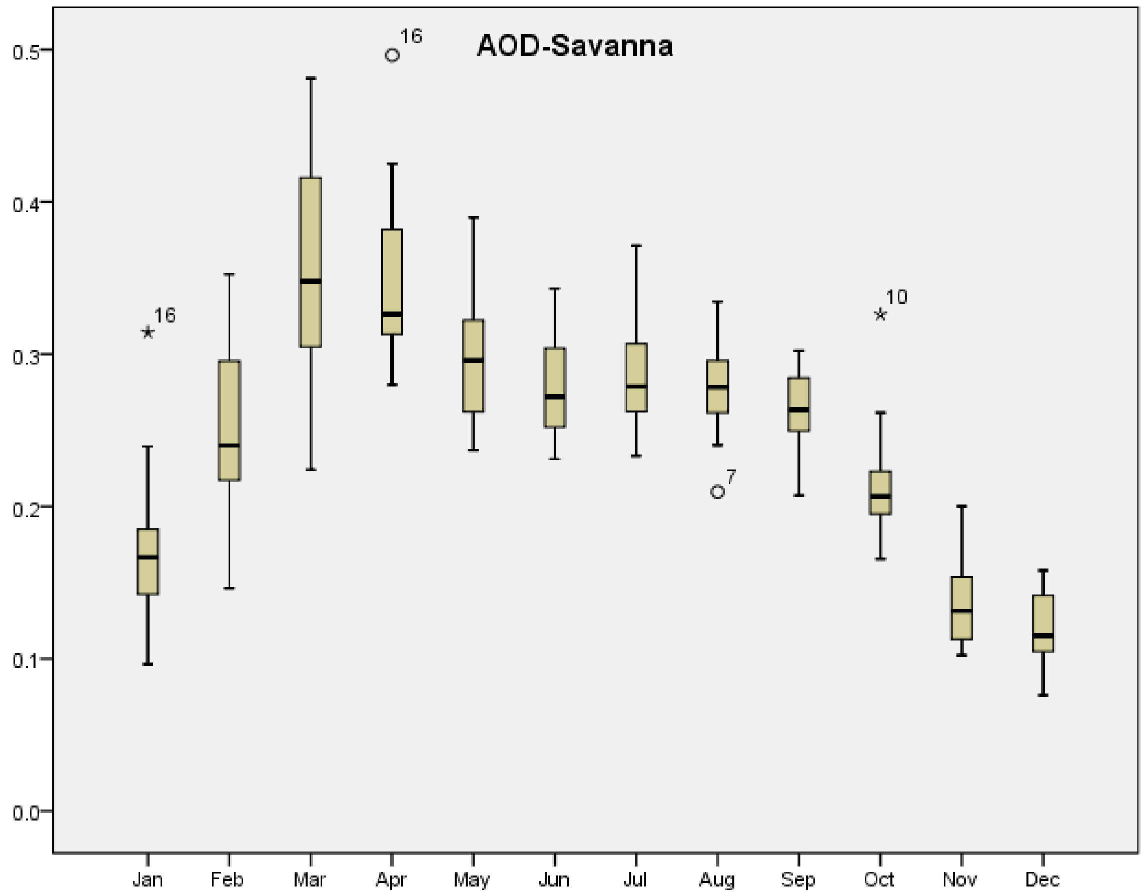
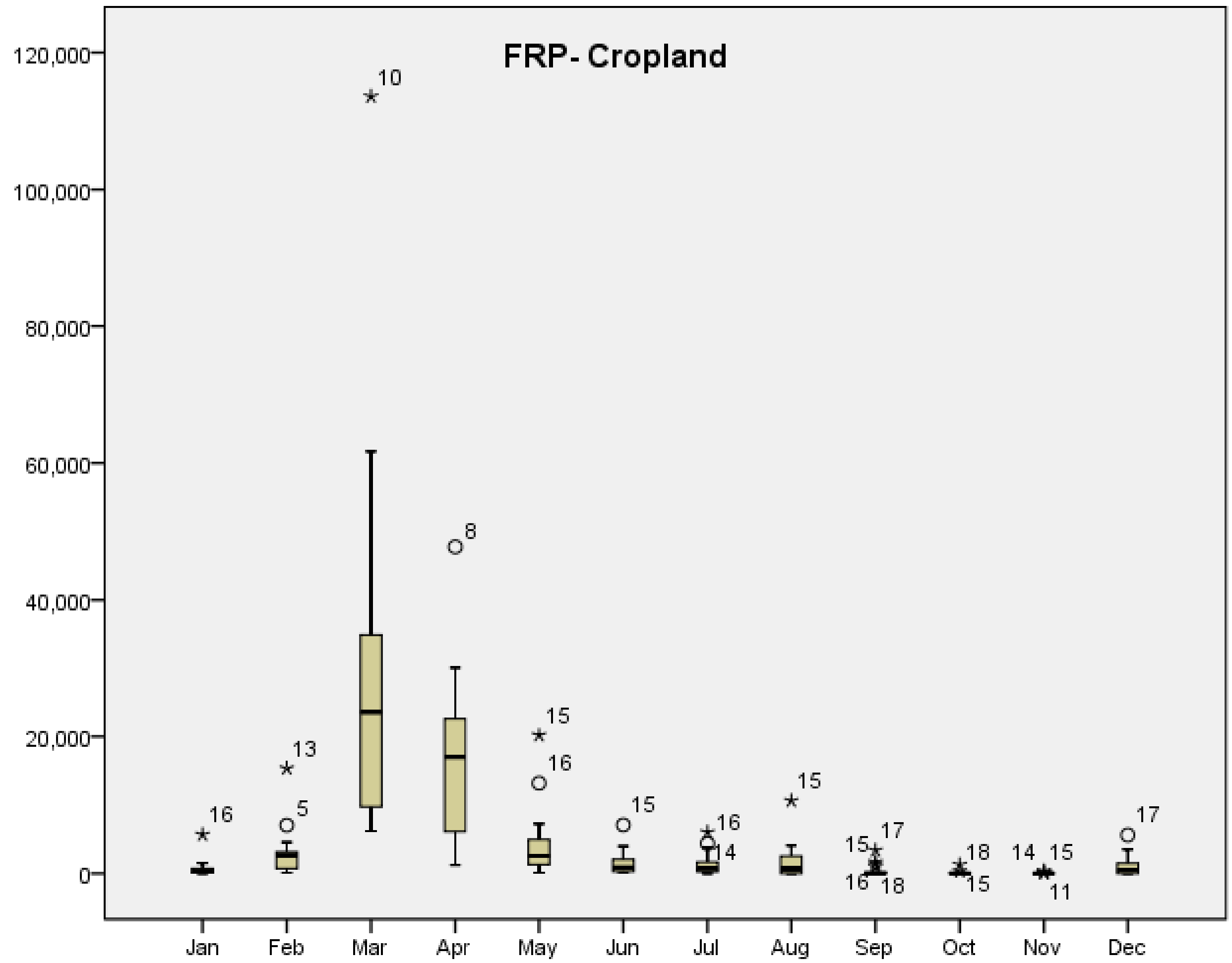


Figure 2.12. Monthly composite of FRP during 2001- 2018 from MODIS MOD14A2 and monthly mean of AOD from MODIS MCD19A2 within savanna area.


FRP- Cropland
120,000
100,000
80,000
60,000
40,000
20,000
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
10
8
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11
17

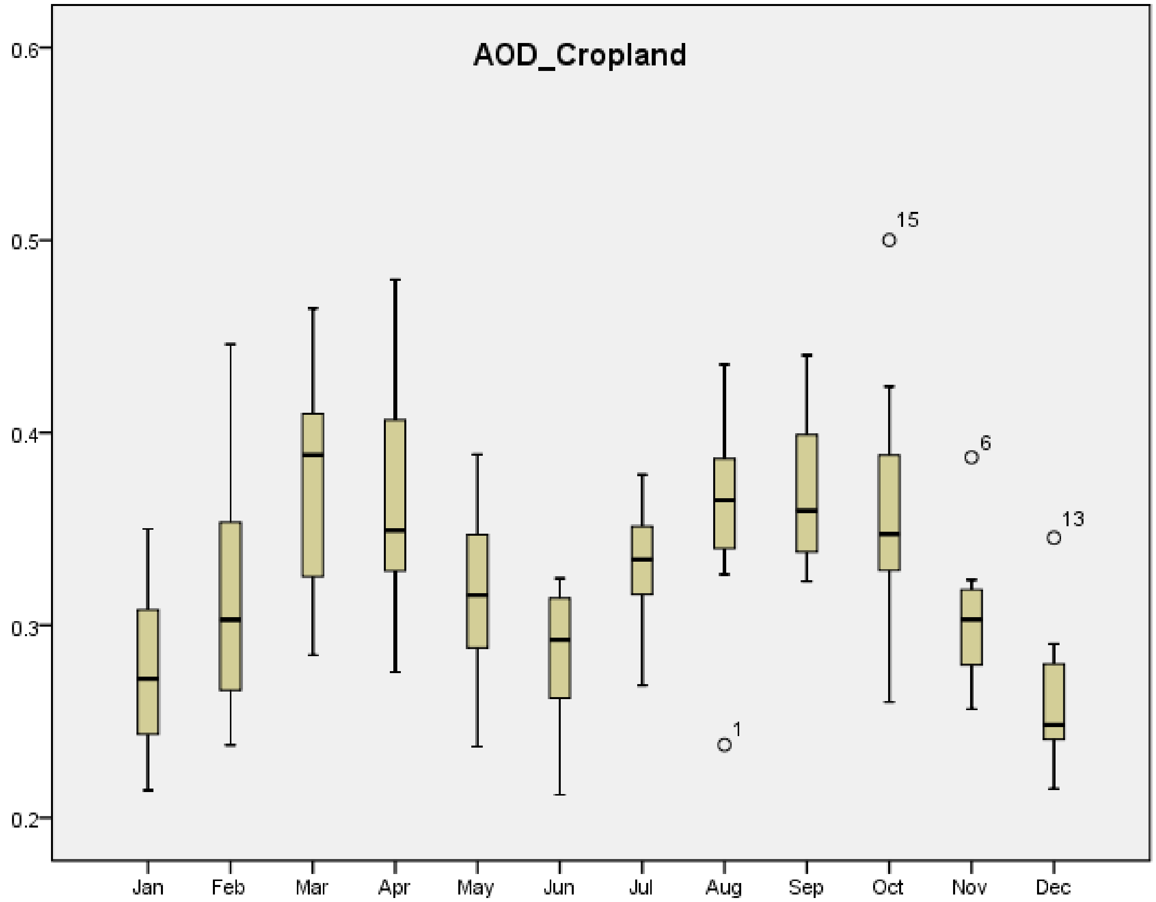


Figure 2.13. Monthly composite of FRP during 2001- 2018 from MODIS MOD14A2 and monthly mean of AOD from MODIS MCD19A2 within cropland area.

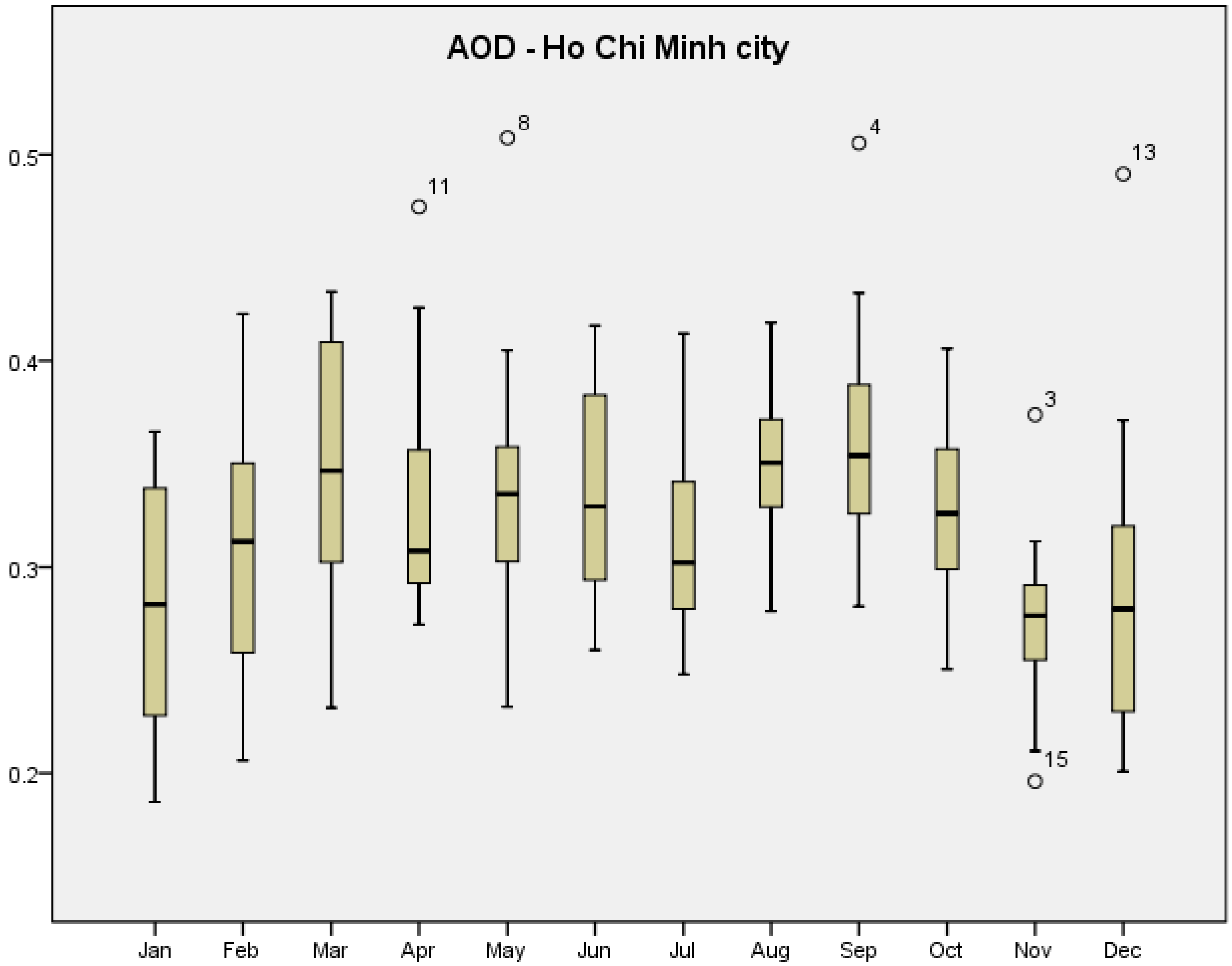
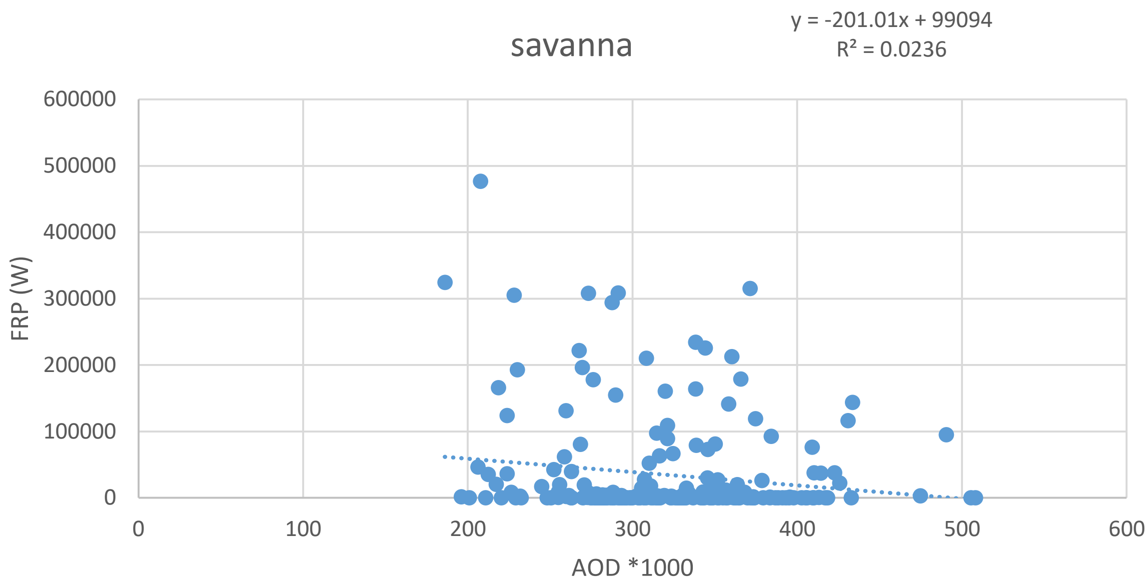


Figure 2.14. Monthly mean of AOD from MODIS MCD19A2 within HCMC.



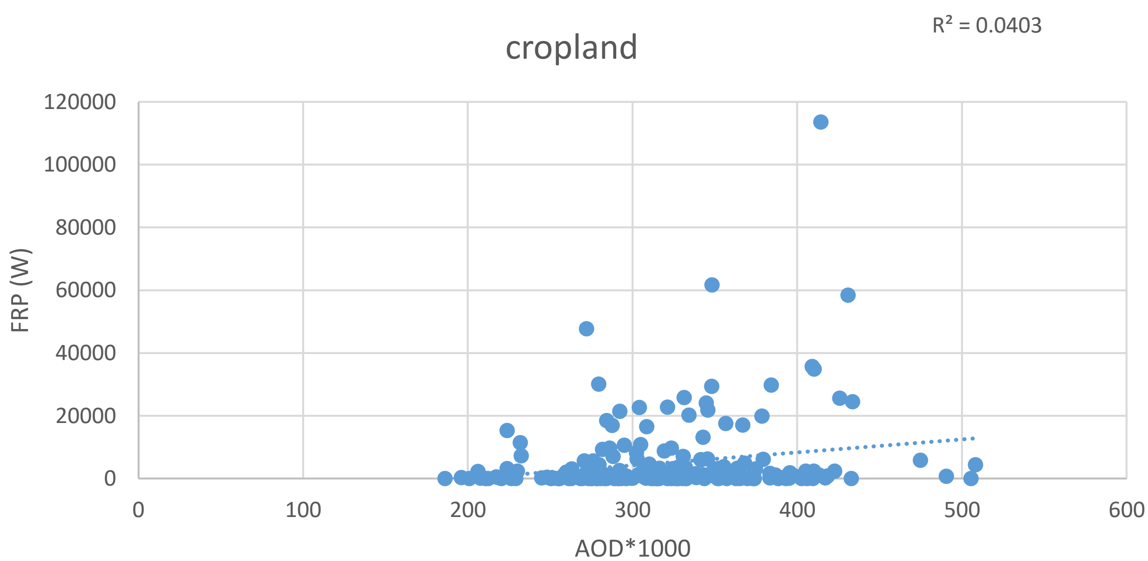


Figure 2.15. Correlations between FRP in Savanna and Cropland with AOD in HCMC.

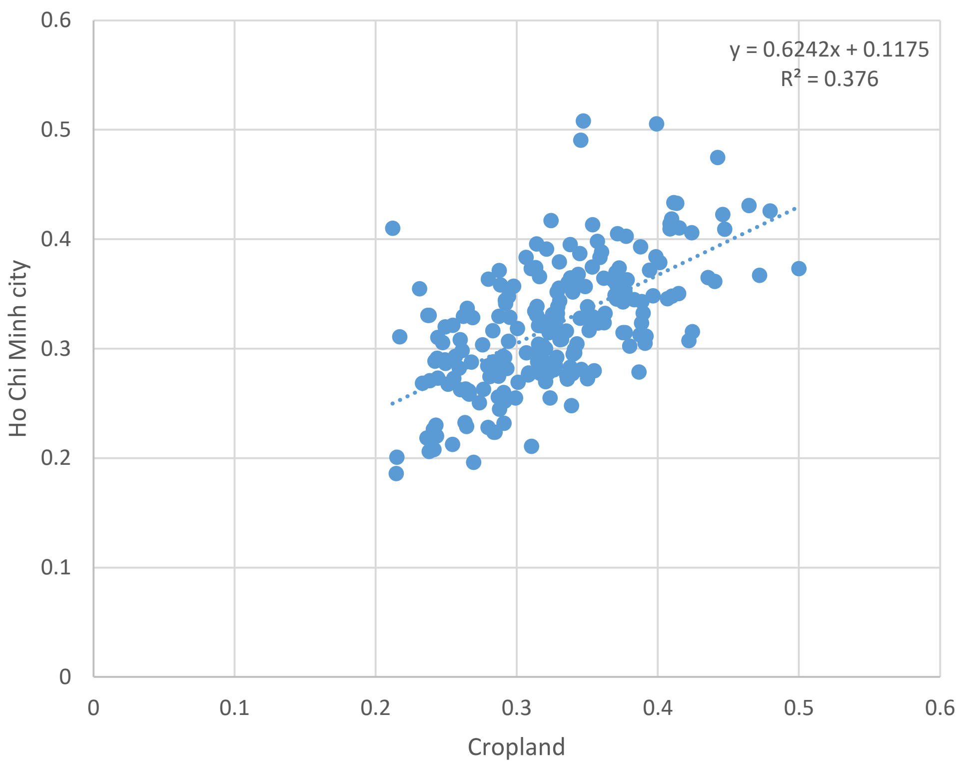
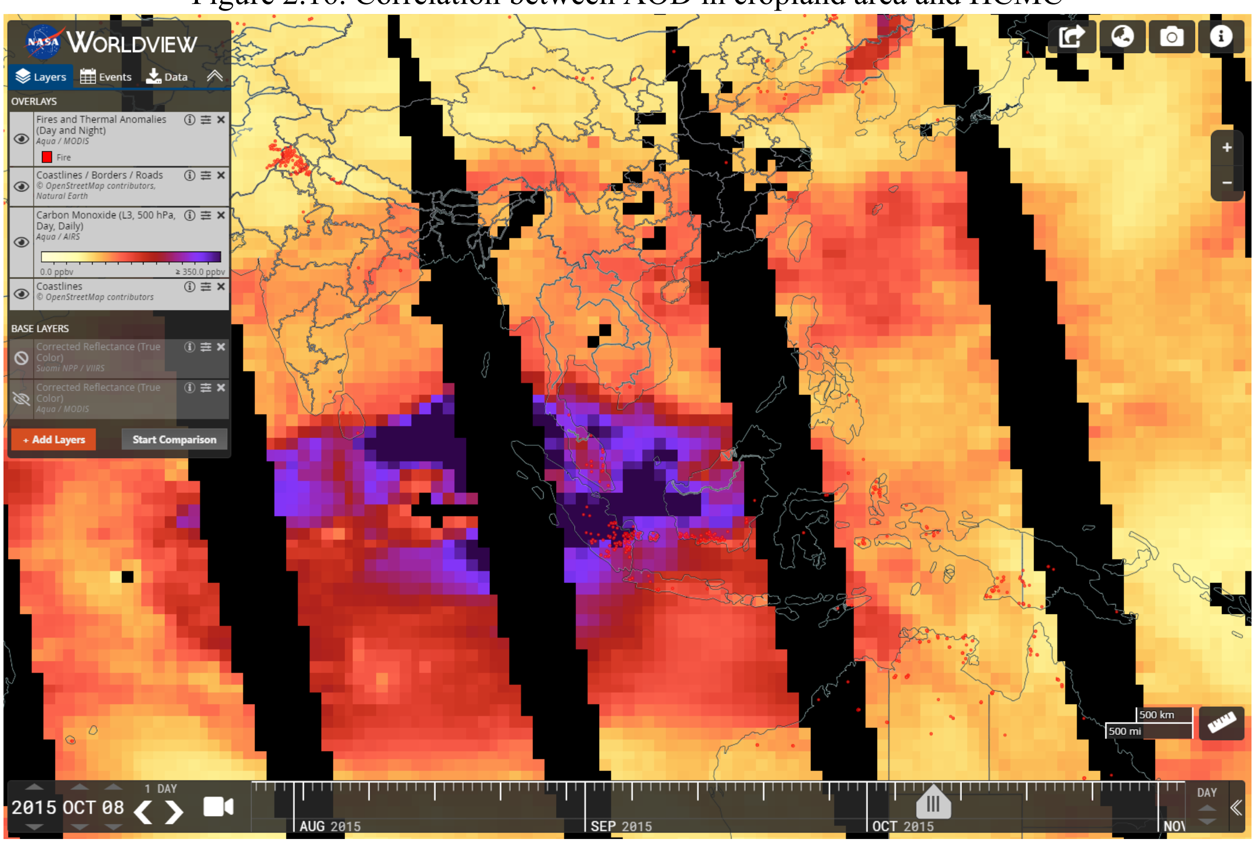


Figure 2.16. Correlation between AOD in cropland area and HCMC



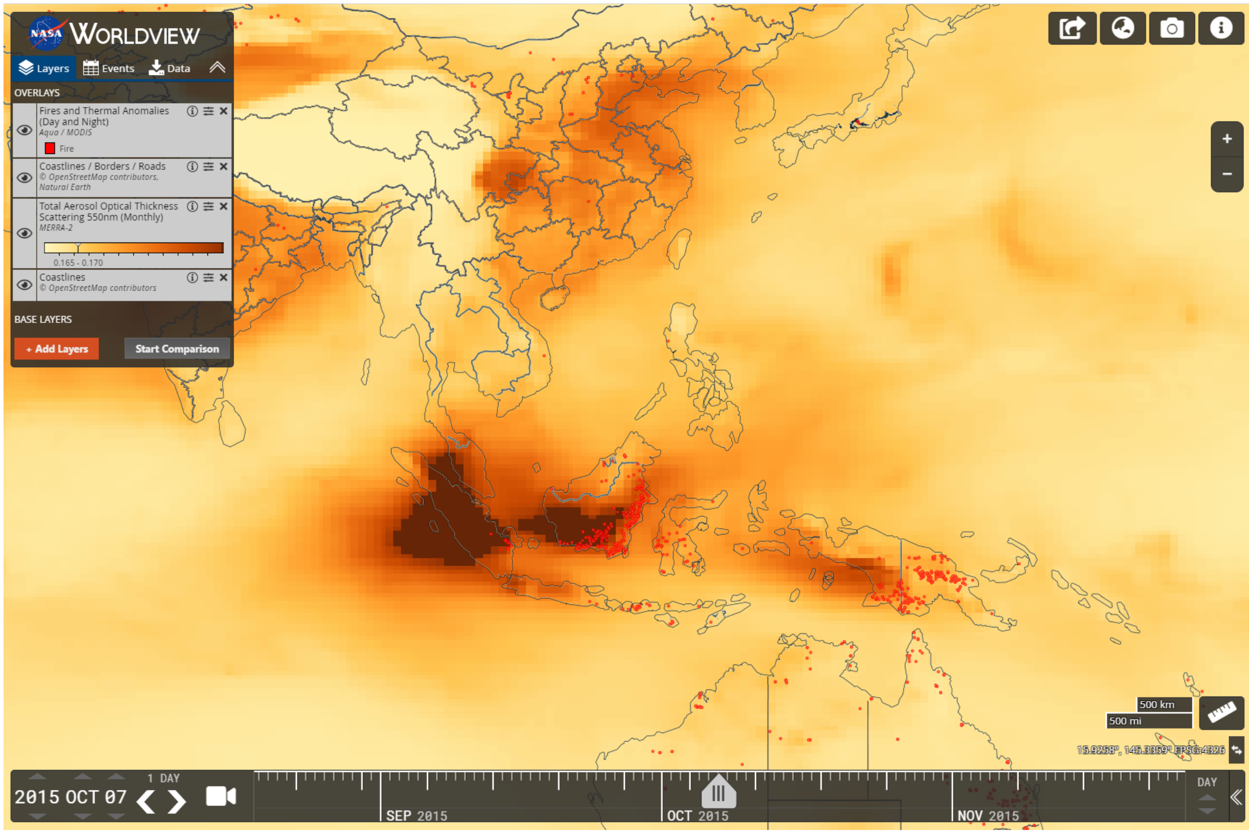
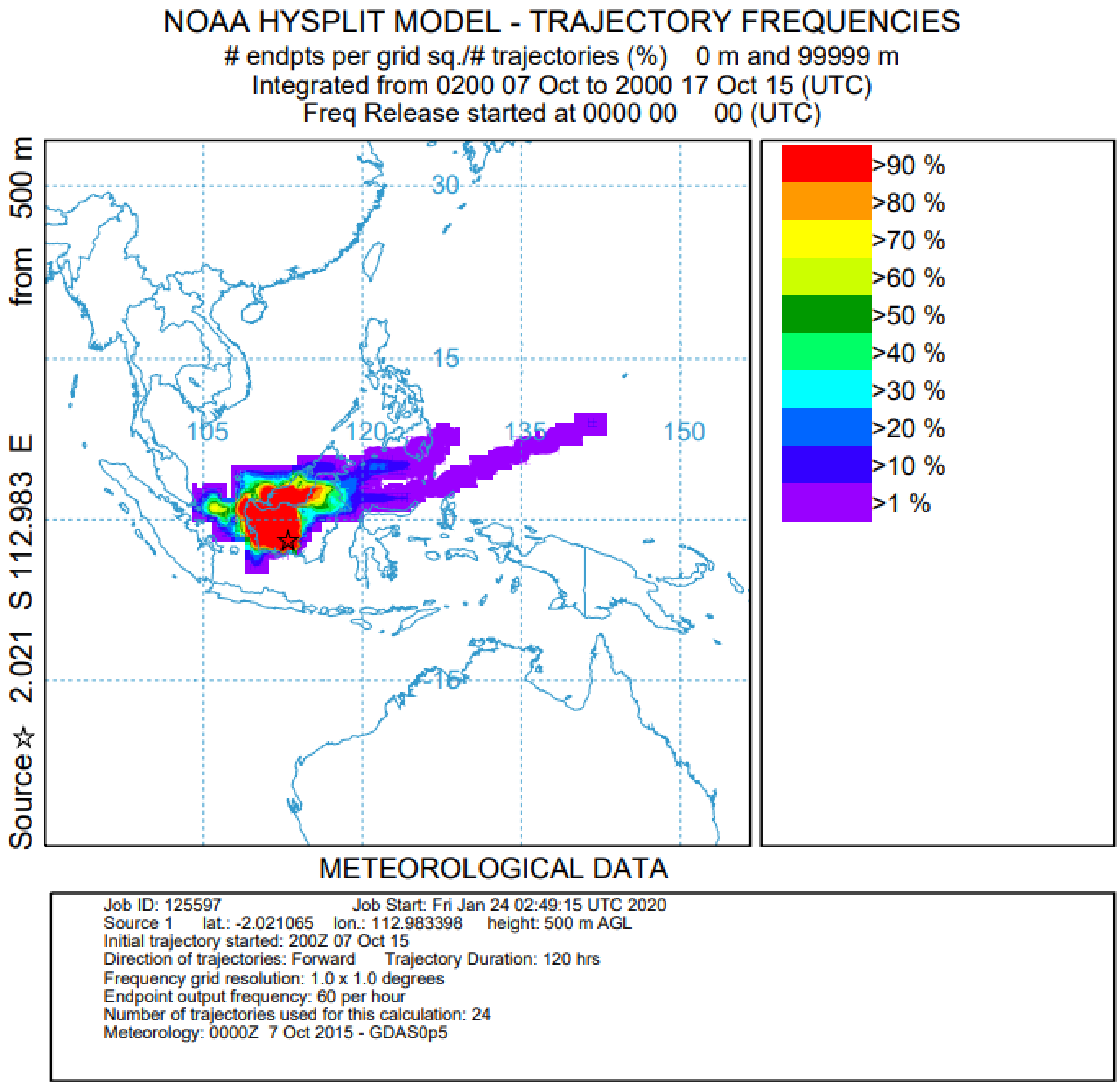


Figure 2.17. CO image from Aqua/AIRS satellite and monthly AOT image from MERRA-2 revealed the impacted region of extreme forest fire in Indonesia in October 2015


NOAA HYSPLIT MODEL - TRAJECTORY FREQUENCIES
endpts per grid sq./# trajectories (%) 0 m and 99999 m
Integrated from 0200 07 Oct to 2000 17 Oct 15 (UTC)
Freq Release started at 0000 00 00 (UTC)
Source ☆ 2.021 S 112.983 E from 500 m
30
15
105
120
135
150
-15
>90 %
>80 %
>70 %
>60 %
>50 %
>40 %
>30 %
>20 %
>10 %
>1 %
METEOROLOGICAL DATA
Job ID: 125597 Job Start: Fri Jan 24 02:49:15 UTC 2020
Source 1 lat.: -2.021065 lon.: 112.983398 height: 500 m AGL
Initial trajectory started: 200Z 07 Oct 15
Direction of trajectories: Forward Trajectory Duration: 120 hrs
Frequency grid resolution: 1.0 x 1.0 degrees
Endpoint output frequency: 60 per hour
Number of trajectories used for this calculation: 24
Meteorology: 0000Z 7 Oct 2015 - GDAS0p5

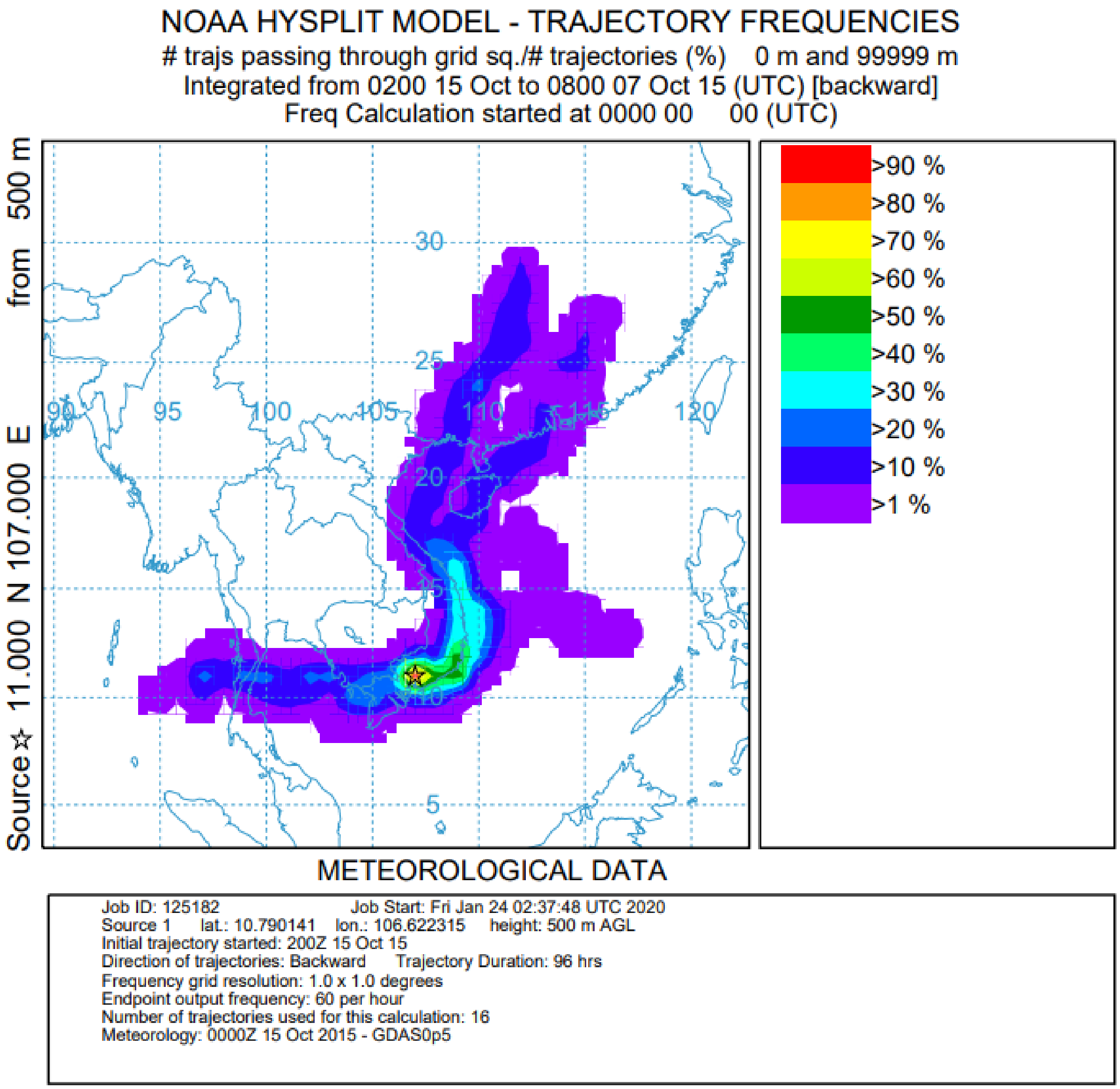
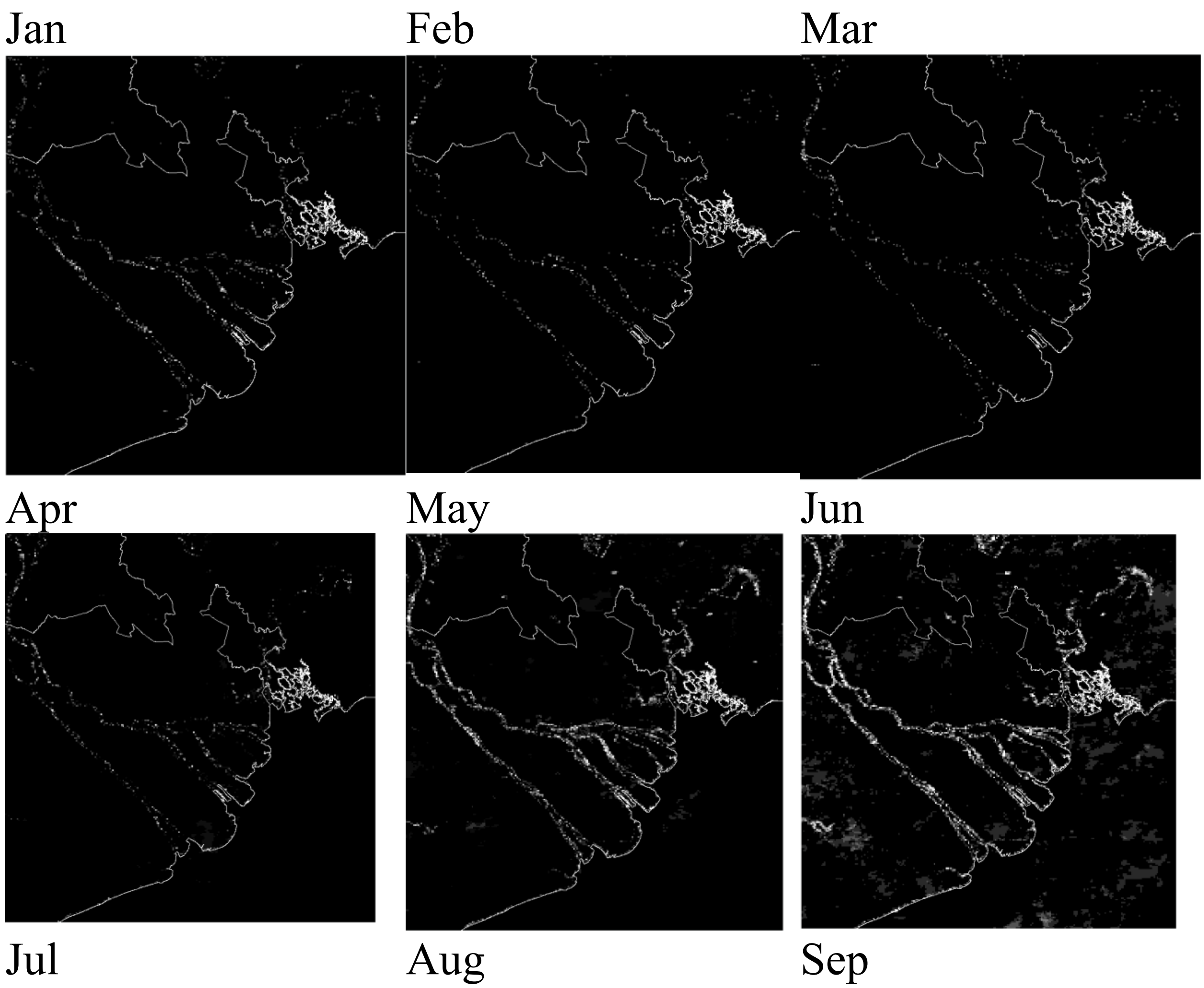


Figure 2.18. The simulation of wind trajectory frequencies that originated from forest fire hot spots in Indonesia (forward trajectories) (top) and trajectory frequencies of wind that was likely to transport pollution to HCMC (backward trajectories) by NOAA HYSPLIT model.

Moreover, the second peak of AOD in cropland and HCMC can be the result of AOD overestimation of MODIS. MCD19A2 is MAIAC aerosol product. In fact, AOD retrievals are sensitive to land cover types. MAIAC retrievals were more accurate and better correlated with AERONET measurements over forest, mixed, savanna, and grassland than those of urban, shrub land, and barren areas. The study about MAIAC aerosol product over South America show that AOD is systematically overestimated over some bright surface (V. S. Martins et al, 2017) Because urban features impose many challenges for satellite aerosol retrievals at high resolutions, such as (i) multiple anthropogenic sources and a high ensemble of aerosol optical properties and (ii) bright surfaces with a mixture of concrete building and roads. Meanwhile, TOA reflectance is less sensitive to aerosol loading over a bright surface.

In short of, the underestimation of FRP and the overestimation of AOD from MODIS data explains for shorter gap expected between BB emission and high level of AOD observed in southwest monsoon season in HCMC and Cropland area. It means that the burn of agricultural residuals is likely to happen in harvest months (Aug) in Mekong River delta, but the impact on pollution is not severe, especially in HCMC, where bimodal trend of AOD is not so clear and AOD is likely to be overestimated.



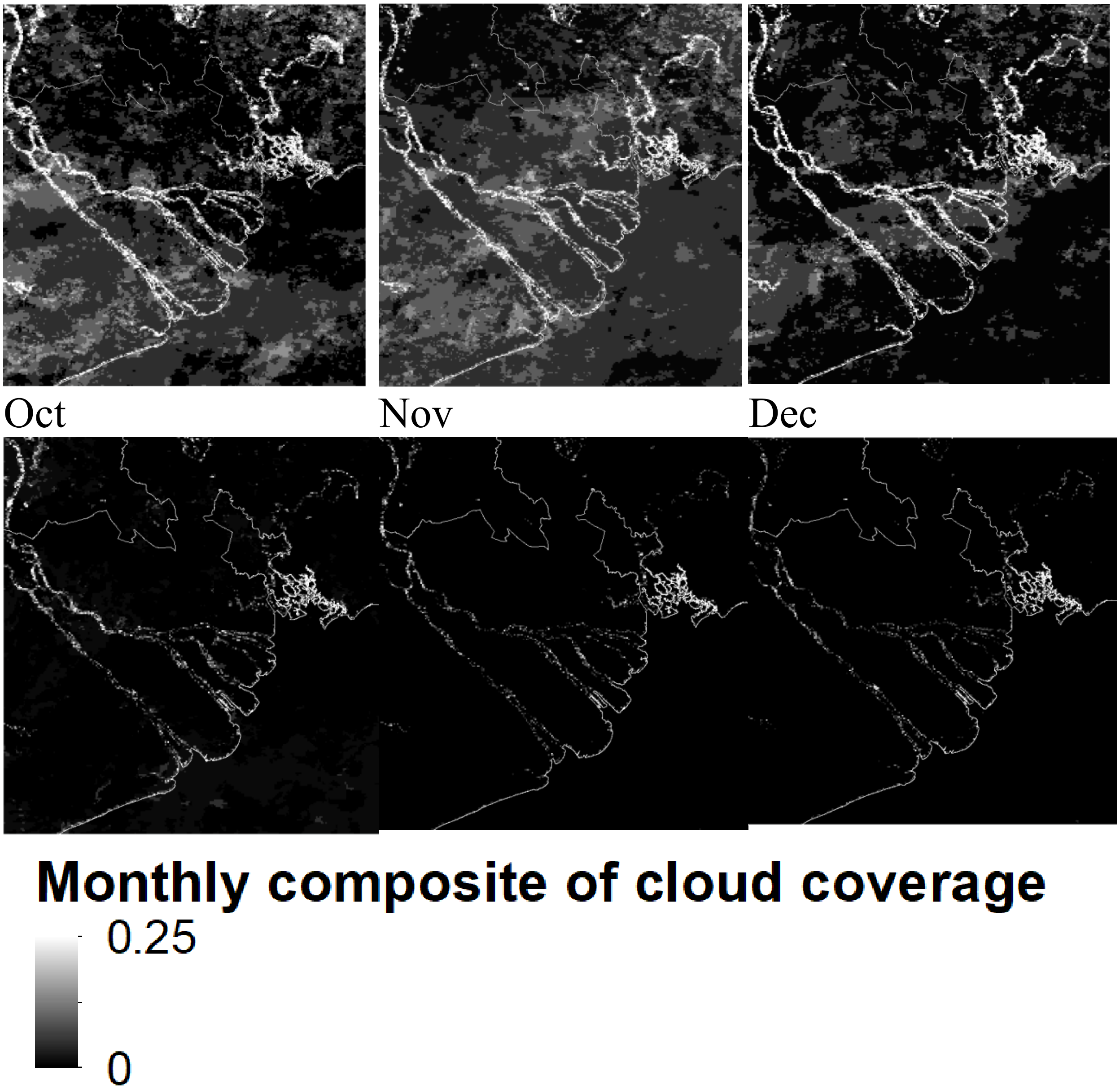


Figure 2.19. Monthly composite of cloud coverage for MOD14A2 (from 2001-2018)

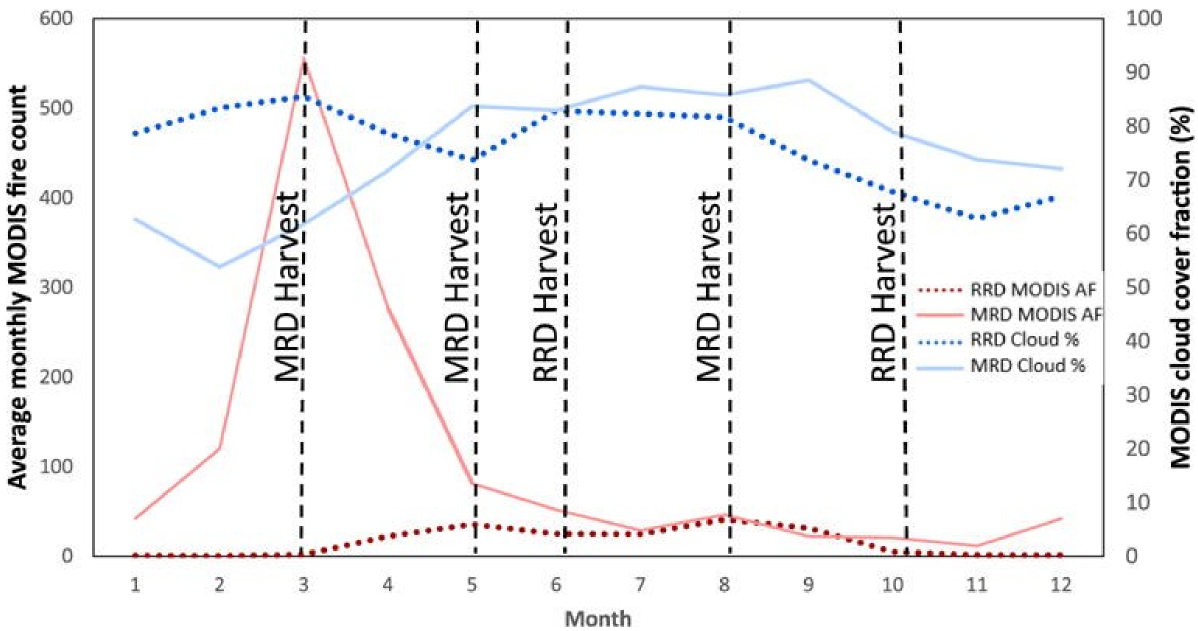


Figure 2.20. MODIS collection 6 Active Fire counts for the Red River Delta (RRD) and Mekong River Delta (MRD) averaged with 2003–2015 data, provided by K. Lasko, 2018

2.4 Conclusions

WRF Chem was run for pre monsoon season (from Jan to Apr) over the southern part of Vietnam with two options: with and without Biomass burning emission. WRF Chem simulation demonstrates the little contribution of BB to air pollution over HCMC generally. However, the comparing outputs of WRF Chem with in situ data and satellite images revealed low accuracy of model simulations. The rationale is mainly the shortcomings of emission inventories. The anthropogenic EI applied in WRF Chem has poor spatial allocation of emission, making the missing of pollution hot spots in simulations. Besides, it is likely to underestimate the real emission level because it was modeled in national scale and was updated until 2010.

So remote sensing data was analyzed as complementary approach. The seasonal trends of FRP, AOD over Savanna and Cropland area around HCMC and AOD within HCMC were shown. AOD monthly variation does not express the clear seasonal difference, does not show the agreement with FRP in Savanna. However, it demonstrates the moderate similar with AOD over Cropland area, which has bimodal trend. Basing on auxiliary data, the impact of BB from Indonesia in southwest monsoon season on air quality in HCMC is neglected. The burning of agricultural residuals in harvest season in Mekong river Delta has chance to influence HCMC. But not clear seasonal trend of AOD in HCMC and the possibility of AOD overestimation in rainy season and over urban area of MODIS data reduce the impact opportunity of this remote source. In future work, the simulation of WRF Chem over SEA region in southwest monsoon season is recommended to confirm the influenced area of dominated BB in Kalimantan and Sumatra during those months.

Finally, by taking everything in to consideration, BB is not primary emission sector that impact strongly on local air quality in HCMC. Therefore, in the next Chapter, I will focus on estimation of key anthropogenic emission sectors only.

Chapter 3.

Evolution of key emission sectors in Ho Chi Minh city

3.1. Introduction

The Regional Emission inventory in Asia (REAS) was developed to cover East, Southeast, South, and Central Asia. Asian part of Russia from 2000 to 2008 (J. Kurokawa et al, 2013) Monthly gridded data with a 0.25° × 0.25° resolution are provided. It includes four main sectors:

- Fuel combustions in power plants, industry, transport, and domestic sectors;
- Industrial process;
- Agricultural activities (fertilizer application and livestock);
- Others (fugitive emissions, solvent use, human, etc.)

These emissions were estimated on district and country levels then spatial allocation was carried out basing on population data; information on the positions of large point sources (LPSs); land cover data sets; land area data sets and road network. The activity data (AT) of this Emission inventory is Fuel consumption data from IEA Energy Balances (IEA, 2004) For non-combustion sources, an industrial activity data set (production of non-ferrous metals, sulfuric acid, iron, and steel) was derived from international statistics. For transportation, AT was based on vehicle numbers, annual distance traveled. Regarding emission factors, default factors from 2006 IPCC Guidelines and other reference data were applied for countries which do not have their own emission factor dataset (J. Kurokawa et al, 2013) The major role of the REAS inventory is to provide emission input data for atmospheric chemistry models, so it is Scope 1 inventory, which is the direct territorial emissions from residential and industrial heating, transport, industrial sectors and power plants within the territory of cities. For territorial (scope 1) accounting, emissions from grid-supplied energy are calculated at the point of energy generation.

In 2017, The Green House Gases Inventory of HCMC was prepared with the assistance of the Japan International Cooperation Agency (JICA) under the Project to Support the Planning and Implementation of Nationally Appropriate Mitigation Actions in a Measurement, Reporting and Verification Manner (SPI-NAMA). This is the first comprehensive GHG inventory of HCMC. The compilers used Global Protocol for Community-Scale GHG Emission Inventories (GPC) and the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (2006 IPCC Guidelines) to prepare this inventory. Global Protocol for Community Scale Greenhouse Gas Emission Inventories or GPC is a standard to measure GHG emissions from cities. GPC is promoted by the C40 Cities Climate Leadership Group, that is a network of the world's mega cities committed to addressing climate change, including HCMC.

This city – level GHG inventory includes five main sectors:

- Stationary energy
- Transportation
- Waste
- Industrial process and product use (IPPU)
- Agriculture, forestry, and other land use (AFOLU)

According to this project report Transportation and Stationary energy are two most prominent emission sectors in Ho Chi Minh city. Within Stationary energy sector, manufacturing industries accounts for the highest portion, followed by Residential buildings (Fig. 3.1)

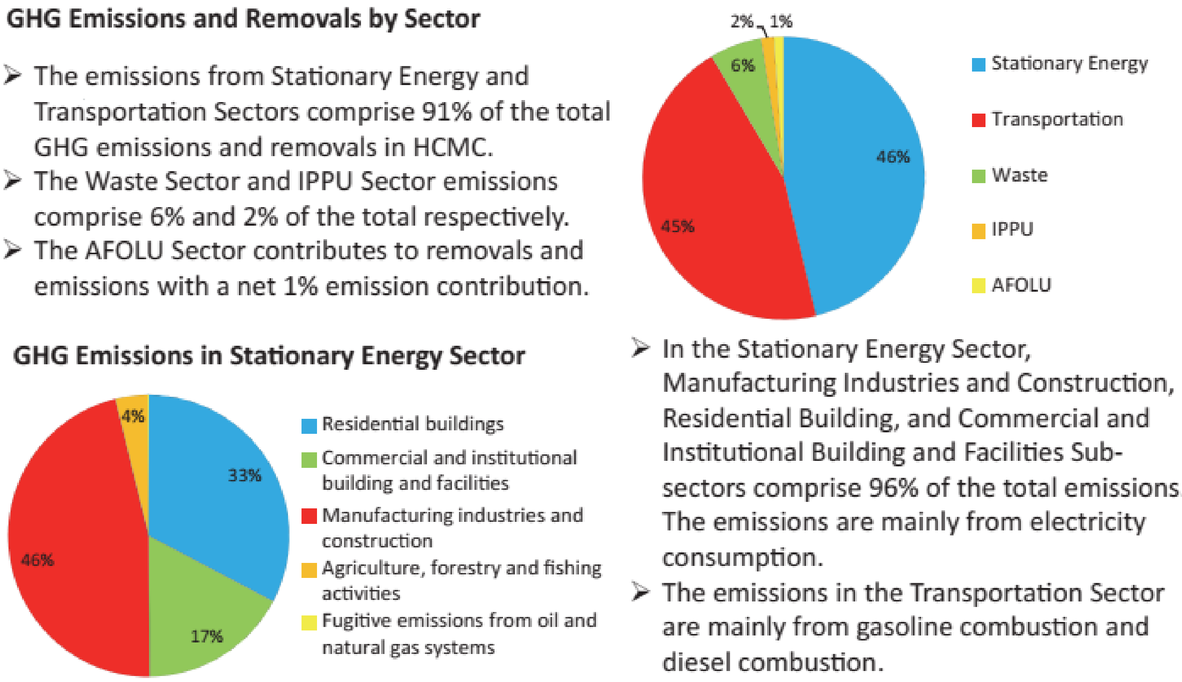


Figure 3.1. GHG emissions by sector in Ho Chi Minh city, 2013.

For Transportation, fuel consumption was used as activity data, which were provided by HCMC Department of Industry and Trade (DOIT), fuel companies, and government offices, etc. Emission factors are IPCC default factors from the 2006 IPCC Guidelines. In terms of Stationary energy, the main activity data are the electricity consumption and fuel consumption in each sub-sector:

1) Residential building,
2) Commercial and institutional building and facilities,
3) Manufacturing industries and construction,
4) Energy industries,
5) Energy generation supplied to the grid,
6) Agriculture, forestry and fishing activities.
7) Non-specified sources.

The electricity consumption was provided by Electricity of Vietnam (EVN) and fuel consumption from HCMC DOIT, fuel companies, and government offices etc. Similar as transportation sector, IPCC default factors from the 2006 IPCC Guidelines were used. This GHG inventory covers Scope 1 and Scope 2 emissions from Stationary Energy and Transportation, as well as in-boundary generated waste. Scope-2 are the emissions from purchased energy generated upstream from the city, mainly electricity. Total Emissions are the sum of the two scopes.

Both two EIs mentioned above applied Tier 1 approach in the 2006 IPCC Guidelines and they are not up to date anymore. REAS2.1 was updated till 2008, while GHG inventory by JICA was updated till 2013. The long term evolution of main emission sectors going along with up to date local emission inventory is valuable data for both policy makers and air quality numerical model users. Therefore, the objective of this part is compiling long term trend of three main emission sectors that was defined by JICA (Transportation, Residential building and Manufacturing industries) in HCMC and create maps of emissions by open accessed statistical data and remote sensing data.

3.2. Methodology

3.2.1. Transportation sector

For a given area, annual emissions from vehicles registered in that city were calculated as follows:

$E_k = \sum_i VP_i * \ Daily\ VKT_i * 365 * \ EF_i$ (2)

Where i represents vehicles types, including motorcycle (MC), taxi, car, bus and heavy duty vehicle – truck; k represents pollutant type (SO2, NOx, CO, NMVOC, PM10, PM2.5, BC, OC, NH3, CH4, N2O and CO2 in this work); daily VKT is the average daily vehicle mileage traveled of vehicle type i (km/ day); VP_i is the population of vehicle type i; EF_i is the emission factor of pollutant k of vehicle type i. This method is similar with the one used in REAS 2.1. In which, emissions were based on vehicle numbers, annual distance traveled, and emission factors for each vehicle type. Their vehicle numbers for cars, buses, trucks, and motor cycles were from the World Road Statistics (IRF, 2006–2010) and then subdivided into vehicle types by using the national and sub-regional statistics and database of the Greenhouse Gas and Air Pollution Interaction and Synergies (GAINS) INDIA database (IIASA, 2012).

The daily VKT of each vehicle type in HCMC, 2013 were extracted from study of Van. H. H et al, 2015 and was assumed to be constant over years. Accordingly:

- Motorcycle: 19 km per vehicle per day.

- Bus: 195.6 km per vehicle per day.

- Taxi: 124 km per vehicle per day.

- Personal car: 33.4 km per vehicle per day.

- Truck: 31.4 km per vehicle per day.

Vehicle fleet are classified into five main types: motorcycle (MC), personal car, taxi, bus and truck. The vehicle population data were synthesized by different data sources, such as the statistic of The Transport Department of HCMC and previous studies about vehicle emission in HCMC. However, the annual number of registered vehicle in some types were missing, such as population of truck and bus over years. So I calculated the number of trucks basing on the data in 2013 (Van. H. H et al, 2015), and proportionally estimated for other years basing on annual volume of freight carried that were provided by HCMC Statistical Yearbook. The bus population and the taxi population in 2015, 2016 were proportional with number of cars (Tab. 3.1)

Table 3.1. Number of registered vehicles by type in HCMC over years

	MC	Car	Taxi	Bus	Truck	Total
2009	4013208 [b]	257132 [b]	10300 [c]	2814 [d]	85623 [e]	4369077
2010	4340530 [b]	283810 [b]	12600 [c]	3016 [d]	101961 [e]	4741917
2011	4721123 [b]	317816 [b]	13900 [c]	3370 [d]	114052 [e]	5170261
2012	5171000 [b]	337743 [b]	15000 [c]	3587 [d]	162676 [e]	5690006
2013	5558000 [a]	315943 [a]	15500 [a]	3358 [a]	185501 [a]	6078302

2014	6318000 [b]	379763 [b]	17000 [c]	3596 [d]	197057 [e]	6915416
2015	6863707 [b]	532835 [f]	23853 [d]	3833 [d]	226677 [e]	7650905
2016	7266000 [b]	595349 [f]	26651 [d]	4283 [d]	269294 [e]	8161577

(a) Van. H. H et al, 2015
(b) Statistical data provided by The Transport Department of HCMC.
(c) Report on Ho Chi Minh City – Osaka City Cooperation Project for Developing Low Carbon City, 2016.
(d) Proportional estimation basing on number of cars.
(e) Proportional estimation basing on annual volume of freight carried that were provided by HCMC Statistical Yearbook.
(f) L.P.Linh et al, 2018

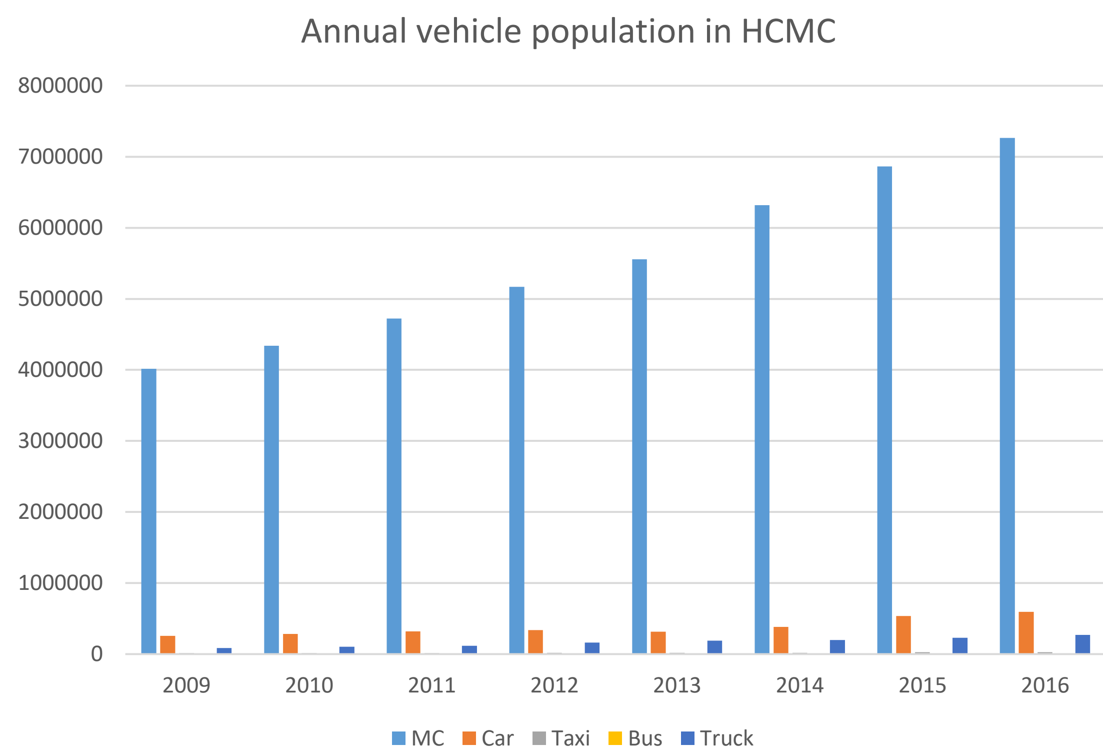


Figure 3.2 Number of registered vehicles by type in HCMC from 2009 to 2016

It is obvious from Fig 3.2 that motorcycle dominated the vehicle fleet in HCMC over 8 years because light motorbikes and scooters has been the key means of transport for people in this city. MC shared around 90% of totally vehicle population and showed the linear growth from 2009 to 2016. Personal car was ranked in 2nd among five transportation options. After 2013, a steady rise was observed in number of cars, making its contribution increase to 7% of total vehicle fleet in HCMC.

The emission factors were extracted from seven different studies (Tab 3.2), covering 12 pollutant species.

Table 3.2 The emission factors (g.km-1.vehicle-1) from literature review

Pollutant	MC	Car and Taxi	Bus	Truck
CO	12.592[b]	2.21 [b]	6.905 [a]	3.1 [b]
NOx	0.195 [b]	1.05 [b]	16.954 [a]	17 [b]
SO2	0.01 [c]	0.17 [b]	0.64 [b]	1.06 [b]
CH4	0.115 [d]	0.0031 [d]	0.077 [d]	0.062 [d]
PM2.5	0.018 [f]	0.03 [f]	0.9 [f]	1.1 [f]
PM10	0.094 [c]	0.3 [b]	2.08 [a]	3.28 [b]
NMVOC	2.34 [e]	15.02 [e]	89.92 [e]	89.92 [e]
BC	0.004039 [f]	0.000932 [f]	0.00112 [f]	0.000746 [f]
OC	0.0178 [f]	0.00342 [f]	0.012 [f]	0.00808 [f]
NH3	0.0019 [g]	0.1043 [g]	0.0029 [g]	0.0029 [g]
N2O	0.00429 [f]	0.00423 [f]	0.0018 [f]	0.001926 [f]
CO2	221 [g]	530 [g]	2050 [g]	486 [g]

Source: [a] T.T.Trang et al, 2015 (Study in Hanoi)
[b] N.T.Hung et al, 2014 (Study in Hanoi)
[c] N.T.Kim Oanh et al, 2012 (Study in Hanoi)
[d] Wang. G et al, 2016 (Study in China)
[e] Belalcazar et al., 2009; Ho et al., 2008 (Studies in HCMC)
[f] Hao Cai et al, 2015 (Updated Emission Factors of Air Pollutants from Vehicle Operations in GREETTM Using MOVES)
[g] EMEP/EEA air pollutant emission inventory guidebook 2016, updated in 2018.

In equation (2), emission factors and daily VKT of each vehicle type were assumed to be constant over years. Therefore, the annual emission were mainly driven by vehicle populations. In order to make grid emissions, the road density from road network downloaded from Open street map was applied for spatial disaggregation (Fig 3.3) In which, the grid net was created and road density was estimated for each "square", with different weights for three types of roads: 2 for Primary roads, 1 for Secondary roads and 0.5 for Tertiary roads. These weights were derived from Modeled road capacity in HCMC in 2016 by HOUTRANS project, JICA, 2004 (Fig 3.4) In which, the assigned traffic volume in Primary road is over 85,000 Passenger Car Unit (PCU) per day, Secondary one is 44,000 to 85,000 and the smallest road have under 44,000 PCU per day. In terms of monthly distribution, I assume that all the months have the same transportation emission level.

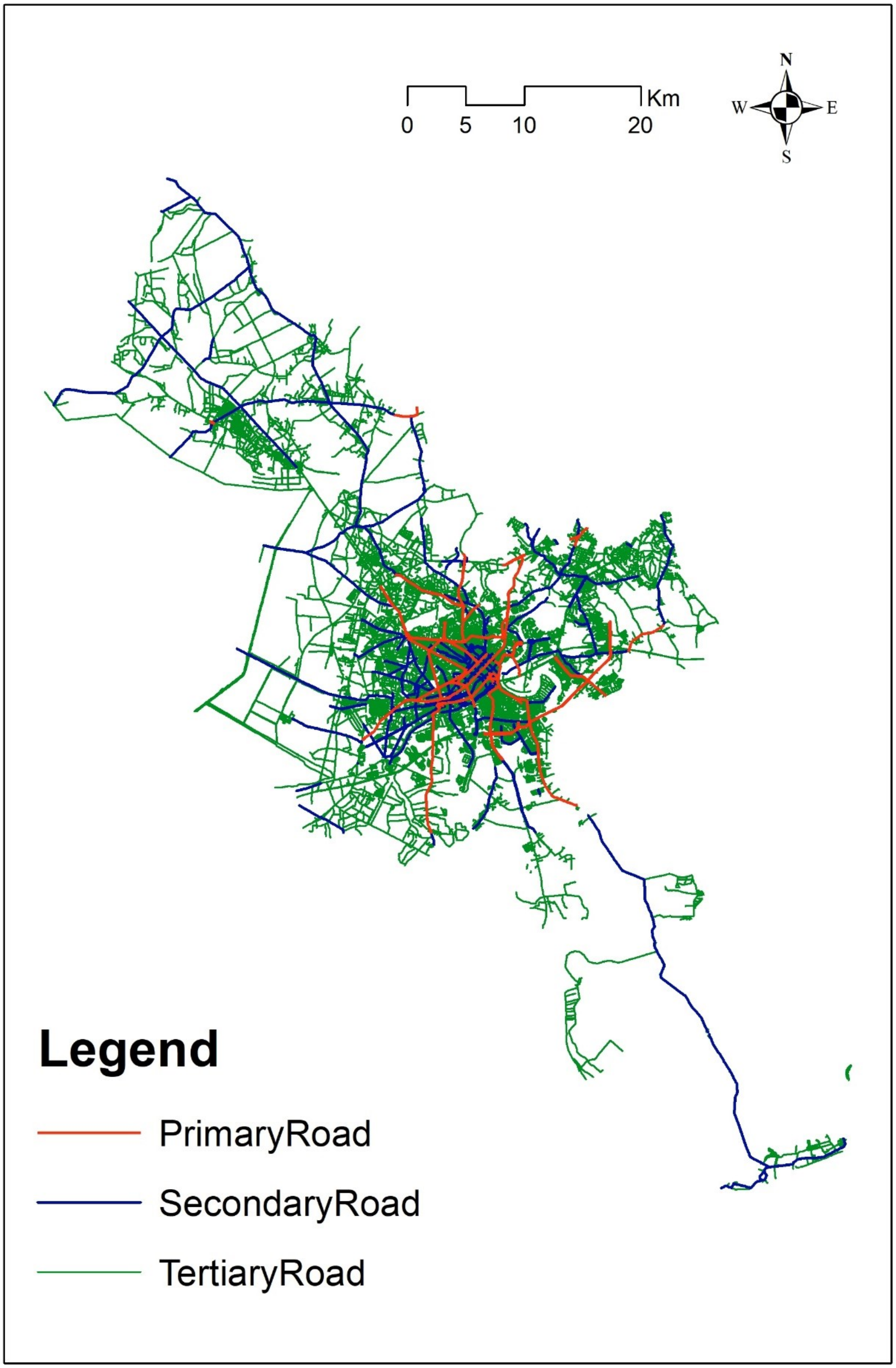
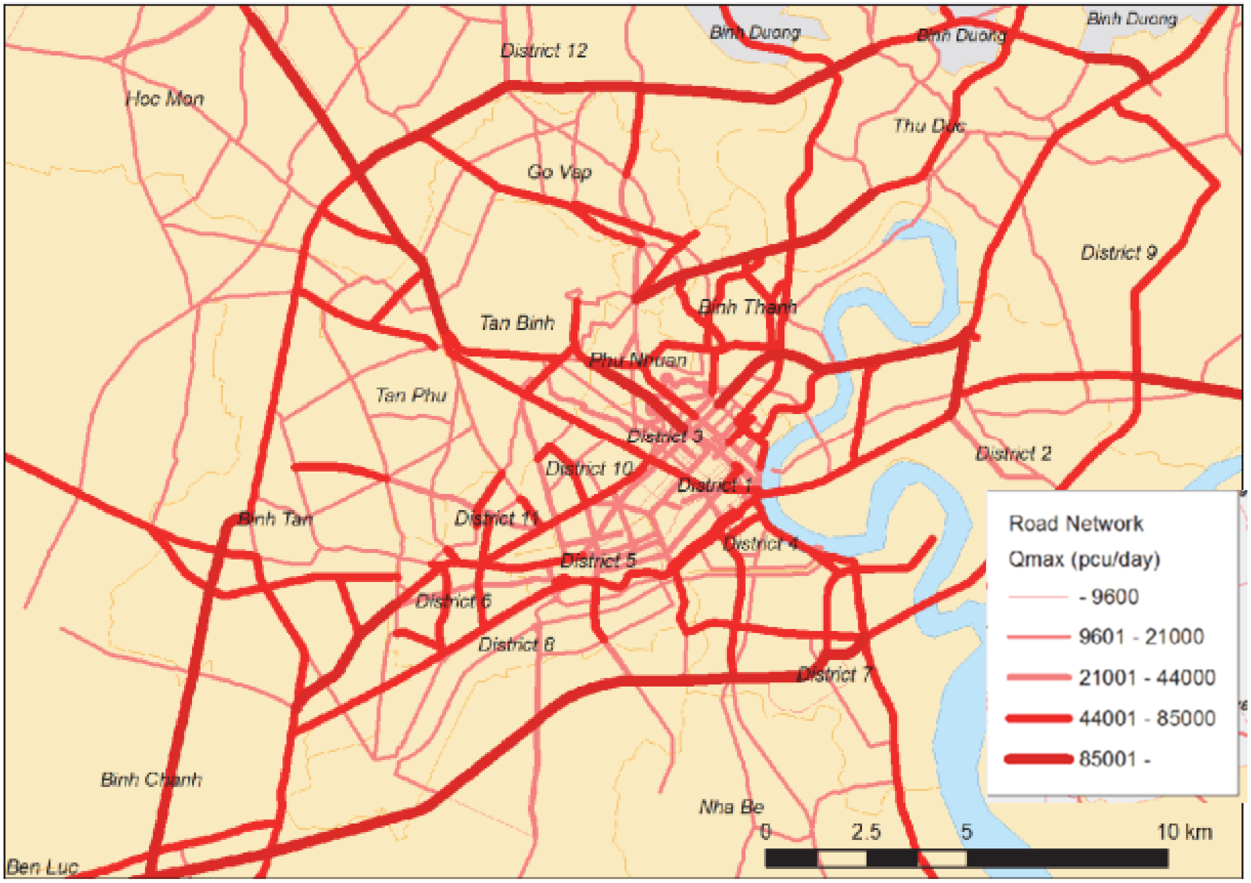


Figure 3.3. Road network with three types of road: Primary, Secondary and Tertiary road provided by Open Street Map



Source: JICA Survey Team

Figure 3.4. Modeled traffic volume in road network in HCMC, 2016 (HOUTRANS project, JICA, 2004)

3.2.2. Manufacturing industries and construction sector and Residential sector

According to the GHG emission inventory compiled by JICA, 2017, the main sources of stationary energy are electricity consumption and fuel consumption. This study considers Scope 1 that are emissions GHG emissions from sources located within the city boundary and Scope 2 - consumption-based accounting separately.

3.2.2.1 Fuel consumption

Emission from fuel consumptions of two sectors were calculated from the following equation:

$E = \sum_i A_i \times EF_i$ (3)

Where E is emissions, i is fuel type, A is activity data, here is amount of fuel consumption, disaggregated by fuel type, EF_i is emission factor of that pollutant, equivalent with Manufacturing industry sector or Residential sector.

The total fuel consumption in HCMC in 2013, 2014 and 2015 with Ratio of Final Fuel Consumption by Sub-Sector and Fuel Type (Tab.3.3 and Tab 3.4) were provided in the GHG emission inventory compiled by JICA, 2017. Basing on this GHG emission inventory, the fuel consumption of Manufacturing industrial and Residential sectors, including gasoline, diesel, heavy oil, kerosene, liquefied petroleum gas (LPG) and natural gas can be estimated for three years: 2013 to 2015. The emission factors were extracted from the compiled database presented in the Atmospheric Brown Cloud - Emission Inventory Manual (ABCEIM) by Shrestha et al. (2013) ABCEIM has included EFs from several databases including the AP-42 (USEPA, 1995), EMEP/ CORINAIR (2006) and IPCC (1997), as well as available measurement data reported for various sources in Asia.

The consumptions of Manufacturing industrial sector in five other years (2009 to 2012 and 2016) were inferred using annual Gross output of industry at current prices by industry activity in HCMC, provided by HCMC Statistical Yearbook (Tab 3.9) So, the annual emission from fuel consumption of Manufacturing industrial sector is function of annual Gross output of industry and emission factors, with the assumption that during 8 years, the emission factors had been constant:

$E_{Industry}$ = f (annual Gross output of industry, $EF_{Industry}$) (4)

The monthly Index-Industry Products deriving from HCMC Statistical Yearbook were applied to allocate total annual emission into monthly emissions (Tab. 3.8)

The residential sector energy data are often not disaggregated by end use devices, such as household stoves and fire places/heating stoves. Kerosene, liquefied petroleum gas (LPG) and natural gas are used for cooking, while kerosene is used for lighting in the residential sector in many regions. Coal, biomass fuels, such as wood are used mostly for domestic cooking and heating stoves in rural. Meanwhile, electricity or natural gas is common in urban area. Regarding Residential sector, the fuel consumptions in other years were inferred using population provided by HCMC Statistical Yearbook, also. Therefore, the annual emission from fuel consumption of Residential sector is function of annual population and emission factors, with the assumption that during 8 years, the emission factors had been constant, like Manufacturing industrial sector:

$E_{Residential}$ = f (annual Population, $EF_{Residential}$) (5)

Normally, the temporal allocation of residential sector was based on monthly heating degree day (HDD) and cooling degree day (CDD) approach that derived from meteorological data. However, fuel consumption in households in HCMC mainly is for cooking. Moreover, this city has a tropical climate, the variation of temperature among 12 months is not significant. So, the monthly fuel consumption of Residential sector was assumed to be the same over 12 months.

Regarding spatial allocation, urban morphology map for period 2009 - 2016 in HCMC were created, using the methodology proposed by Prakhar. M, 2018. Urban morphology maps including three land use types: Residential, Commercial and Industrial land. In which, city height from AW3D digital surface model (DSM) data, Night Time light data - VIIRS and land cover from Landsat 8 and Landsat 7 data were used to classify these three land use types (Landsat 7 for 4 years: 2009 to 2012 and Landsat 8 for other four years: 2013 to 2016) These maps were used for spatial distribution of Manufacturing industrial and Residential emissions into the same grid net – 1 km resolution with Transportation sector.

In terms of removal efficiencies for PM2.5, BC, OC, SO2 and NOx, emission reduction efficiencies of various technology types in the manufacturing industry are presented in ABCEIM. However, the data and information regarding technology for emission control reductions in HCMC is not available. Therefore, the emissions of Manufacturing industrial sector was calculated simply by fuel consumptions multiplied with emission factors, according to City - Level GHG Inventory Preparation Manual compiled by JICA to Support the Planning and Implementation of NAMAs in a MRV Manner in HCMC.

Table 3.3 Annual fuel consumption in HCMC in 2013, 2014, 2015 provided by JICA, 2017

		Fuel consumption (TJ/ year)			Fuel consumption (ton/ year)		
	Fuel type	**2013**	**2014**	**2015**	**2013**	**2014**	**2015**
1	Gasoline	115855	119247	134544	3582529	3582529	3582529
2	Diesel	120218	141229	180686	3582529	3909982	3909982
3	Heavy oil	15976	16540	19334	404333	418625	418625
4	Kerosene	1664	1607	1901	47204	45577	53906
5	Jet fuel	37569	42658	52638	1054995	1197892	1478138
6	LPG	2268	2246	2541	47956	47483	53728
7	Natural gas	1463	1441	1567	29000	28000	30000

Table 3.4 Ratio of Final Fuel Consumption by Sub-Sector (Manufacturing industrial and Residential sectors) and Fuel Type in Vietnam in 2014, provided by JICA, 2017.

Fuel type	Manufacturing industrial sector	Residential sector
Gasoline	0	0
Diesel	16%	1%
Heavy oil	86%	1%
Kerosene	12%	74%
LPG	15%	55%
Natural gas	100%	0%

Table 3.5 Emission factors for Manufacturing industrial and construction sector from the compiled database provided by the Atmospheric Brown Cloud - Emission Inventory Manual (ABCEIM) by Shrestha et al. (2013) (unit: kg/ TJ)

unit: kg/ TJ	Diesel	Heavy oil	Kerosene	LPG	Natural gas
CO	15.00	15.00	15.00	10.00	2000.00
NOx	222.00	145.00	167.00	56.00	53.00
SO2	46.20	49.80	44.60	0.20	0.19
CH4	3.00	3.00	3.00	1.00	1.00
PM2.5	0.83	17.00	10.00	-	0.04
PM10	3.30	27.40	10.80	-	0.04
NMVOC	5.00	5.00	5.00	5.00	5.00
BC	3.90	0.90	5.50	-	0.00
OC	0.00	0.37	1.70	-	0.02

NH3	0.01	0.10	-	-	1.31
N2O	0.60	0.60	0.60	0.10	0.10
CO2	74100.00	77400.00	71900.00	63100.00	56100.00

- Not available.

CS_{fuel} : Sulfur content in fuel, % weight.

Table 3.6 Emission factors for Residential sector (Cooking/Household Stoves) from the compiled database provided by the Atmospheric Brown Cloud - Emission Inventory Manual (ABCEIM) by Shrestha et al. (2013) (unit: g/kg)

unit: g/kg	**Kerosene**	**LPG**
CO	7.39	3.72
NOx	1.1	1.76
SO2	0.025	0.33
CH4	0.025	0.14
PM	0.13	0.26
NMVOC	0.39	1.6
BC	0.9	0.2
OC	0.09	0.05
NH3	-	-
N2O	0.07	0.09
CO2	3130	2980

- Not available.

Table 3.7 Emission factors for Residential sector (Cooking/Household Stoves) from the compiled database provided by the Atmospheric Brown Cloud - Emission Inventory Manual (ABCEIM) by Shrestha et al. (2013) (unit: kg/ TJ)

unit: kg/ TJ	**Diesel**	**Heavy oil**	**Kerosene**	**LPG**	**Natural gas**
CO	-	-	167.57	78.65	-
NOx	-	-	24.94	37.21	-
SO2	-	-	0.57	6.98	-
CH4	-	-	2.04	2.96	-
PM	-	-	43.08	5.50	-
NMVOC	-	-	8.84	33.83	-
BC	-	-	20.41	4.23	-
OC	-	-	2.04	1.06	-
NH3	-	-	-	-	-
N2O	-	-	1.59	1.90	-
CO2	-	-	70975.06	63002.11	-

- Not available.

Table 3.8. The monthly Index-Industry Products in 2015, 2016 provided by HCMC Statistical Yearbook

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2015	109.76	104.98	105.88	105.48	105.68	105.9	106.42	106.52	107.06	107.36	107.67	107.85
2016	108.19	105.66	105.72	106.17	106.41	106.9	107.05	107.19	107.2	107.28	107.23	107.33
Monthly index	1.000	0.966	0.971	0.971	0.973	0.976	0.979	0.981	0.983	0.985	0.986	0.987

Tab 3.8 expressed the monthly variation of Industry production in HCMC. The Industry product got peak in January and considerably plunged in February. This trend can be explained by the fact that Lunar new year in Vietnam is often in February. So after this month, the production gradually increases again with steady speed to December.

Table 3.9 Annual Gross output of industry at current prices by industry activity in HCMC and Population of HCMC over years provided by HCMC Statistical Yearbook

Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Annual Gross output of industry at current prices by industry activity (Mil. VND)	520128.7	596755.6	640125.8	683496.0	753805.0	823184.0	883475.0	959063.0
Population (1000 people)	5981	6189	6406	6629	6861	7100	7348	7605

Tab 3.9 showed the annual growth in gross output of industry and population of HCMC over 8 years. A steep rise was seen in Manufacturing industry sector (about 4.4 time higher) while population increased by only 20% from 2009 to 2016. This will lead to different annual evolution of emission between these two key sectors.

3.2.2.2 Electricity consumption

According to City - Level GHG Inventory Preparation Manual, Scope-2 are the emissions from purchased energy generated upstream from the city, mainly electricity. Consumption-based emissions encompass those emissions produced by consumption within those same boundaries, regardless of the origin of those emissions. Typical sources of consumption-based emissions include purchased electricity, steam, or chilled water. Local governments often include scope 2 emissions if or when they do not have electric generating plants within their boundaries but still wish to evaluate the impacts of electricity use in the community.

Emission from electricity consumptions of two sectors were calculated from the following equation:

$E = \sum \quad A \times EF$ (6)

Where E is emissions, A is activity data, here is amount of electricity consumption, disaggregated by fuel type, EF_i is Grid Emission Factor, specific for each region.

In GHG emission inventory compiled by JICA, the electricity consumption by sub-sectors is collected from Electricity of Vietnam (EVN) using the data collection forms. The electricity consumption consists of five sub-sectors (Residential Buildings; Commercial and Institutional

Buildings and Facilities; Manufacturing Industries and Construction; Energy Industries and Agriculture, Forestry and Fishing Activities)

The emission factor on electricity consumption varies every year. Emission factors depend on: combustion technology; emission source category; fuel type; combustion technology type and emission control technology. In GHG emission inventory of JICA, Grid Emission Factor on Electricity Consumption in Vietnam were provided for 2013, 2014 and 2015 (Tab 3.11) As a result, in this study, EF on Electricity Consumption in 2009 to 2012 was assumed to be the same with 2013 and EF on Electricity Consumption in 2016 was assumed to be the same with 2015.

In this study, the electricity consumptions in 2013, 2014, 2015 were extracted directly from GHG emission inventory prepared by JICA, 2017 (Tab 3.10) Fig 3.5 implied the significant linear relationships during these three years between electricity consumption of Industry sector and Residential sector with Annual Gross output of industry and Annual population, respectively. So, electricity consumptions in other years were inferred using the same parameters used in Fuel consumption part:

- Manufacturing Industries and Construction sector: used Annual Gross output of industry at current prices by industry activity.
- Residential: used Annual population of HCMC.

As a result, similar to fuel consumption part, the emission from electricity consumptions of industry sector is function of Annual gross output of industry and grid EFs. Also, the emission from electricity consumptions of residential sector is function of Annual population and grid EFs.

Moreover, the GHG emission inventory provided by JICA estimated two parts of electricity consumption emission (Tab 3.12):

- Emissions from Consumption of grid Supplied Energy Consumed within the city boundary.
- Emissions from Transmission and distribution Loss from grid Supplied Energy.

Table 3.10 Electricity consumption of Manufacturing Industries and Construction and Residential sectors in HCMC in 2013, 2014 and 2015, provided by Electricity of Vietnam (EVN)

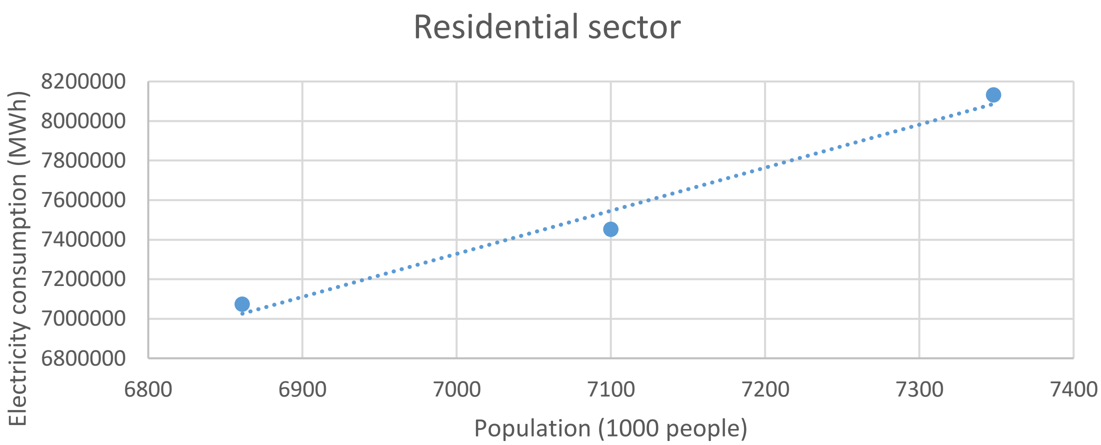
Unit: kWh/year	**2013**	**2014**	**2015**
Manufacturing Industries and Construction	7186161.416	7557369.663	8094021.380
Residential	7073622.593	7452131.412	8132452.777

Table 3.11 Grid emission factor on electricity consumption provided by Electricity of Vietnam

Unit: ton – CO2/MWh	**2013**	**2014**	**2015**
Operating Margin emission factor	0.7495	0.7802	0.7950

Table 3.12 CO_2 emission in 2013 from Electricity Consumption in HCMC, provided by JICA, 2017

Unit: $GgCO_2$/ year	Emissions from consumption of grid-supplied energy consumed within the city boundary	Emissions from transmission and distribution losses from grid-supplied energy
Residential	5301.68	262.96
Manufacturing Industries and Construction	5386.03	267.15



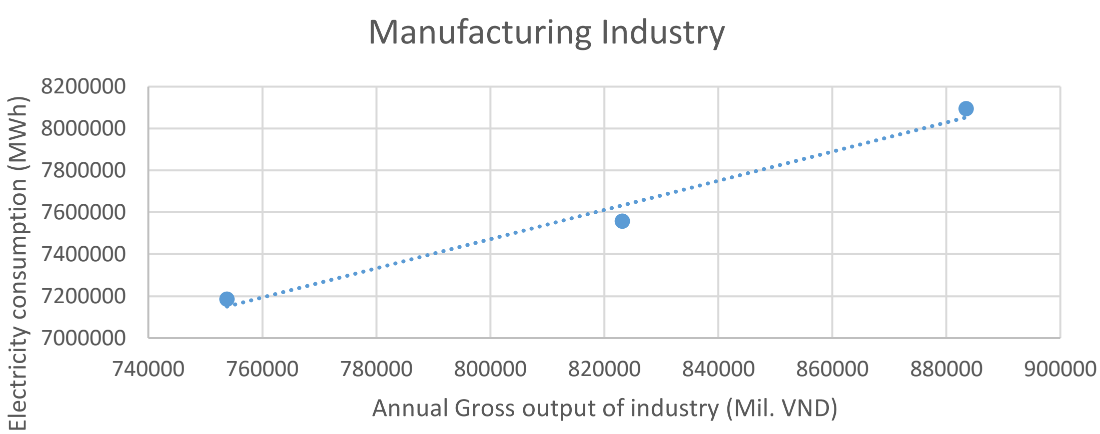


Figure 3.5 Correlations between electricity consumptions of Manufacturing industry sector with Annual gross output of industry in HCM, and electricity consumptions of Residential sector with Annual population in HCM

3.3. Results and discussion

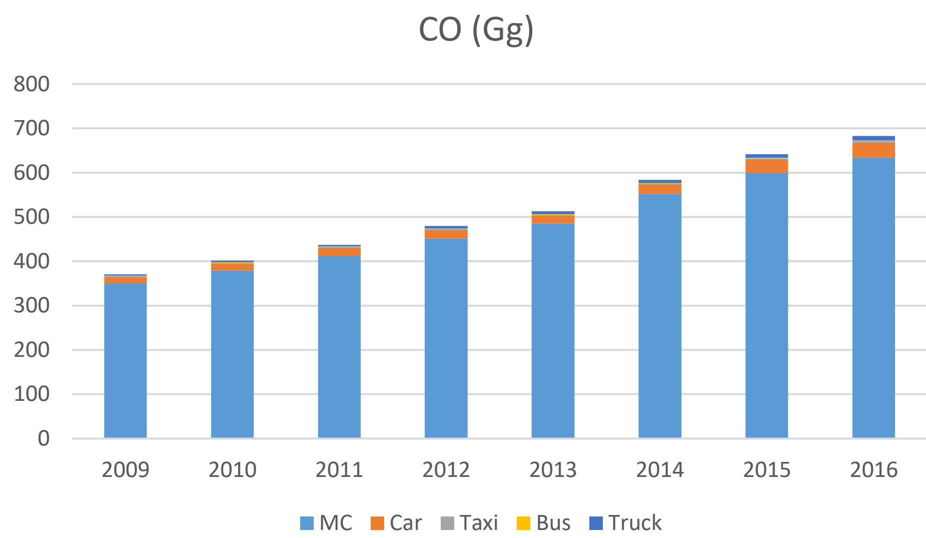
3.3.1. Transportation

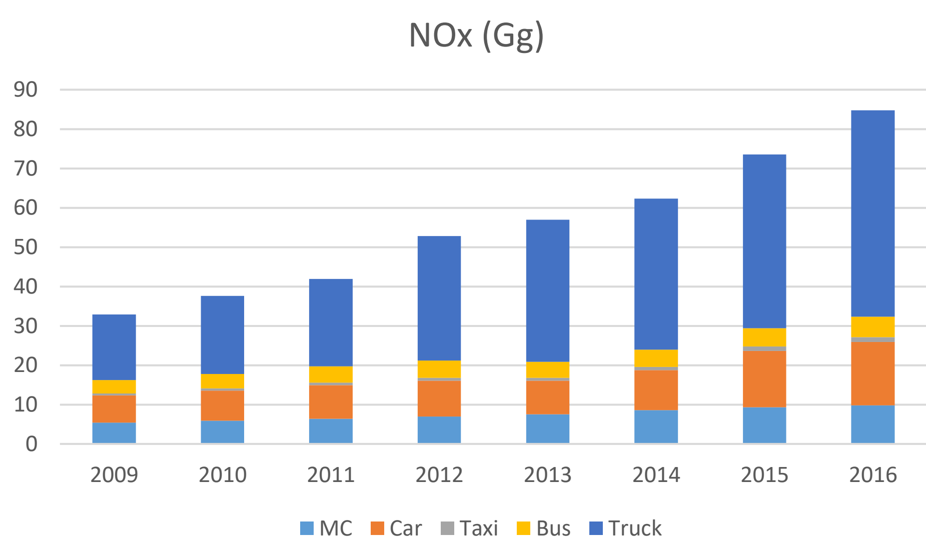
Tab 3.13 and Fig 3.6 showed the annual evolution of emission from Transportation in HCMC from 2009 to 2016. On the whole, all 12 pollutants expressed the same gradual growing trend over 8 years. The reason is that the increase in emissions of all species were driven by the same data set of vehicle population. There had been an increase by 44% in CO emission from 2009 to 2016. Similarly, the on road emission of CO2 got doubled (from 11 Gg to 22.5 Gg). On the other hand, the sharing ratios among five vehicle types in each pollutants are different. Obviously, motorcycles contributed the highest ratios in case of CO and CO2. Over 95% CO emission from transportation was accounted by Motorcycle. Meanwhile, truck was the main vehicle emission source of NOx and PM, although the population of trucks in HCMC was quite modest. For example, truck was accounted for 50-60% of the total NOx emission, 40-50 % of PM10 emission. Apart from that, the contribution of personal car was considerable in terms of SO2, NMVOC and CO2. The sharing of car rose from 4 Gg to 9 Gg, equivalent to 40% of total CO2 emission from 2009 to 2016. Finally, by taking everything in to consideration, although MC is the most dominated vehicle type in HCMC, it contributed the highest percentage of CO and CO2 emission only. Regarding NOx and PM, truck is claimed as the biggest emission source.

As a result, the change in number of MC or in emission factors of MC can impact significantly on the change in CO and CO2 emission. The fact is quite high percentage of MC in HCMC used the old emission standard engines (the most common type is Euro 3, followed by Euro 2 and Euro 1 (C.T.Dung et al, 2015)), making emission factors of MC in HCMC are still high. Nonetheless, to control NOx and PM emission, truck fleet should be more considered, in spite of small population of this vehicle type in HCMC. HDVs use diesel engines which emit higher amount of PM and NOx. Besides, the truck fleet in HCMC is quite old, the average age is 11.7 years, leading to high sharing ratio of out of dated engines (75% trucks used Euro 2 engines) (H.H.Van et al, 2014)

Table 3.13 Annual emissions from Transportation sector

Unit (Gg)	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
CO	370.496	401.503	437.401	479.761	513.068	583.732	641.922	682.613
NOx	32.933	37.632	41.908	52.842	56.972	62.330	73.576	84.785
SO2	2.648	3.012	3.360	4.087	4.290	4.784	5.913	6.773
CH4	3.299	3.575	3.892	4.288	4.610	5.231	5.702	6.061
PM2.5	1.973	2.257	2.507	3.207	3.512	3.819	4.403	5.072
PM10	8.372	9.466	10.501	12.822	13.738	15.215	17.990	20.441
NMVOC	277.534	312.825	347.725	414.957	435.228	486.614	591.171	670.503
BC	0.120	0.130	0.142	0.155	0.166	0.189	0.208	0.222
OC	0.530	0.575	0.626	0.688	0.736	0.837	0.922	0.982
NH3	0.793	0.880	0.983	1.049	0.999	1.187	1.637	1.825
N2O	0.152	0.165	0.181	0.197	0.207	0.237	0.272	0.292
CO2	10784	11824	13020	14309	14712	16879	20162	21999


CO (Gg)
800
700
600
500
400
300
200
100
0
2009
2010
2011
2012
2013
2014
2015
2016
MC
Car
Taxi
Bus
Truck


NOx (Gg)
90
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2009
2010
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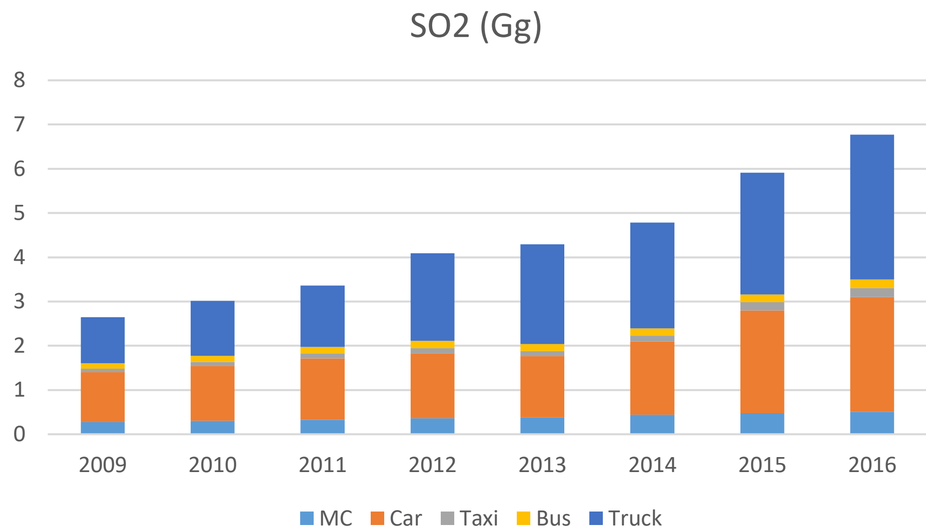
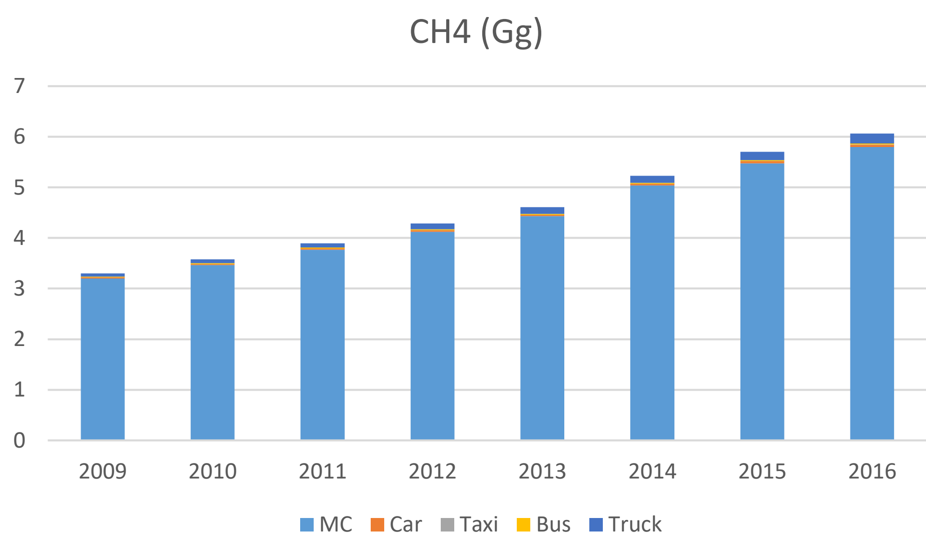
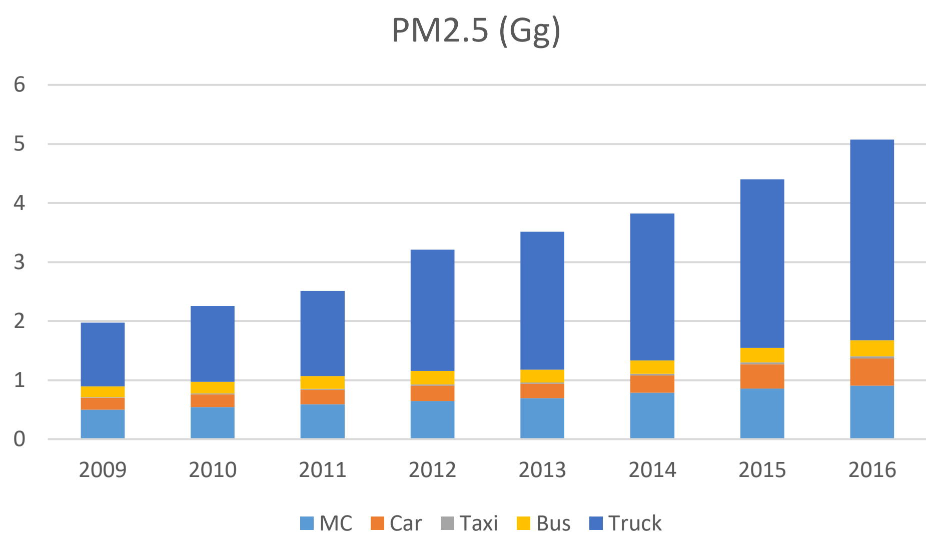
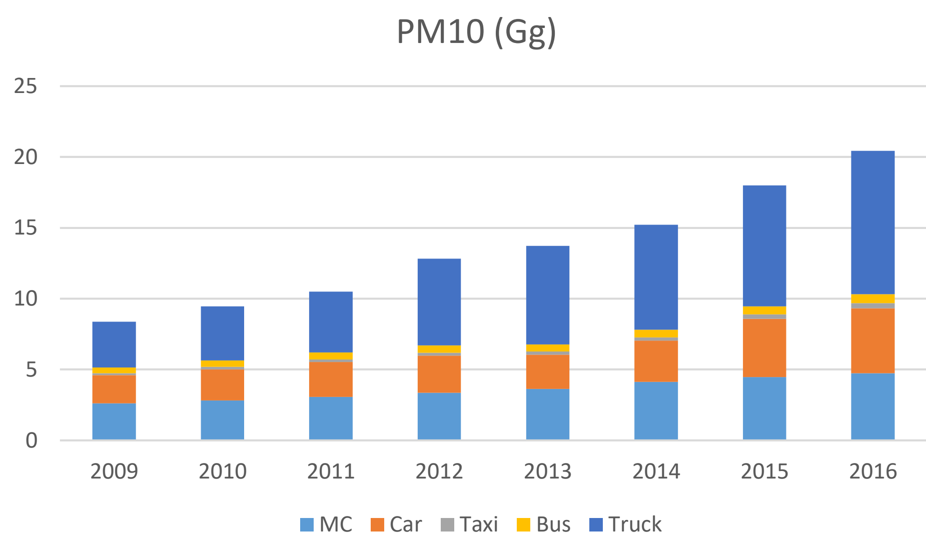
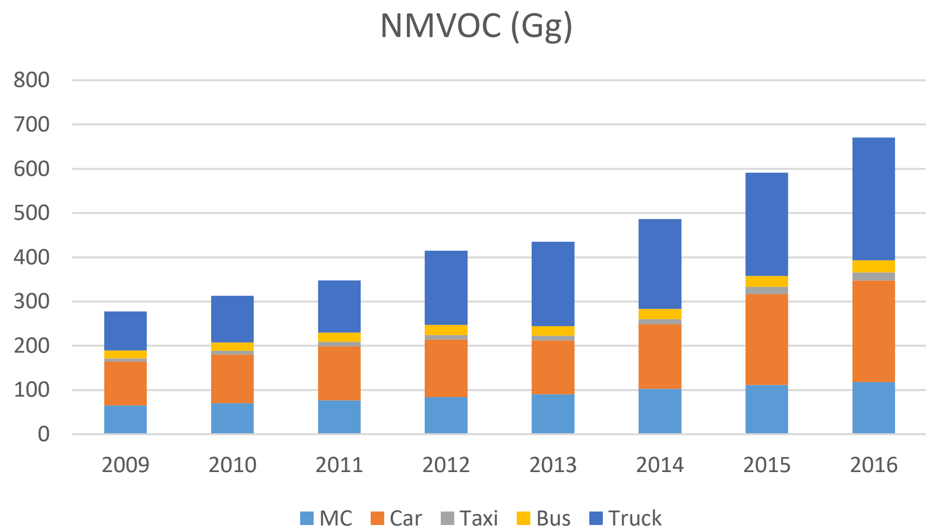
2016
MC
Car
Taxi
Bus
Truck

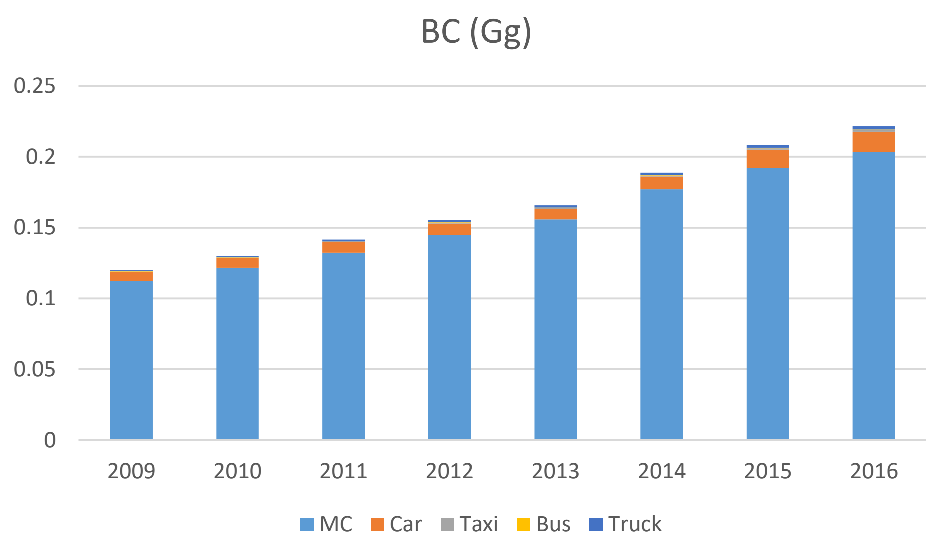

SO2 (Gg)
8
7
6
5
4
3
2
1
0
2009
2010
2011
2012
2013
2014
2015
2016
MC
Car
Taxi
Bus
Truck

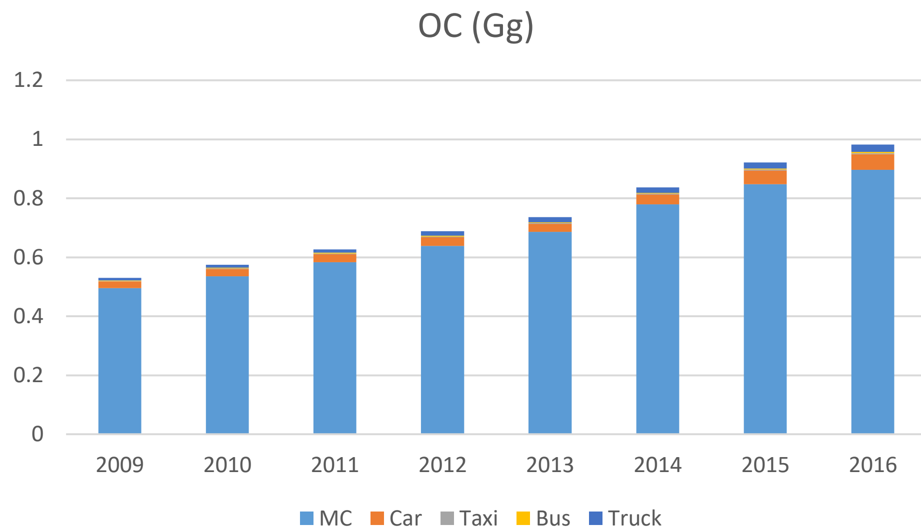

CH4 (Gg)
7
6
5
4
3
2
1
0
2009
2010
2011
2012
2013
2014
2015
2016
MC
Car
Taxi
Bus
Truck

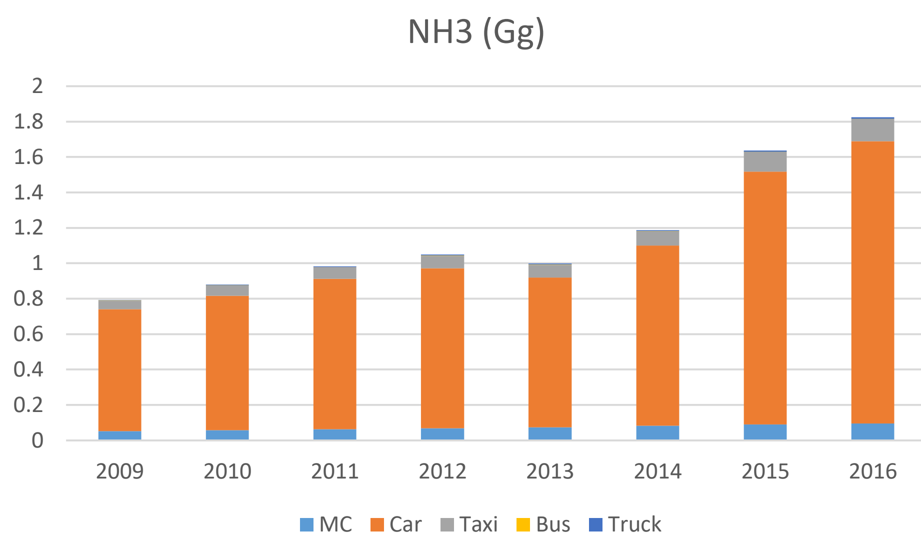

PM2.5 (Gg)
6
5
4
3
2
1
0
2009
2010
2011
2012
2013
2014
2015
2016
MC
Car
Taxi
Bus
Truck


PM10 (Gg)
25
20
15
10
5
0
2009
2010
2011
2012
2013
2014
2015
2016
MC
Car
Taxi
Bus
Truck


NMVOC (Gg)
800
700
600
500
400
300
200
100
0
2009
2010
2011
2012
2013
2014
2015
2016
MC Car Taxi Bus Truck


BC (Gg)
0.25
0.2
0.15
0.1
0.05
0
2009
2010
2011
2012
2013
2014
2015
2016
MC Car Taxi Bus Truck


OC (Gg)
1.2
1
0.8
0.6
0.4
0.2
0
2009
2010
2011
2012
2013
2014
2015
2016
MC Car Taxi Bus Truck


NH3 (Gg)
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2009
2010
2011
2012
2013
2014
2015
2016
MC Car Taxi Bus Truck

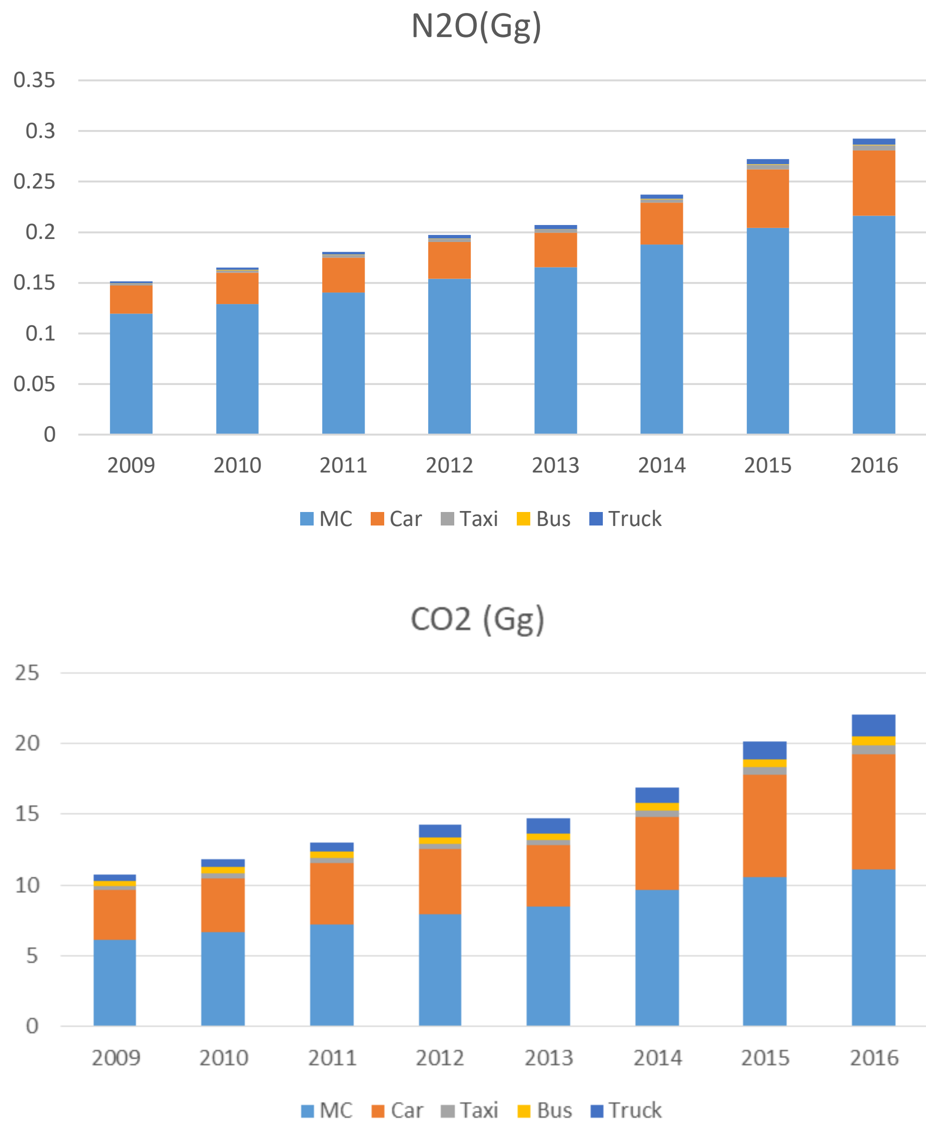
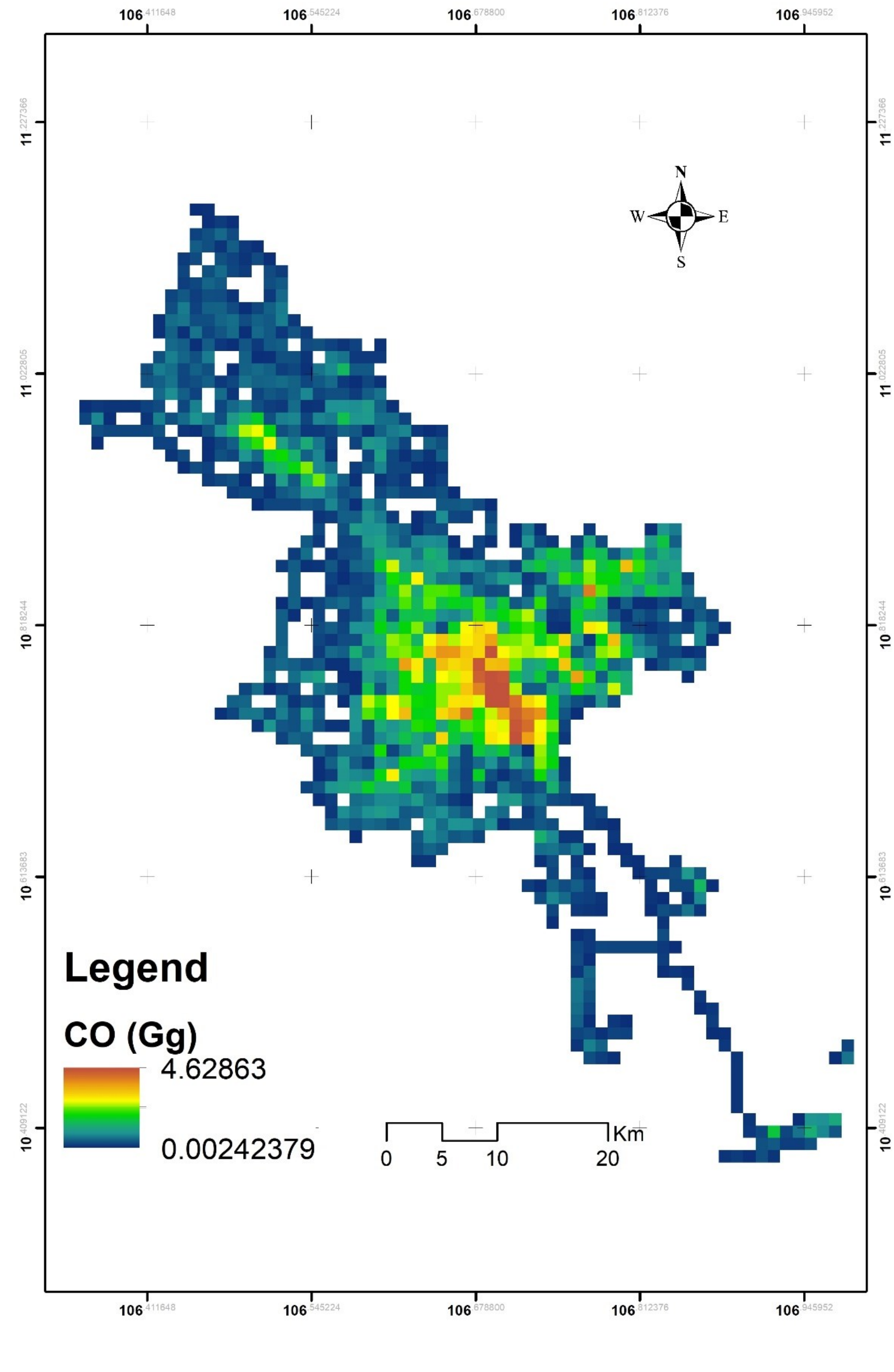


Figure 3.6 Annual evolution of transportation emission in HCMC from 2009-2016.

Figure 3.7 showed the spatial variation of CO and NOx emission from transportation sector in HCMC. As mentioned before, the spatial allocation of transportation sector was based on road density map in HCMC so transportation emission got peak where road density is highest. As a result, the central business district of HCMC is hot spot of traffic emission, followed by surrounding area like ring roads. In the outskirt parts of city, the level of vehicle emission dropped significantly.



106 411648
106 545224
106 678800
106 812376
106 945952
11 227366
11 022805
10 818244
10 613683
10 409122
N
W
E
S
Legend
CO (Gg)
4.62863
0.00242379
0
5
10
20
Km

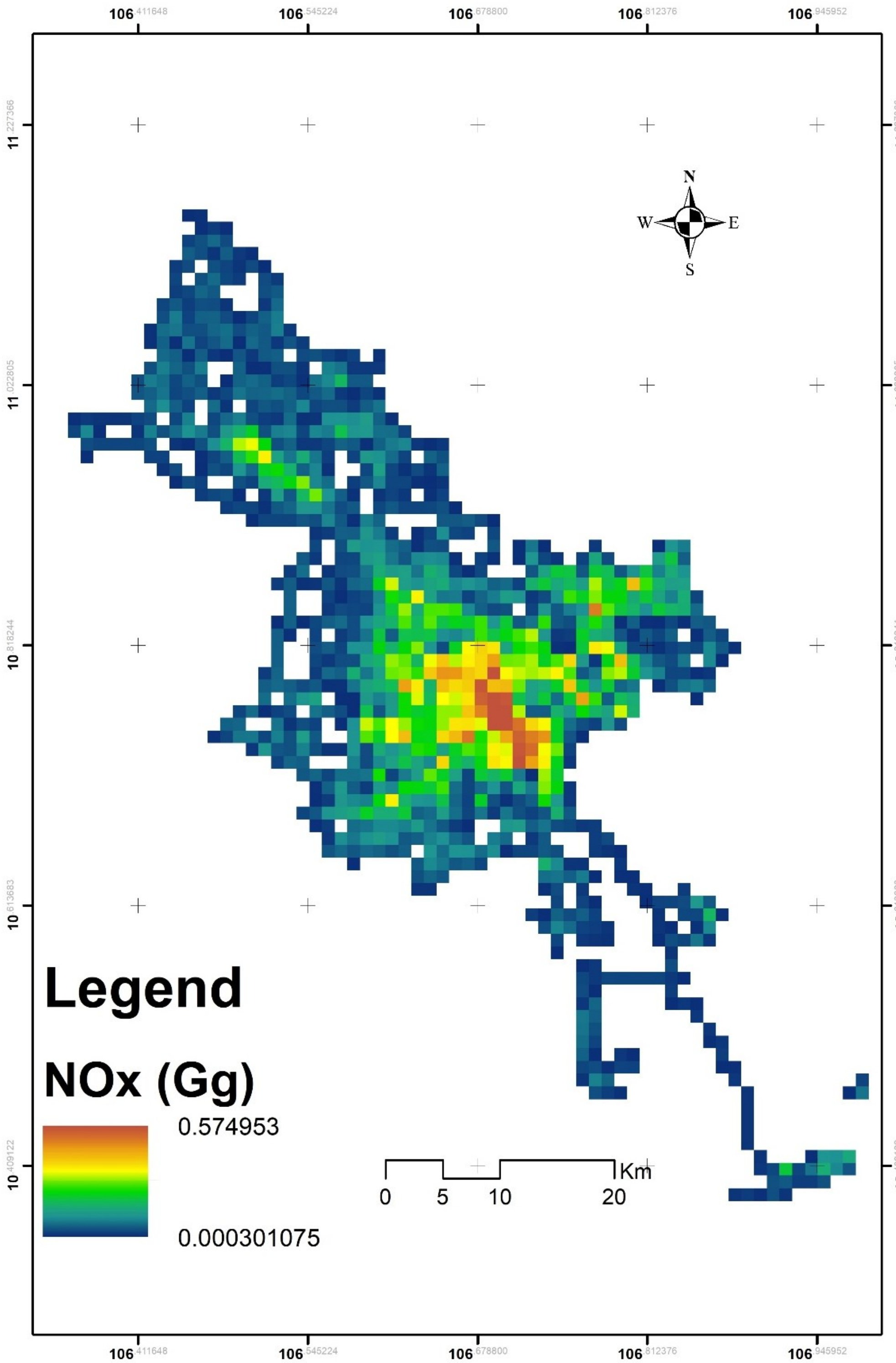


Figure 3.7 CO and NOx emissions from transportation sector in HCMC in 2016

3.3.2. Manufacturing industry and residential sector

3.3.2.1. Fuel consumption

Tab 3.14 and 3.15 showed the annual evolution of emissions from fuel consumptions in Manufacturing industrial and construction sector and Residential sector over 8 years. Again, the same rising trend was observed in all 12 pollutants because their emissions were mainly impacted by the same dataset of annual fuel consumption. From 2009 to 2016, Manufacturing industry emission from fuel consumption rose by about 43%. Meanwhile only 25% growth was seen in Residential sector. The sharp rise in Annual industry output is the main driver of this trend. There was an increase in Annual population in HCMC also, but the growth pace is slower in compare with Industry sector (Tab. 3.10)

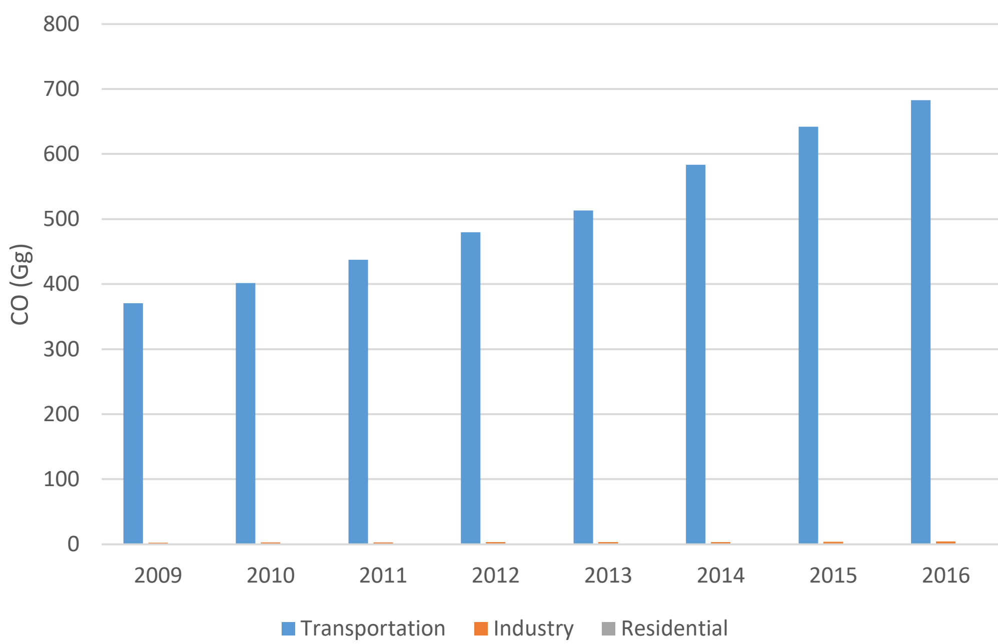
Fig 3.8 showed the comparison of annual emissions among three main sectors in HCMC from 2009 to 2016. Generally, the emission of fuel consumption from Transportation was by far dominated in compare with Manufacturing industry and Residential, especially in terms of CO and PM. Besides, the growth paces of Industrial and Residential emissions were much slower than Transportation. Manufacturing industry emitted much more pollution than Residential, particularly regarding SO2, CO2 and NOx. Among three primary sectors, fuel consumption of Residential was quite modest. This phenomenon is reasonable because in HCMC, fuel consumption in households mainly is for cooking and lighting only, not including heating like other cities. This finding implied one fact: when considering the emissions from sources that located within the city boundary only, Transportation is still the most key sector which is needed to be in control.

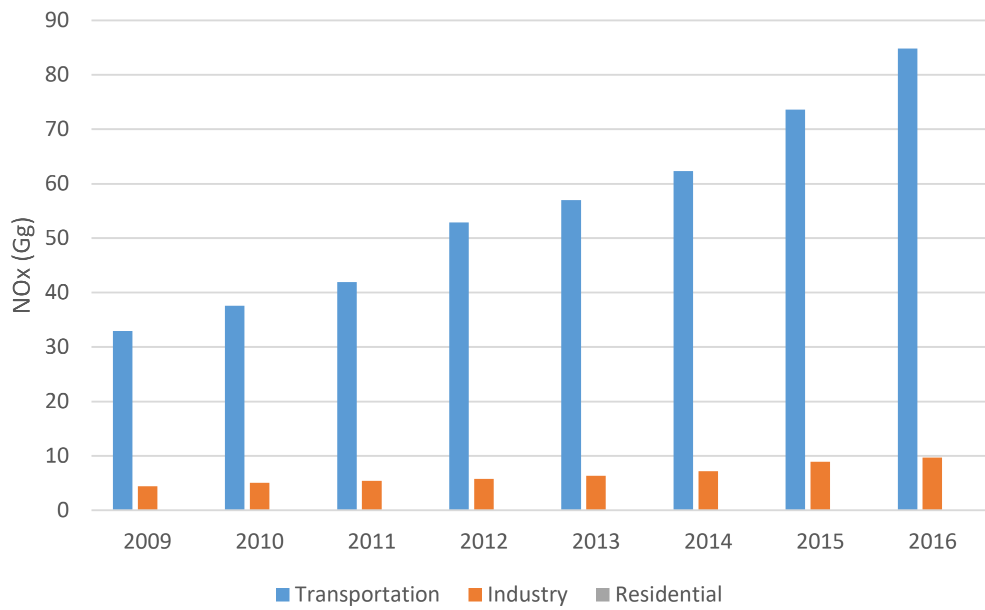
Table 3.14 Annual emissions from fuel consumptions in Manufacturing industrial and construction sector (numbers in grey background were calculated from fuel consumptions provided by JICA, 2017, numbers in white background were calculated proportionally with Annual Gross output of industry at current prices by industry activity in HCMC)

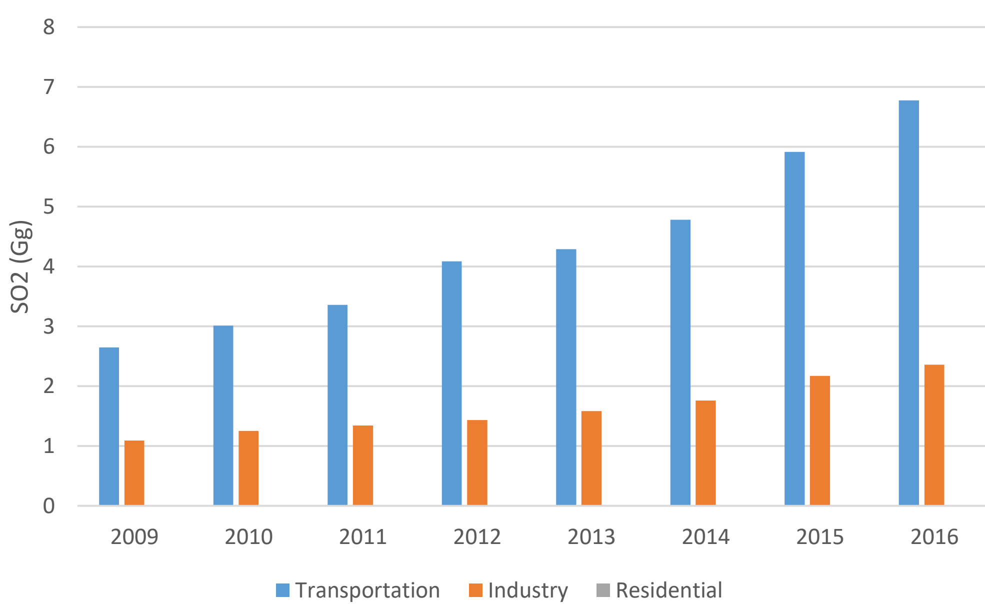
Unit (Gg)	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
CO	2.3647	2.7130	2.9102	3.1074	3.4270	3.4406	3.8243	4.1515
NOx	4.4107	5.0605	5.4283	5.7961	6.3923	7.2064	8.9714	9.7390
SO2	1.0917	1.2525	1.3435	1.4346	1.5821	1.7613	2.1742	2.3602
CH4	0.0699	0.0802	0.0860	0.0919	0.1013	0.1128	0.1392	0.1512
PM2.5	0.1736	0.1992	0.2136	0.2281	0.2516	0.2626	0.3090	0.3354
PM10	0.3051	0.3500	0.3755	0.4009	0.4421	0.4665	0.5535	0.6009
NMVOC	0.1207	0.1384	0.1485	0.1586	0.1749	0.1940	0.2386	0.2590
BC	0.0611	0.0700	0.0751	0.0802	0.0885	0.1020	0.1290	0.1400
OC	0.0038	0.0043	0.0046	0.0049	0.0055	0.0056	0.0066	0.0071
NH3	0.0024	0.0027	0.0029	0.0031	0.0034	0.0035	0.0039	0.0043
N2O	0.0139	0.0159	0.0171	0.0182	0.0201	0.0224	0.0277	0.0300
CO2	1798.5852	2063.5580	2213.5306	2363.5031	2606.6290	2891.3433	3557.5227	3861.8958

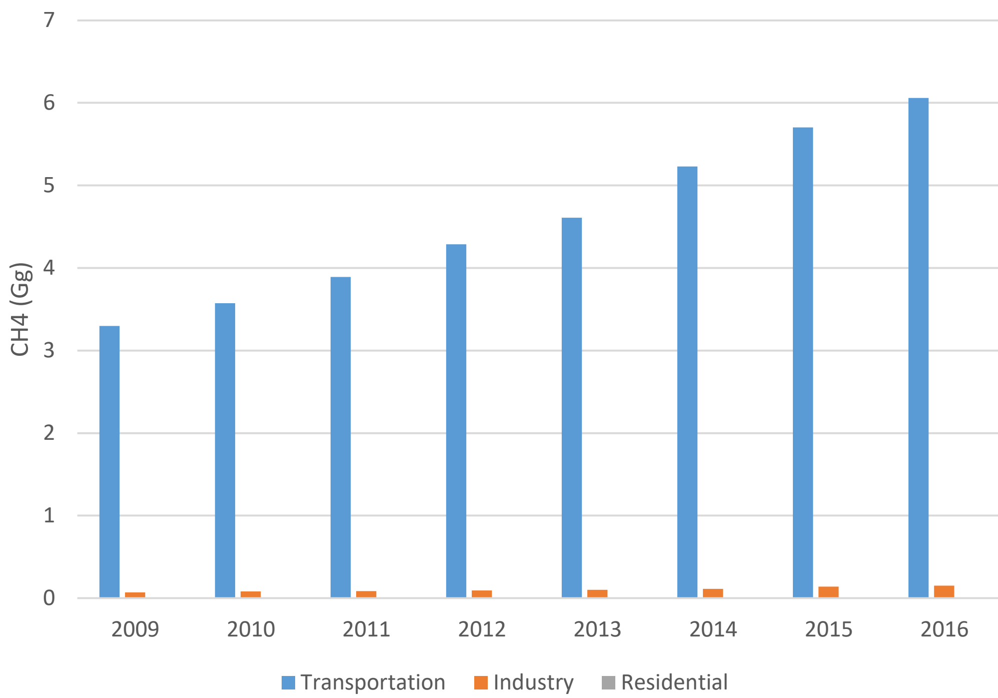
Table 3.15 Annual emissions from fuel consumptions in Residential sector (numbers in grey background were calculated from fuel consumptions provided by JICA, 2017, numbers in white background were calculated proportionally with Annual population in HCMC)

Unit (Gg)	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
CO	0.3106	0.3214	0.3326	0.3442	0.3563	0.3464	0.4047	0.4189
NOx	0.0740	0.0765	0.0792	0.0820	0.0848	0.0831	0.0959	0.0992
SO2	0.0083	0.0086	0.0089	0.0093	0.0096	0.0095	0.0107	0.0111
CH4	0.0040	0.0041	0.0043	0.0044	0.0046	0.0045	0.0051	0.0053
PM	0.0099	0.0103	0.0106	0.0110	0.0114	0.0112	0.0129	0.0133
NMVOC	0.0487	0.0504	0.0521	0.0539	0.0558	0.0549	0.0628	0.0650
BC	0.0320	0.0331	0.0343	0.0355	0.0367	0.0356	0.0418	0.0433
OC	0.0039	0.0040	0.0042	0.0043	0.0045	0.0043	0.0051	0.0052
NH3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N2O	0.0042	0.0043	0.0045	0.0047	0.0048	0.0047	0.0055	0.0056
CO2	163.8292	169.5266	175.4706	181.5789	187.9338	183.3901	212.9173	220.3642

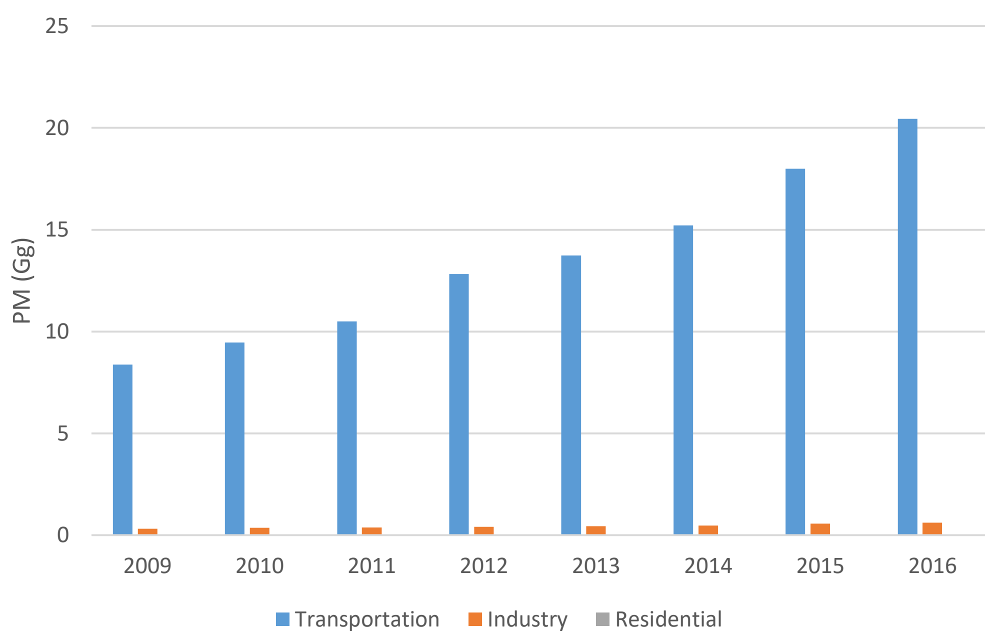



NOx (Gg)
90
80
70
60
50
40
30
20
10
0
2009
2010
2011
2012
2013
2014
2015
2016
Transportation
Industry
Residential


SO2 (Gg)
8
7
6
5
4
3
2
1
0
2009
2010
2011
2012
2013
2014
2015
2016
Transportation
Industry
Residential



7
6
5
4
3
2
1
0
CH4 (Gg)
2009
2010
2011
2012
2013
2014
2015
2016
Transportation
Industry
Residential



25
20
15
10
5
0
PM (Gg)
2009
2010
2011
2012
2013
2014
2015
2016
Transportation
Industry
Residential

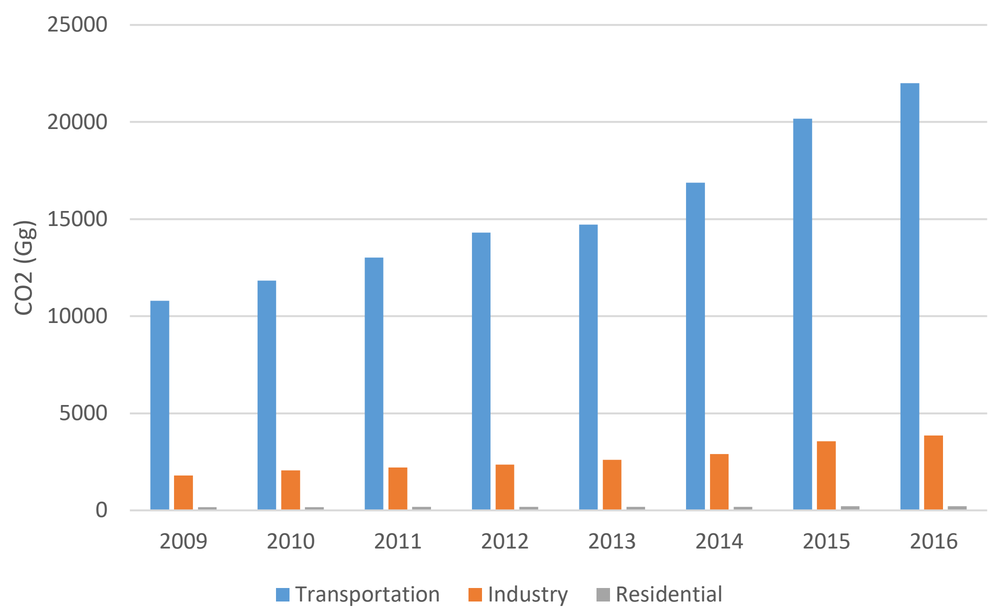


Figure 3.8 Comparison of annual emissions (Scope 1) among three main sectors in HCMC from 2009 to 2016

3.3.2.2. Electricity consumption

According to GHG emission inventory prepared by JICA, 2017, electricity consumption is the largest emission source in terms of Manufacturing industry and Residential sectors. Therefore, the pattern is quite different from Fuel consumption emission. The emission of Scope 2 was considered in terms of CO2 only.

Gradual increase trend in CO2 emission from electricity consumption was recorded in both Industry and Residential sectors (Fig 3.9 and Tab 3.16) However, Manufacturing industry showed stronger growth (increased by almost 1.9 times during 8 years). Consequently, by 2012, CO2 emission from electricity consumption of Industry had been lower than Residential. But from 2013 to 2016, the emission of this sector surpassed the emission from household area. On the other hand, the distinction between these key sectors was not so significant over 8 years. Besides, the dissimilarity in emission between fuel consumption and electricity consumption were not the same for Industry and Residential sector. In terms of Manufacturing industry, electricity consumption emitted almost double than fuel consumption. Meanwhile, the emission from electricity consumption of households by far surpassed the fuel consumption of this sector. Clearly, the electricity consumption from Residential sector should not be neglected in the controlling pollution plan of HCMC.

The comparison of CO2 emissions among three key sectors was shown in Fig 3.10. Transportation still contributed the highest ratio, always double than total emission of Manufacturing industry. The lowest emission was observed in Residential sector, which was only a third of Traffic CO2 emission. Another characteristic that can be seen in Fig 3.10 is that Transportation rose quicker than two other key sectors. Moreover, over 8 years, CO2 emissions of Industry were always higher than Residential but this gap expanded gradually. Therefore, in terms of GHG emission, vehicle emission and manufacturing industrial emission should have more consideration from local government.

In compare with CO2 emission in 2013 estimated by JICA, 2017, my calculations were not much different (Fig 3.11)The most dominant sharing was accounted by Transportation sector which emitted almost 15 000 Gg CO2 in 2013, followed by Industry and Residential. It should be noticed that this study used the same fuel consumption and electricity consumption data for Manufacturing industrial and Residential sector with JICA inventory. But the different method was applied to estimate emission from on road vehicle emission. This similarity proved that the finding of this study is in acceptable rank.

Table 3.16 Annual CO2 emissions from electricity consumptions in Manufacturing industrial and construction sector and Residential sector (numbers in grey background were calculated from electricity consumptions provided by JICA, 2017, numbers in white background were calculated proportionally with Annual Gross output of industry at current prices by industry activity and Annual population in HCMC)

Unit (Gg)	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Manufacturing industrial and construction	3716.38	4263.89	4573.78	4883.66	5386.03	5896.26	6434.75	6985.29
Residential	4621.68	4782.41	4950.09	5122.41	5301.68	5814.15	6465.30	6691.43

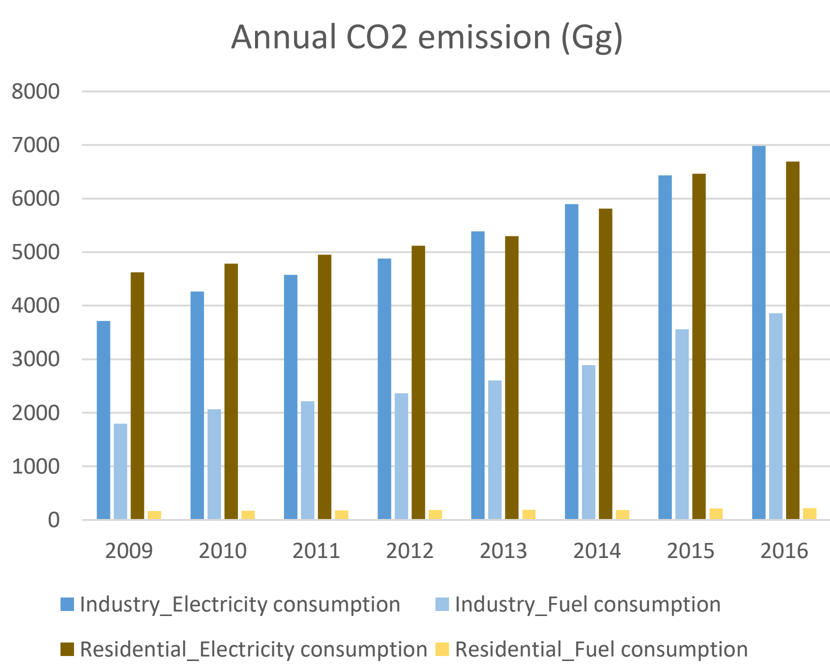


Figure 3.9 Annual CO2 emissions of Electricity consumption and Fuel consumption of Manufacturing industry and Residential sector in HCMC

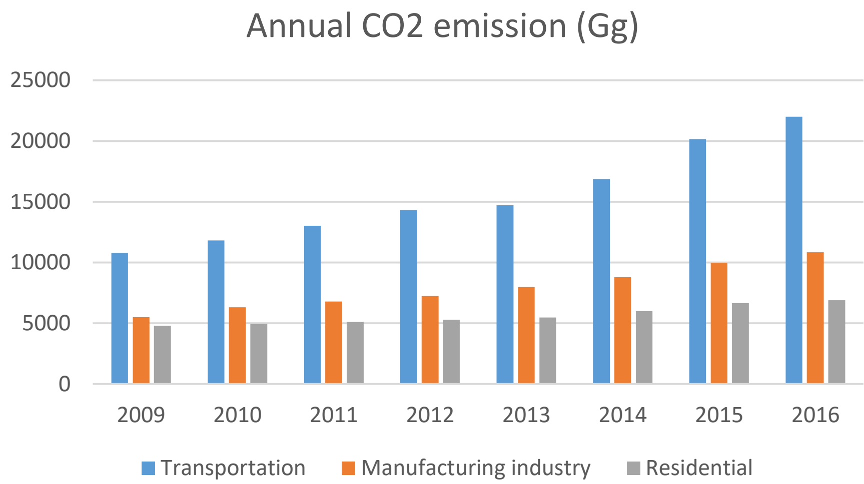


Figure 3.10 Annual CO2 emissions of three key sectors: Transportation, Manufacturing industry and Residential sector in HCMC

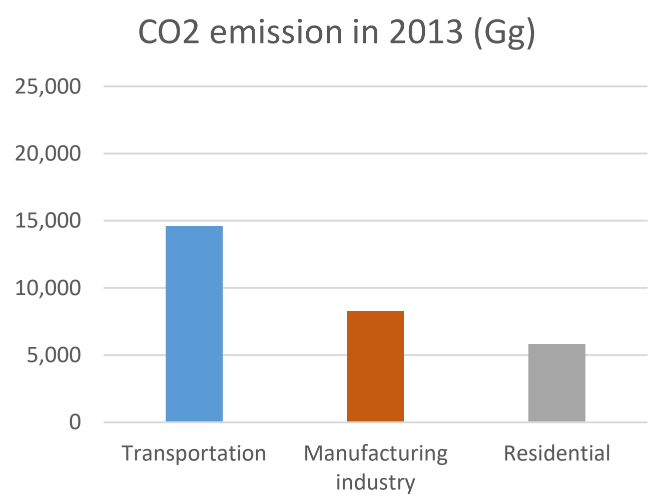


Figure 3.11 CO2 emissions of three key sectors: Transportation, Manufacturing industry and Residential sector in HCMC in 2013, according to JICA (2017)

3.3.2.3. Urban morphology maps

As can be seen in Fig 3.12 over 8 years, Residential was by far the most dominated land use type, accounting for 94% in 2016 among 3 land use categories and spread over the northern and central parts of HCMC (Fig 3.13) The commercial areas mainly locate in the central business district of city, meanwhile industrial zones are scattered around the central part and locate along main ring roads. Industrial land contributed only 4% of total build up area in HCMC in 2016, followed by commercial land. On the whole, the obvious change in the urban morphology in HCMC over 8 years was hard to be seen. However, residential area expressed the gradual rising trend (Tab. 3.17) From 2009 to 2016, this dominated land use type expanded by 27%, which can be explained by the remarkable growth in population. Meanwhile, the variation in Industry and Commercial zones were not considerable. The difference between land use maps in 2009 and 2016 suggested that the development of the residential area mainly happened in the North (Fig 3.14) In the central and the Eastern parts, the expansion of built-up land can be observed but not too significant. The spread of Residential area can lead to the evolvement of road network and the formation of new pollution hot spots and the change in pollution distribution as well. Therefore, the spatial allocation of annual emission should not neglect the urban sprawl, especially for city which still has high urbanization rate and population increasing like HCMC.

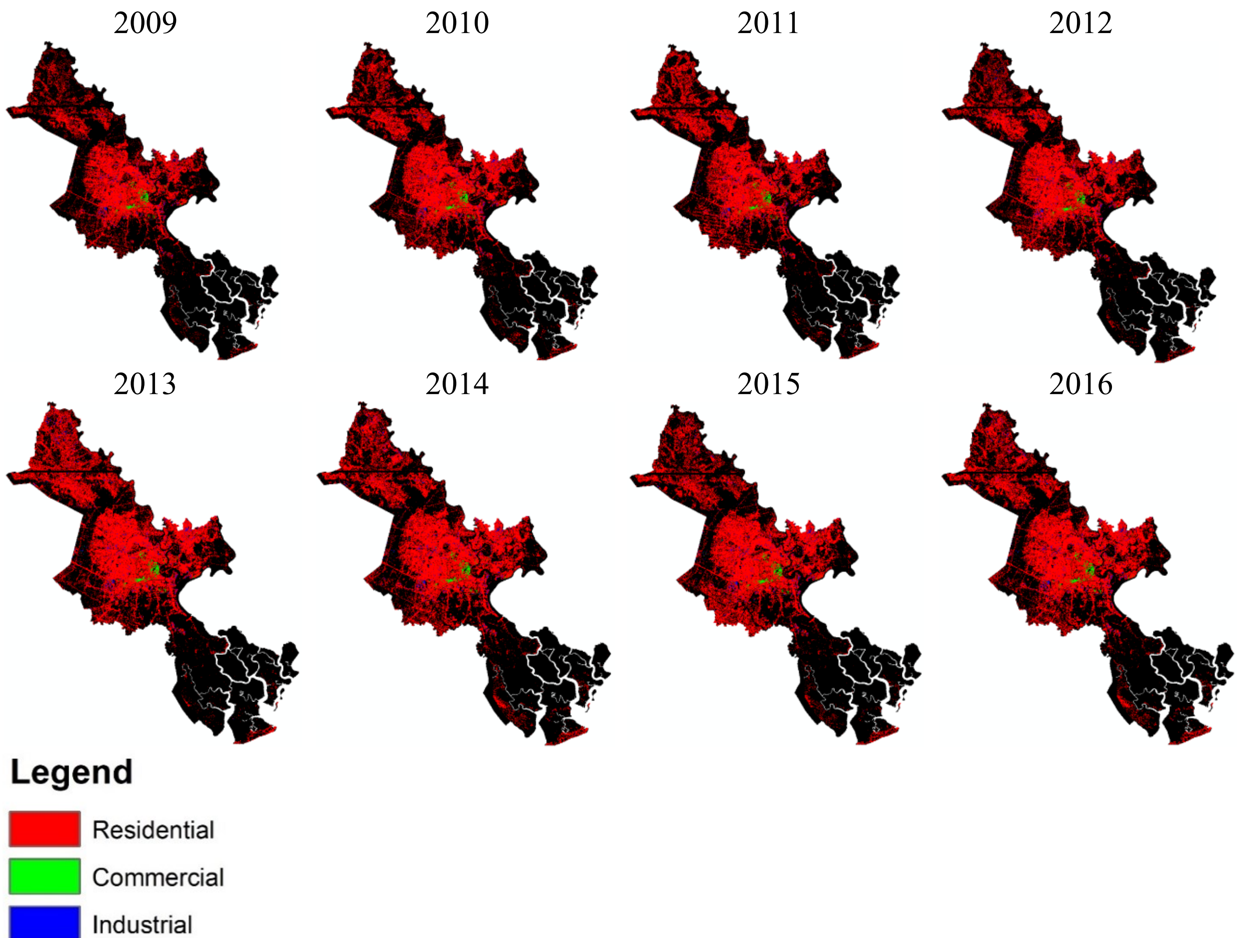


Figure 3.12. Urban morphology map over 8 years in HCMC

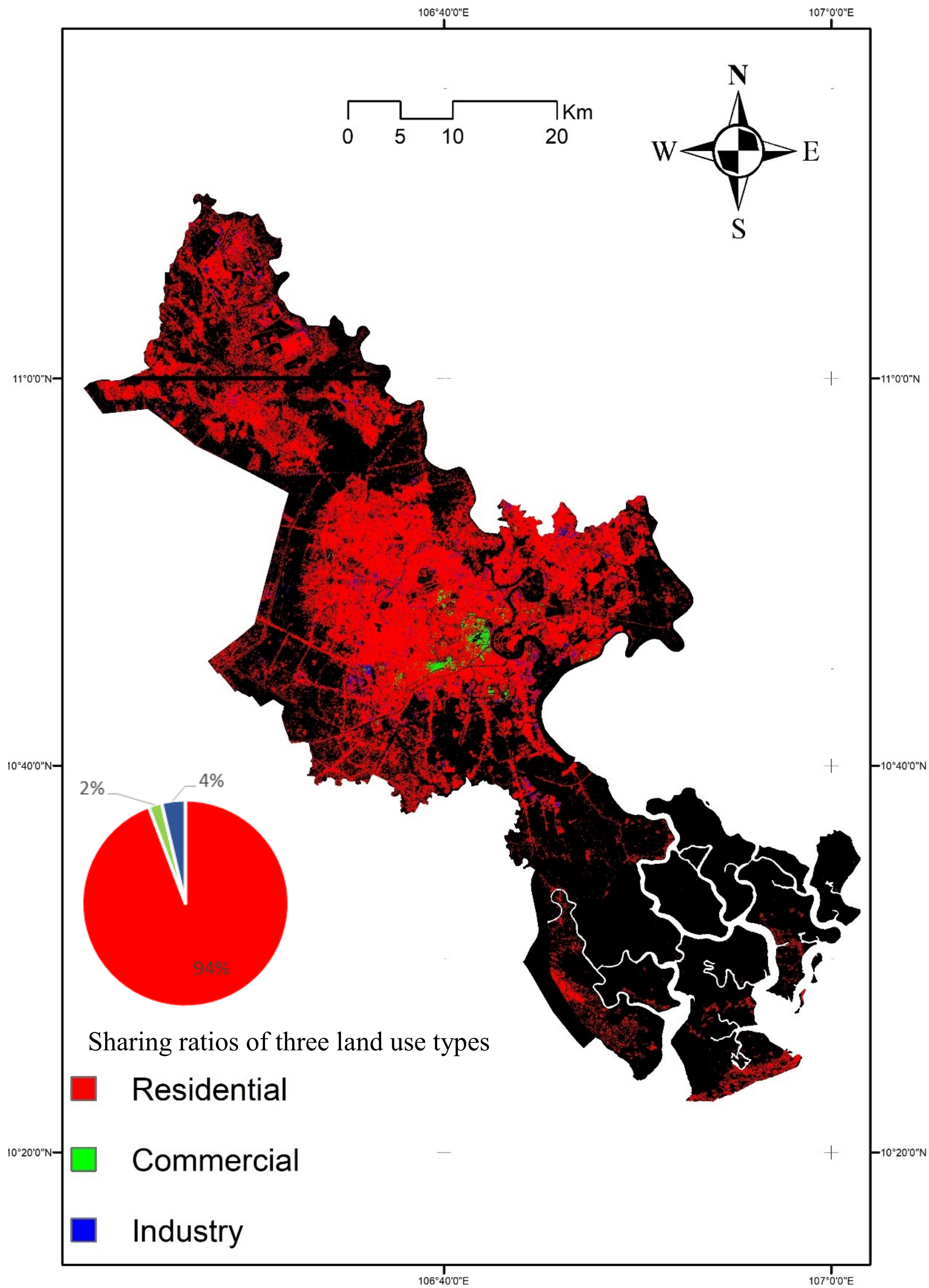


Figure 3.13 Urban morphology map in HCMC and sharing ratio among three land use types in 2016

Table 3.17 Annual Residential area in HCMC based on urban morphology maps (Unit: ha)

2009	2010	2011	2012	2013	2014	2015	2016
5564.61	6556.77	6660.18	6670.89	7074.81	7346.61	7470.45	7690.93

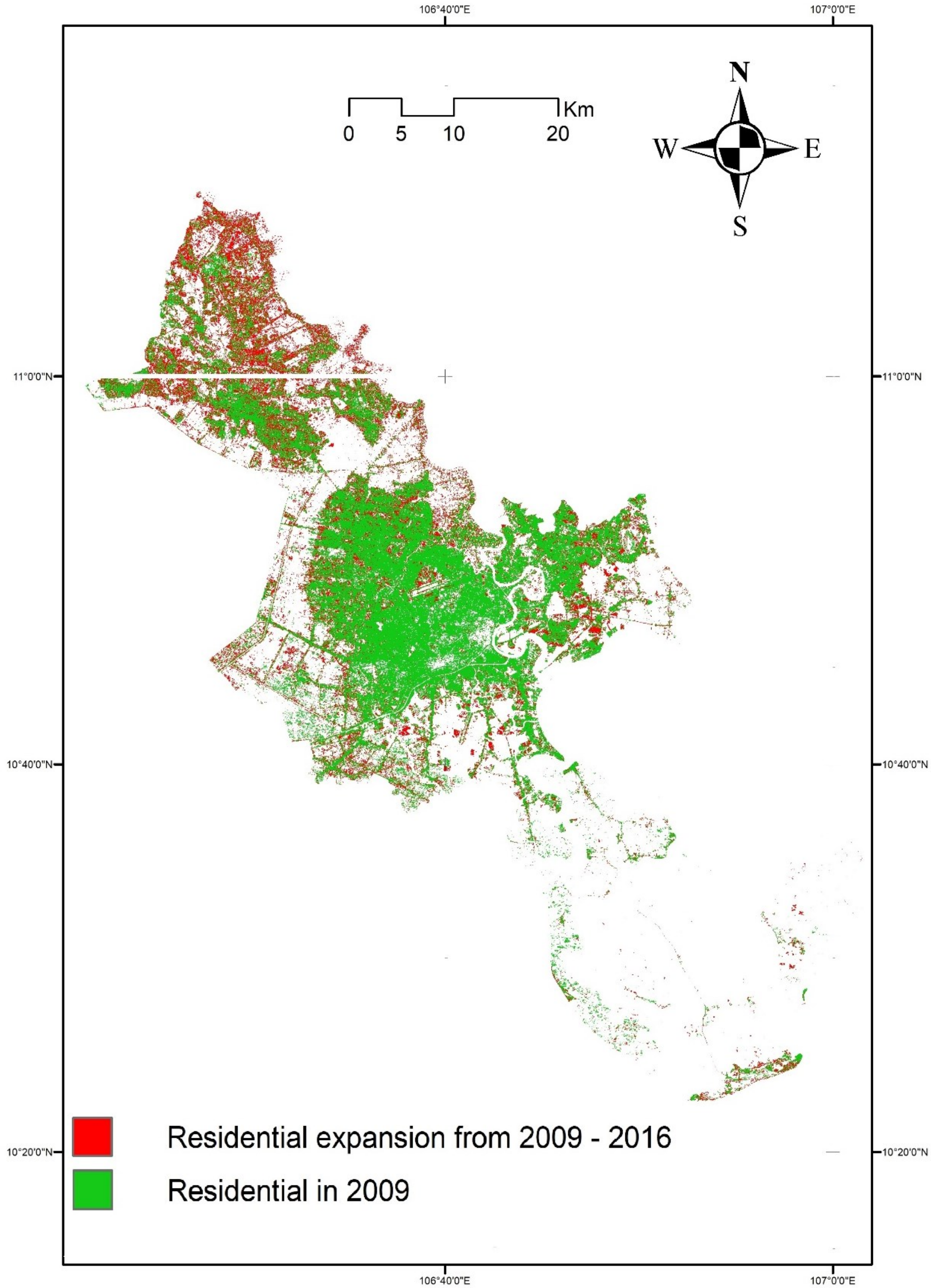
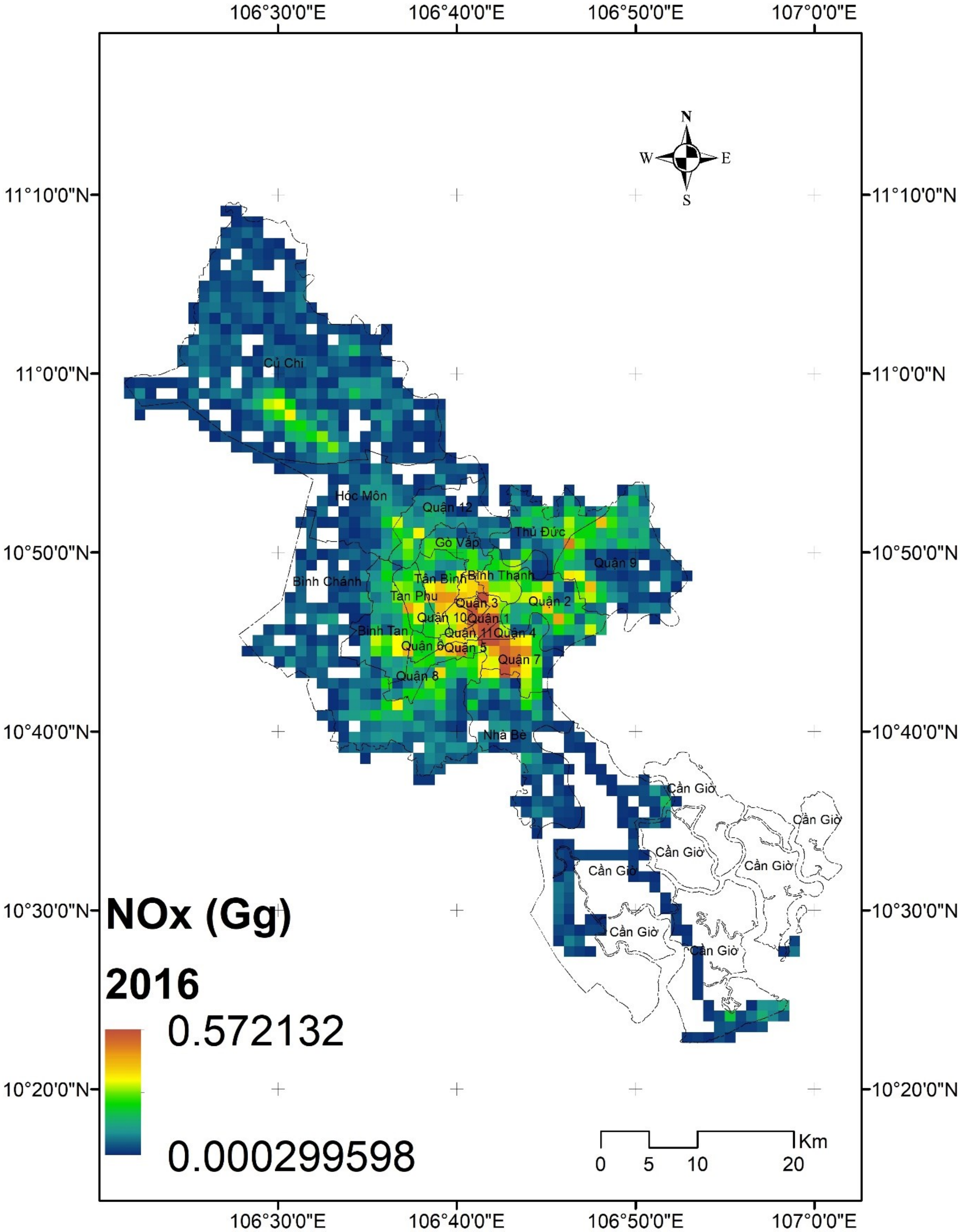


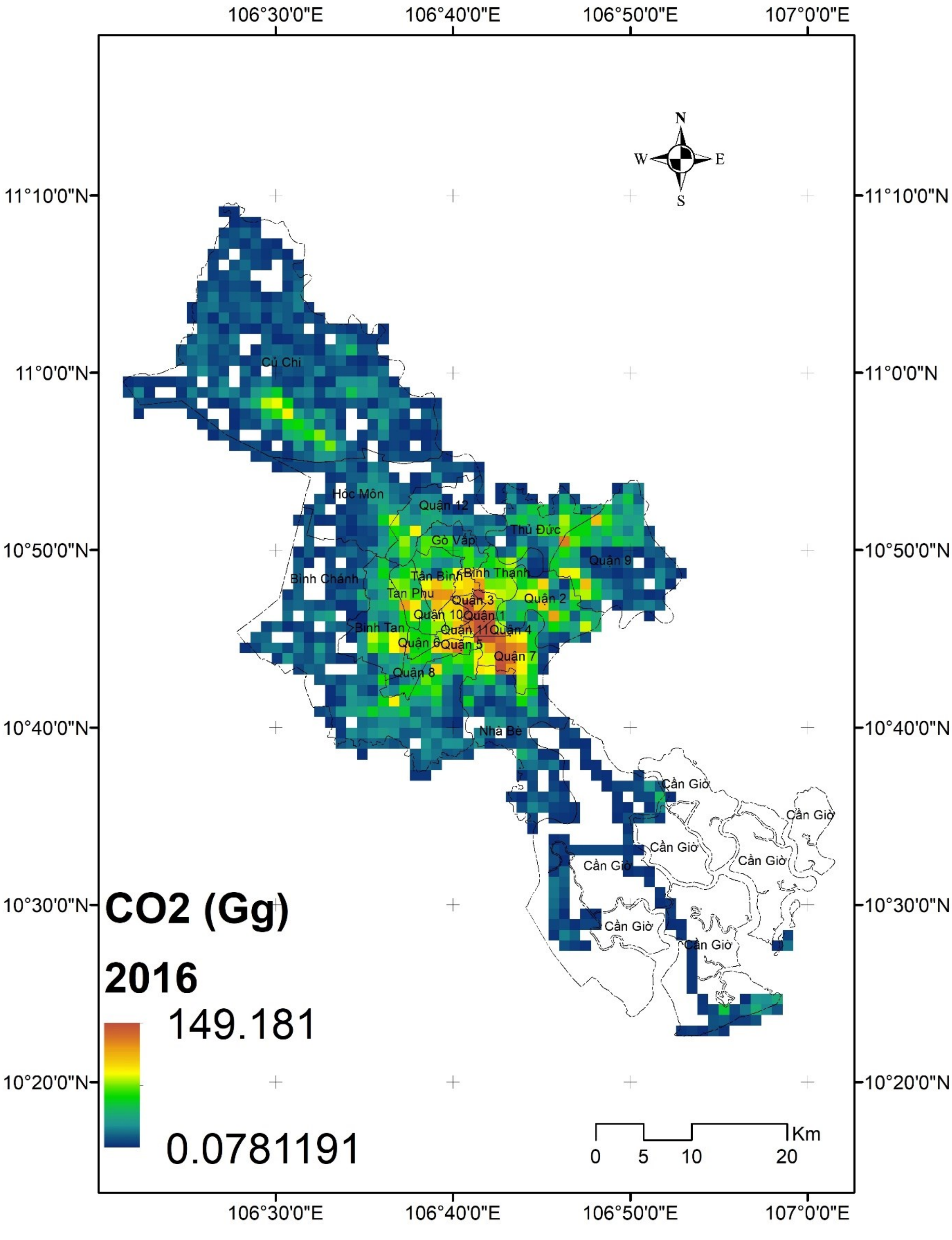
Figure 3.14 Residential expansion in HCMC from 2009 - 2016

3.3.3. Spatial distribution of emission from three key sectors

Emission maps can reveal the spatial intensities and where emission come from. The data is valuable for residences and local authorities in these areas. It helps identify areas of pollution concentration where special activities may be needed to control pollution. Also, it provides necessary input to air quality simulation models.

Fig 3.15 revealed the spatial distribution of different pollutants as sum of three key sectors in HCMC in 2016. It should be noted that these 1km resolution maps show only Scope 1 emissions that is the sum of Transportation emission and emission from Fuel consumption of Manufacturing industry and Residential sectors, not including emission from Electricity consumption. According to Fig 3.8, Transportation emission is by far dominated than two other source types, in terms of all pollutant species. It explained for the similarity among emission maps of various pollutions shown in Fig 3.15 and the similarity in spatial distribution of emission from Transportation (Fig 3.7) and total emission from three key sectors (Fig 3.15) Because of high road densities, the central business districts (CBD) like Quan 1, Quan 4 and Quan 7 shown the highest emission intensities. Suburban districts demonstrated much better situation, like low emission amplitudes observed in Can Gio, Cu Chi and Binh Chanh. Emission within each kilometer squares in CBD can be higher over 1900 times than the ones in surrounding districts. Therefore, the policies to control emissions in CBD are the most crucial to improve air quality in HCMC.


106°30'0"E
106°40'0"E
106°50'0"E
107°0'0"E
11°10'0"N
11°0'0"N
10°50'0"N
10°40'0"N
10°30'0"N
10°20'0"N
N
W
E
S
Củ Chi
Hóc Môn
Quận 12
Thủ Đức
Gò Vấp
Quận 9
Bình Chánh
Tân Bình
Bình Thạnh
Tân Phú
Quận 3
Quận 2
Quận 10
Quận 1
Bình Tân
Quận 11
Quận 4
Quận 6
Quận 5
Quận 7
Quận 8
Nhà Bè
Cần Giờ
NOx (Gg)
2016
0.572132
0.000299598
Km
0
5
10
20


106°30'0"E
106°40'0"E
106°50'0"E
107°0'0"E
11°10'0"N
11°0'0"N
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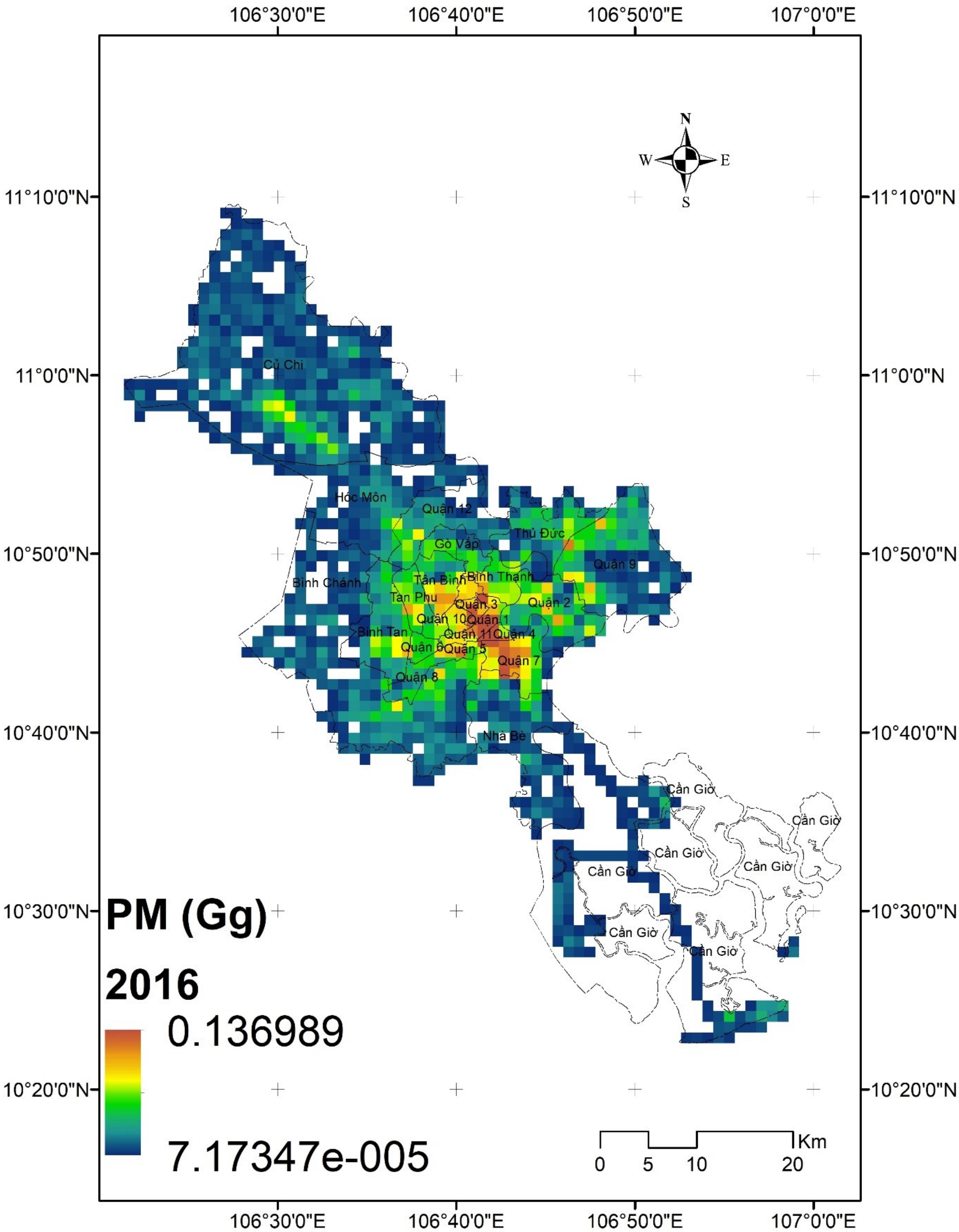
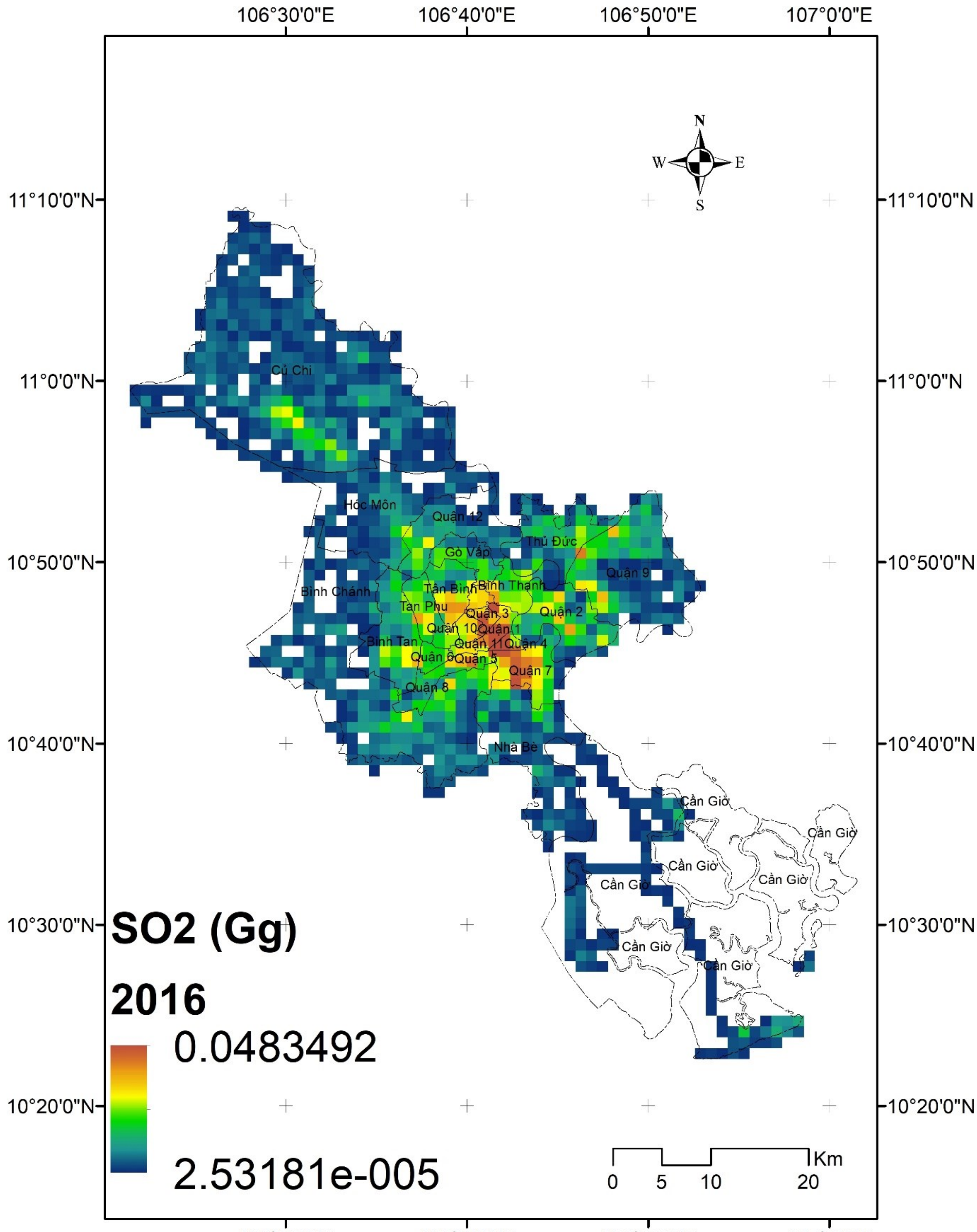
10°40'0"N
10°30'0"N
10°20'0"N
N
W
E
S
Củ Chi
Hóc Môn
Quận 12
Thủ Đức
Gò Vấp
Quận 9
Bình Chánh
Tân Bình
Bình Thạnh
Tân Phú
Quận 3
Quận 2
Quận 10
Quận 1
Bình Tân
Quận 11
Quận 4
Quận 6
Quận 5
Quận 7
Quận 8
Nhà Bè
Cần Giờ
CO2 (Gg)
2016
149.181
0.0781191
0 5 10 20
Km


106°30'0"E
106°40'0"E
106°50'0"E
107°0'0"E
11°10'0"N
11°0'0"N
10°50'0"N
10°40'0"N
10°30'0"N
10°20'0"N
N
W
E
S
Củ Chi
Hóc Môn
Quận 12
Gò Vấp
Thủ Đức
Quận 9
Bình Chánh
Tân Bình
Bình Thạnh
Tân Phú
Quận 3
Quận 2
Quận 10
Quận 1
Bình Tân
Quận 11
Quận 4
Quận 6
Quận 5
Quận 7
Quận 8
Nhà Bè
Cần Giờ
PM (Gg)
2016
0.136989
7.17347e-005
Km
0
5
10
20


106°30'0"E
106°40'0"E
106°50'0"E
107°0'0"E
11°10'0"N
11°0'0"N
10°50'0"N
10°40'0"N
10°30'0"N
10°20'0"N
N
W
E
S
Củ Chi
Hóc Môn
Quận 12
Thủ Đức
Gò Vấp
Quận 9
Bình Chánh
Tân Bình
Bình Thạnh
Tân Phú
Quận 3
Quận 2
Quận 10
Quận 1
Bình Tân
Quận 11
Quận 4
Quận 6
Quận 5
Quận 7
Quận 8
Nhà Bè
Cần Giờ
SO2 (Gg)
2016
0.0483492
2.53181e-005
Km
0 5 10 20

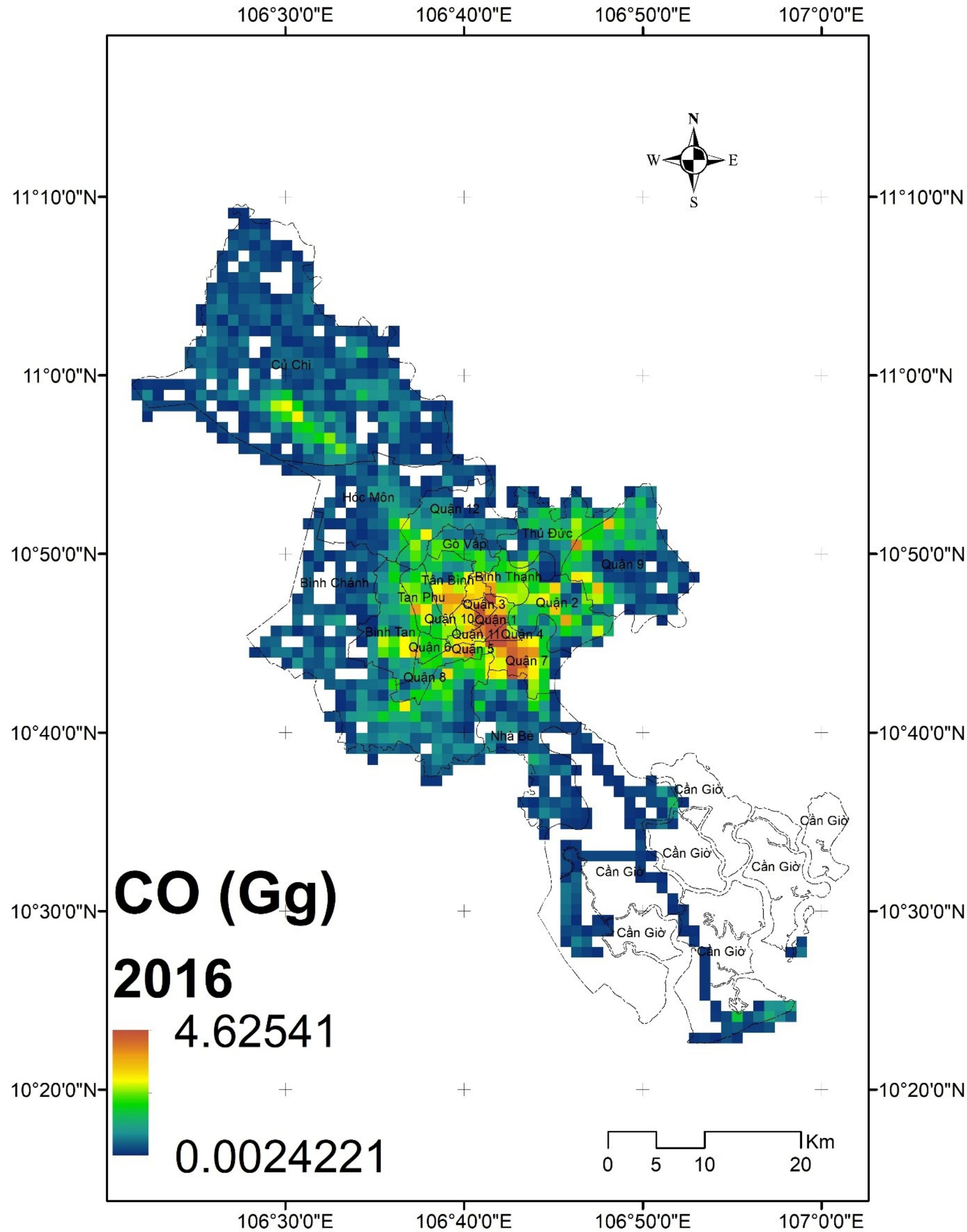


Figure 3.15 Emission maps of NOx, CO2, PM, SO2 and CO in 2016 in HCMC as sum of three key sectors: Transportation, Manufacturing industry and Residential Sectors.

3.3.4. Comparison with other inventories

3.3.4.1. Comparison of transportation emission inventories

The transportation emission estimated in this study was compared with four previous studies about vehicle emission in HCMC (Tab 3.18) Study of H.H.Van, 2015 applied the same method with this study. Activity data were number of active vehicles, divided by 5 vehicle types and daily VKT of each vehicle type. Besides, this research considered the daily number of startups per vehicle categories and average speed to estimate detailed emission factors. EFs were separated into startup EFs and running EFs. Their output is annual emission in HCMC in 2013 for CO, VOC, NOx, SO2, PM, BC, OC, CO2, N2O and CH4.

The second study is GHG emission inventory of JICA. This study applied different method: activity data was fuel consumption of Transportation sector (Mainly Gasoline and Diesel), EFs were extract from 2006 IPCC Guidelines.

Another GHG emission inventory for HCMC was study of L.T.P.Linh, 2018. This author used activity data that were vehicle counts, by type of vehicles and daily VKT as study of H.H.Van, 2015. Their vehicle counts derived from Field measurement and vehicle registry data. Regarding CO2 emission factor, they did not apply the EF of 2006 IPCC Guidelines and used country-specific EFs from COPERT model instead. Noticeably, they divided vehicle fleet into 4 types only: MC, bus, diesel car and gasoline car.

Another high detail level vehicle emission inventory in HCMC was prepared by H.Q.Bang, 2010. The activity data was hourly traffic counts, including 5 categories, namely car, light truck, heavy truck, bus and MC. EFs were extracted from literature review and were assumed to be constant on each street category and constant in time. The output is hourly emission from vehicle fleet in HCMC. The contribution percentage of each vehicle types for each pollutants in this study was compared with the estimation in this study.

Firstly, my CO2 emission in 2013 was quite close with the calculation of JICA but higher than finding of H.H.Van, 2015 around 4000 Gg. This study applied the same number of active vehicles and daily VKT used in research of H.H.Van, 2015 but this author applied EFs in much more detail levels As a result, the different emission factors are likely the reason of this gap. In addition, my CO2 estimation in 2016 was double in compare with the finding of L.T.P.Linh, 2018. As mentioned before, this author classified vehicle fleet in HCMC into only 4 types, without considering truck. Besides, the difference in daily VKT, vehicle population, and emission factor is likely to contribute to the inconsistency with my study.

In terms of other pollutants, my estimations were lower by factors of 2- 10 in compare with study of H.H.Van, 2015. The vehicle populations and daily VKT was the same for both of two studies. The smallest gap was observed for NOx emission, while BC and OC emission showed significant distinctions. The emission factor dataset used in the study of H.H.Van, 2015 was not clarified in their publication but it is expected to explain the gap between two researches. Their study applied International Vehicle Emission (IVE) model. This tool produces the pollutant emission factors that are relevant to the local driving conditions and local fleet composition and considers the engine technology distribution in vehicle fleet. Meanwhile, my study applied constant the emission factors from different previous researches about transportation emission in HCMC, Hanoi and China.

Table 3.18. Comparison of transportation emission estimated in this study with emission calculated in previous studies for 2013 and 2016.

Unit (Gg)	Van. H. H et al, 2015	JICA, 2017	L.T.P.Linh, 2018	This study	
	2013	**2013**	**2016**	**2013**	**2016**
CO	1252			513.0680531	
NOx	61			56.97214	
CH4	33			4.610224	
BC	1.77			0.165746	
OC	6.65			0.736276	
N2O	0.5			0.207143	
CO2	10722	14693	10890	14711.59	21998.72

Furthermore, the sharing ratios of emission from MC and personal car in this study were also compared with two previous research (Tab 3.19) Basing on my estimation, MC was accounted for 94.4 % of total CO emission from Transportation sector in 2010. This finding had high agreement with hourly emission inventory of H. Q. Bang, 2010. However, the emission of NOx, SO2 and NMVOC from MC in my study was much lower than the calculation of H. Q. Bang, by factors of 2, 6 and 3 respectively. The EF of NMVOC was the same for both of two studies. The EF of SO2 in their study was higher than mine 3 times but my NOx EF was higher than the one they applied 4 times. Regarding the portion of MC number in whole vehicle fleet, two studies had the similar input (H.Q. Bang claimed that MC is accounted for 92 % the total vehicle population, in this study, that ratio was over 90%, as mentioned in previous part) Therefore, this discrepancy in final contribution emission of MC fleet can be from EFs of both MC and other vehicle types applied in two studies.

In compare with the study of H.H.Van, 2015, the sharing proportion of MC from my estimation is higher but the contribution from personal car is lower in terms of CO. The significant gap was recorded in the sharing percentage of MC for NOx emission. According to their calculation, MC fleet was responsible for 80% of total NOx emission from transportation in HCMC. This ratio was much higher than finding of H.Q. Bang (29%) for vehicle emission in 2010, also. As mentioned before, my study applied the same number of active vehicles, the same daily VKT data with study of H.H.Van for emission in 2013. As a result, this gap is expected to come from inconsistent EF datasets between two studies.

Table 3.19. Comparison of ratio sharing of emission from MC and personal car (PC) in this study and previous studies for 2010 and 2013.

Unit (%)	Ho Quoc Bang	Van. H. H et al, 2015		This study		
	2010	**2013**		**2010**	**2013**	
	MC	**MC**	**PC**	**MC**	**MC**	**PC**
CO	94	85	12	94.4	94.6	3.5
NOx	29	80	14	15.6	13.2	14.9

3.3.4.2. Comparison with REAS v2.1 inventory

Tab 3.20 And 3.21 Summarizes the general information of REAS2.1 and the data sources applied for three sectors: Transportation, Manufacturing industry and Residential sectors. REAS2.1 mainly used the national statistical data for their activity data. Then the spatial allocation was based on road network or population data to create grid maps with 0.25 deg resolution. Tab 3.22 shows the comparison between the estimations in this study and REAS 2.1 estimation for three key sectors in HCMC. The transportation emissions from REAS for 2008 were much lower than my calculation for 2009, except BC, by factors of 1.5 to 10, depending on pollutant species. It is worth noticing that the data sources applied in two researches were not the same. REAS based on vehicle numbers, annual distance traveled, and emission factors to estimate vehicle emission. Their vehicle population were national one then total emission was allocated to HCMC using road network, so maybe the calculation underestimated the emission from a hot spot as HCMC. In addition to that, the gap between their annual VKT and my daily VKT could be a reason also.

Conversely, the estimation of Industry and Residential emission of REAS surpassed the findings in this study. The difference for Residential sector is more significant then Industry. In this comparison, only Scope 1 part of HCMC emission was compared with REAS emissions. So the activity data – fuel consumption was the same for both of two studies. But REAS fuel consumption data was national data provided by International Energy Agency (IEA) Energy Balances database and the data applied in this study is annual sale data provided by HCMC Department of Industry and Trade (DOIT) and fuel companies. Regarding sum of emission from fuel consumptions of three key sectors, the gap under 25% were seen in the cases of CO, NOx and CO2 only.

Apart from different sources of activity data, Tab 3.23 compares the EFs of fuel consumption in these two sectors that were applied in two research. REAS 2.1 applied EFs of oil and gas only. In terms of Industry sector, EFs of NOx and NMVOC were pretty similar. But REAS used much higher EFs of CO and SO2. CO emission factor was over double the one applied in this study. Regarding oil, SO2 emission factor was higher over 10 times than my EF. The insignificant consistency was seen in EFs used in Residential sector as well.

According to the big difference drawn from this analysis, the limitation when comparing between a regional emission inventory and a local emission inventory can be seen. This gap is expected due to the inconsistency regarding sources of activity data and EF database.

Table 3.20. Description about REAS v2.1 inventory (J. Kurokawa et al, 2013)

Spatial resolution	0.25 deg
Temporal resolution	Monthly
Time domain	2000-2008
Species	SO2, NOx, CO, NMVOC, PM10, PM2.5, BC, OC, NH3, CH4, N2O, and CO2
Coverage	East, Southeast, South, and Central Asia. Asian part of Russia (Far East, Eastern and Western Siberia, and Ural)
Sectors	Stationary combustion and industrial processes, road transport, Agricultural activities, Other sources.

	Power plant, industry, road transport, aviation, International navigation, other transport, domestic and other	

Table 3.21. Data sources used in REAS2.1 for Transportation, Industry and Domestic sectors (J. Kurokawa et al, 2013)

Sector	Transportation	Industry and Domestic
Activity data	Vehicle numbers, annual distance traveled. Vehicle numbers were from the World Road Statistics (IRF, 2006–2010) and then subdivided into vehicle types by using the national and sub-regional statistics and database of the GAINS model	Fuel consumption or amount of industrial product (for industrial process emissions). Energy consumption data for each fuel type including biofuels and sector categories were taken from the International Energy Agency (IEA) Energy Balances database. Activity data for sources other than energy came from a variety of international, national, and regional statistics and studies
Spatial allocation	Road network	Spatial distribution of rural, urban, and total populations.

Table 3.22 Comparison of Transportation, Industry and Domestic emissions estimated for 2009 in this study and emissions estimated by REAS 2.1 for 2008

	Transportation		Industry		Residential		Sum of three sectors	
Unit: Gg	Emission in 2009 – this study	Emission in 2008 – REAS 2.1	Emission in 2009 – this study	Emission in 2008 – REAS 2.1	Emission in 2009 – this study	Emission in 2008 – REAS 2.1	This study (2009)	REAS (2008)
CO	370.5	88.05	2.36	9.1	0.31	456.85	373.17	554
NOx	32.93	6.81	4.41	13.19	0.07	7.73	37.41	27.73
SO2	2.65	1.64	1.09	32.42	0.01	11.18	3.75	45.24
CH4	3.3	0.33	0.07	2.1	0	18.02	3.37	20.45
PM2.5	1.97	0.35	0.17	18.61	0.01	25.99	2.15	44.95
PM10	8.37	0.36	0.31	32.26			8.68	32.62
NMVOC	277.53	24.36	0.12	1.78	0.05	70.02	277.7	96.16
BC	0.12	0.15	0.06	0.94	0.03	5.19	0.21	6.28
OC	0.53	0.1	0	2.24	0	20.36	0.53	22.7
NH3	0.79	0.07	0	0.76	0	5.91	0.79	6.74
N2O	0.15	0.07	0.01	0.15	0	0.3	0.16	0.52
CO2	10784	1414.82	1798.59	7352.87	163.83	8054.68	12746.42	16822.37

Table 3.23 Comparison of emission factors used for *Industry sector* in this study and in REAS v2.1 (grey column)

(unit: kg/ TJ)	Diesel	Heavy oil	Kerosene	Oil (REAS)	LPG	Natural gas	Gas (REAS)
CO	15.00	15.00	15.00	35.30	10.00	2000.00	24.00
NOx	222.00	145.00	167.00	157.00	56.00	53.00	56.40
SO2	46.20	49.80	44.60	538.00	0.20	0.19	0.24
CH4	3.00	3.00	3.00	-	1.00	1.00	-
PM2.5	0.83	17.00	10.00	6.53	-	0.04	0.00
PM10	3.30	27.40	10.80	10.40	-	0.04	0.00
NMVOC	5.00	5.00	5.00	4.38	5.00	5.00	5.00
BC	3.90	0.90	5.50	0.48	-	0.00	0
OC	0.00	0.37	1.70	0.18	-	0.02	0
NH3	0.01	0.10	-	-	-	1.31	-
N2O	0.60	0.60	0.60	-	0.10	0.10	-
CO2	74100.00	77400.00	71900.00	-	63100.00	56100.00	-

Table 3.24 Comparison of emission factors used for *Domestic sector* in this study and in REAS v2.1 (grey column)

(unit: kg/ TJ)	Diesel	Heavy oil	Kerosene	Oil (REAS)	LPG	Natural gas	Gas (REAS)
CO	-	-	167.57	348.00	78.65	-	77.30
NOx	-	-	24.94	93.20	37.21	-	61.00
SO2	-	-	0.57	197.00	6.98	-	0.24
CH4	-	-	2.04	-	2.96	-	-
PM	-	-	43.08	4.18	5.50	-	0.00
NMVOC	-	-	8.84	44.40	33.83	-	5.00
BC	-	-	20.41	0.55	4.23	-	0
OC	-	-	2.04	0.33	1.06	-	0
NH3	-	-	-	-	-	-	-
N2O	-	-	1.59	-	1.90	-	-
CO2	-	-	70975.06	-	63002.11	-	-

3.4. Conclusion

The goal of this part is to compile a consistent and continuous emission inventory for three key sectors with local scale and to fill the gap among inherent EIs developed for HCMC before. The activity data and EFs were synthesized from various sources. And a number of limitations and uncertainties were noted.

Regarding Transportation sector, this study assumed the constant VKT, EFs of vehicle fleet and road network over 8 years. The technology standard distribution for each vehicle types which impacts on the change in EFs was neglected as well. Apart from MC and personal car, the populations of bus, taxi and truck remains the uncertainty due to the limitation of statistical data. Because Traffic shares the highest ratio of emission among three primary sectors, if any of these factors, VKT, EFs and road network, is improved, the accuracy of total emission in HCMC can be enhanced considerably. For example, the spatial distribution of total emission in HCMC can show the noticeable annual variation if road network expansion, which directly links to spatial allocation of the most dominated emission sector, is considered.

In terms of Manufacturing and residential sectors, the activity data come from fuel consumption and electricity consumption data provided by HCMC Department of Industry and Trade (DOIT) and EVN respectively. Meanwhile, this study considers emission within the boundary of HCMC only. The uncertainty relating to administrative boundary of sale data provided by DOIT and EVN can impact on the accuracy of my estimations. Because industrial zones often located around ring road and around city boundary, so the including or excluding these emission zones could lead to considerable change in total emission amount. Apart from that, the grid EFs on electricity consumption were only available in three years. And electricity consumption is typically the largest emission source regarding stationary energy emission. So the limitation of these EFs could have the big impact on final GHG emission amount of HCMC. EFs of fuel consumption for both two stationary energy sectors were assumed to be constant during 8 years, meaning the technology evolution was not considered.

Regarding urban morphology maps, my study relied on only one building height data (AW3D) in 2011 to prepare land use maps for 8 years. The assumption of constant building height must cause inevitable uncertainty in spatial allocation of emission. The field data of building height and land use could improve the reliability of annual urban morphology maps.

This local emission inventory includes most major air pollutants and greenhouse gases: SO2, NOx, CO, NMVOC, PM10, PM2.5, BC, OC, NH3, CH4, N2O, and CO2. The target years are from 2009 to 2016. Emissions are estimated for area within boundary of HCMC and are allocated to grids at a 1km resolution. In terms of Transportation, vehicle fleet in HCMC emitted over 682 Gg CO, 84.8 Gg NOx, 20.4 Gg PM10 and 22000Gg CO2 in 2016. The overall emission of this sector increased significantly from 2009 to 2016, mainly because of the sharp rise in vehicle population. The emissions of CO, NOx, SO2 and CO2 from traffic in 2016 in HCMC were 1.8, 2.6, 2.5 and 2.03 times of the ones in 2009, respectively. Among five vehicle types, MC contributed around 94% to total CO emission, 14 % to total NOx emission and 50- 60% to CO2 emission. Regarding NOx and PM, truck is claimed as the biggest emission source and the sharing of personal car was considerable in terms of SO2, NMVOC and CO2.

The emissions of Manufacturing industry and Residential sectors include both fuel consumption and electricity consumption. Electricity consumption is the most dominated emission source. In 2016, the electricity consumption of Manufacturing industry and Residential sectors in HCMC emitted 6985 Gg and 6691 Gg of CO2, respectively, increasing by 87% and 45% in compare with 2009, respectively. Considering fuel consumption only, both these two sectors account for a very small percentage in compare with Transportation and the growing trend is slower in compare with vehicle emission as well. For example, the CO emission from Transportation in 2016 was 1629 times and 165 times of the ones from Residential and Manufacturing industry sectors, respectively. The sum of CO2 emission from fuel consumption and electricity consumption of these two Stationary energy sectors still could not surpass Transportation sector. In 2016, vehicle fleet emitted 22000 Gg CO_2, almost double Manufacturing sector. Meanwhile Residential area contributed 7000 Gg CO_2 only.

Regarding spatial allocation of final emission, urban morphology maps clearly show that residential is dominated land use type in HCMC. Residential area expended by 27% over 8 years, and mainly happened in the northern part of city. However, Transportation is by far the highest emission source, in terms of all species, so the spatial distribution of all pollutions are similar with Transportation emission map and Road density map. And they are not impacted much by the change in Residential land. Basing on emission maps, the central business districts like Quan 1, Quan 4 and Quan 7 express the highest emission intensities, which can be over 1900 times of the ones in outskirt area. According to these findings, the policymakers must consider suitable future activities and regulations to control pollution in HCMC, especially in central region. Moreover, the findings of this study revealed the highest sharing ratio from Transportation sector. Therefore, the controlling emission policies need to focus on improving this emission source, such as expansion the road network, reducing the number of personal vehicles.

The estimations of this study showed the agreement with several local inherent EIs, in terms of total amount of emission and sharing ratio among elements of EI. However, the big gap was observed when comparing with REAS 2.1. The different data sources of activity data and EFs database explained for this phenomenon. Again, this implied the inevitable gap between regional and local EIs. This situation caused challenges to compile a consistent, continuous yet comparable data with processor EI like REAS.

Chapter 4.

High temporal and spatial resolution traffic emission in Ho Chi Minh city

4.1 Introduction

According to the findings of previous chapter, Transportation is the biggest contributor of total emission in HCMC and the fastest growing emission sector. In addition to that, because of traffic volume changing hourly, vehicle emission is more fluctuated and dynamic than Manufacturing Industry and Residential sources. This leads to the need of downscaled emission inventory for this primary sector, that will be an useful scientific basis for personal exposure studies and effective policy-making in future. Besides, traffic emission is determined by emission factors, vehicle mixing ratio, traffic flow and the length of road network. Among these factors, traffic flow varies by hour and always expresses the high fluctuation. As a result, modeling hourly traffic flow can facilitate the estimation of hourly on-road traffic emission.

The strong demographic growth and the fast development of the economy in HCMC lead to a massive increase of the population in the city. HCMC's reported population of 8.7 million by the end of 2018 with an average population density of over 4,500 per square kilometer (HCMC Statistical Yearbook) In parallel to the increase of the population, HCMC accounted for about 22% of the national GDP and 29% its financial capital in 2018 and it on widely seen as one of the fastest growing markets for technology and manufacturing in the region and the top emerging property market in Asia-Pacific. With rapid economic development, HCMC is experiencing substantial growth in vehicle numbers and motorized mobility (Fig 4.1) Similarly to Hanoi, the number of motorbikes in this city has increased at a steady rate, leading to almost 8.5 million motorbikes in 2019. As a result, it is urgent to quantify emission from transport sector with high resolution and details for HCMC.

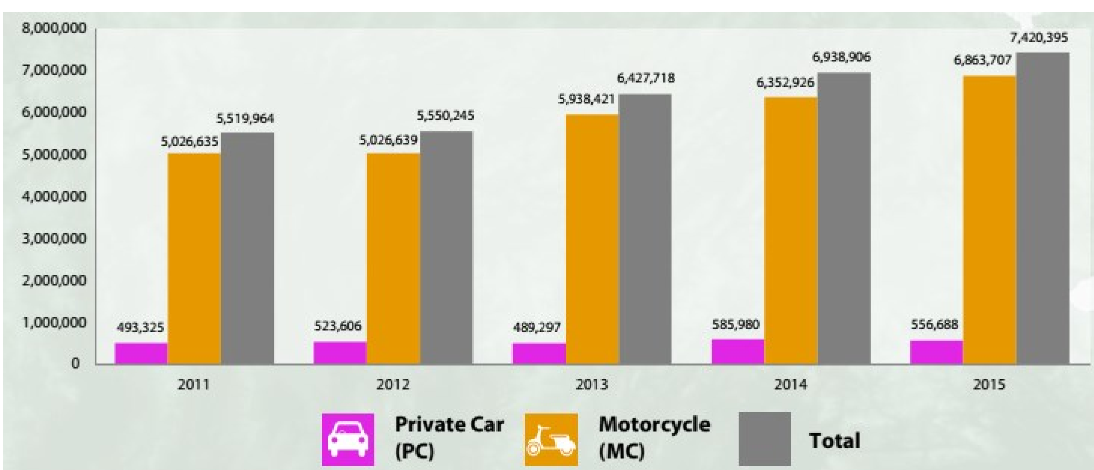


Figure 4.1 Vehicle population of Ho Chi Minh city (Ho Chi Minh city Department of Transportation)

In Hanoi, traffic emission contributed 39.5, 5.9, 3.8, 0.6 and 0.22 Gg for for CO, volatile organic compounds (VOC), NOx, SOx and particulate matter (PM), respectively in 2010. And the fleet of over two million motorcycles (MC) is believed to contribute a substantial emission of air pollutants (T.T.trang et al, 2015).

Similarly, traffic sources accounts for 77.75% of NOx, 89.77% of CO and 89.39% of NMVOC in HCMC, making it the most dominant emission sector (H.Q.Bang, 2010) The motorcycle is considered as the most important of traffic emission source (99% of CH4, 94% of CO, 68% of NMVOC and 61% of SO2) The emission grid net showed that the highest emission is found in the center of the city because of the highest density of streets is found there. Traffic counts in different streets, a constant fleet distribution data for five street categories were input for EMISENS model to generate road traffic emissions with different levels of complexity. Emission factors were defined by literature review from previous studies in HCMC, China and from COPERT IV model. Basing on these findings, fours abatement strategies of emission were also carried out to evaluate the effort of local government and to evaluate the role of public transport to reduce the emissions. If the HCMC government did not follow any control emission plans, the emission of CO and CH4 in 2020 will increase more than 60%.

In 2018, a carbon emission inventory of urban transport for 10 major cities in Vietnam, including HCMC, was introduced, also (L.T.P.Linh, 2018) Vehicle distribution by age, vehicle type and fuel type was extracted from vehicle registry data, parking lot surveys. The average vehicles count per day on various types of roads was based on video survey counting to calculate average annual daily traffic and daily vehicle kilometers traveled. The emission factors were from International Vehicle Emissions (IVE) model and COPERT model.

Both of above studies shown that to calculate emissions from on-road vehicles, a big amount of field measurement and surveys are needed, especially the measurement of the spatial and temporal variations in traffic conditions, such as traffic flow, traffic density and vehicle composition. Another common approach of estimating dynamic link flows is origin-destination matrices that displays the number of trips going from each origin to each destination. This method is often applied in transportation planning, traffic management and operations. However, to operate this model, the probe vehicle data or traffic counting is still needed. It means that the traffic survey and traffic field data, which is time-consuming and labor-intensive, is required. It leads to the fact that mobile sources of air pollution present additional challenges to measurements and are difficult to model in compare with point sources of air pollution such as industrial operations. Recently, the ability to use crowdsourced, user-generated traffic data offers the opportunity of inexpensive, real time traffic monitoring of entire street networks, which cannot be done with traditional traffic monitor methods. There is great potential of using such data in air pollution studies. For instance, Google Traffic works by analyzing the GPS-determined locations transmitted by a large number of mobile phone users. By calculating the speed of users along a length of road, Google is able to generate a live traffic map, providing information about average speed of traffic flow and level of congestion in a specific road segment. Because this traffic information is near real time, with quite high temporal repetition and large coverage, it is promising to capture the spatial variability of traffic-related air pollution. The objective of this part is to generate a bottom up vehicle emission inventory in HCMC from modeled traffic flow using crowdsourced traffic data from Google.

4.2 Methodology

For a specific pollutant, the sum of emissions that considers all emitting vehicle can be computed as:

$E\ (x,y,t) = \sum_{ie}^{nie} EF_{ie}\ \alpha_{ie}\ \mathrm{F.L}$ (7)

Where EF is emission factor of vehicle i, type e (g/km); α_{ie} is the proportion of each type of vehicle in each category; n_{ie} is the number of vehicle in category ie; F is vehicle flow on a specific street segment (veh. /hour); L is the length of road segment (km)

So, to generate vehicle emission inventory, four main factors are required:

- Emission factors
- Road network
- Fleet composition data
- Dynamic traffic flow

4.2.1 Road network

Road network was downloaded from Open street map, with 3 road categories: primary road, secondary road and tertiary road. Primary roads are ring roads and highway, where heavy duty vehicles (HDV) are allowed to run. Tertiary roads include the smallest road like residential streets and service roads (Fig 4.2). Different from the previous chapter, this part will focus on the central part of HCMC only.

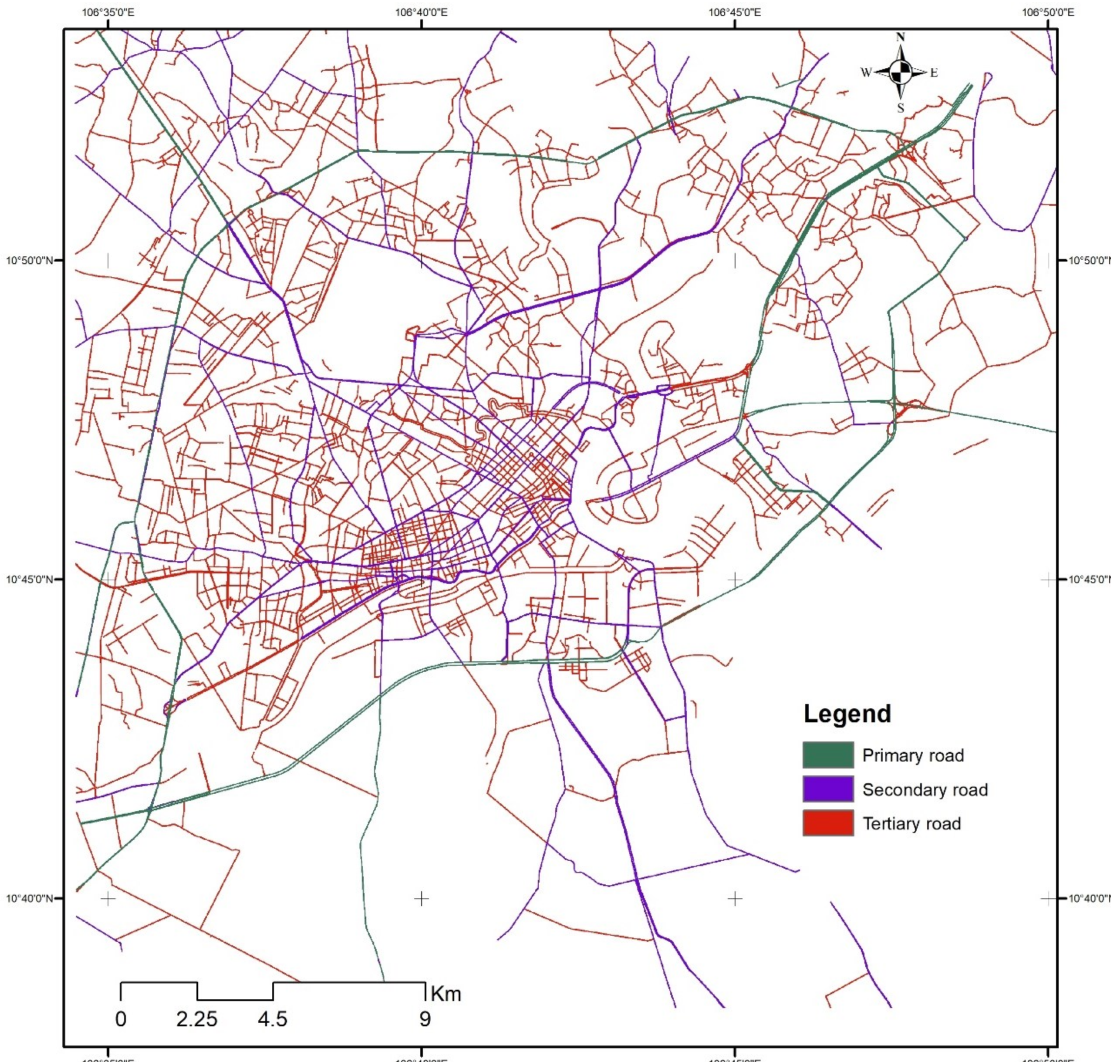
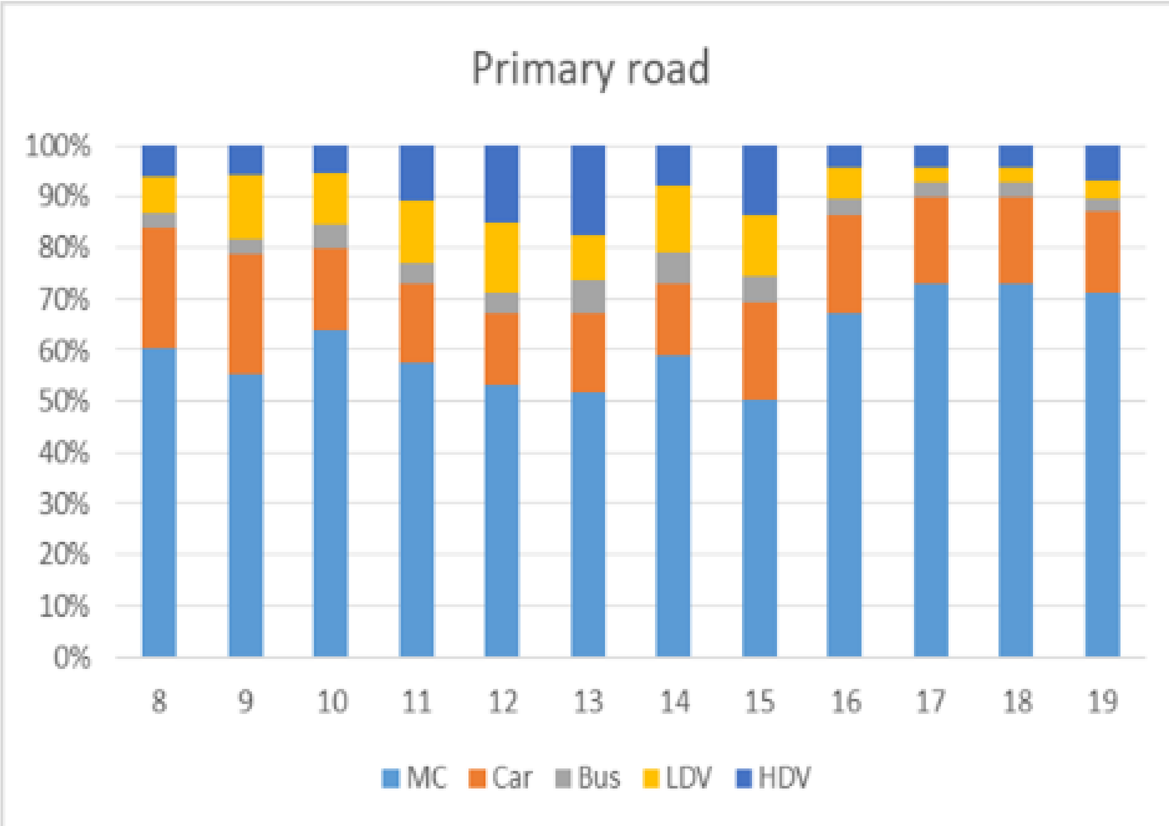


Figure 4.2. Road network with three road categories from Open street map

4.2.2 Fleet composition

The vehicles were grouped into 5 categories, namely motorcycle (MC), personal car, bus, light duty vehicle (LDV) and heavy duty vehicle (HDV) Different from previous studies about vehicle EI in HCMC, that applied constant vehicle mixing data for all road types, we exploited the traffic surveillance camera network provided by HCMC Department of Transportation to survey the temporal variations of fleet mixing in three road categories (Fig 4.3)


Primary road
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
8
9
10
11
12
13
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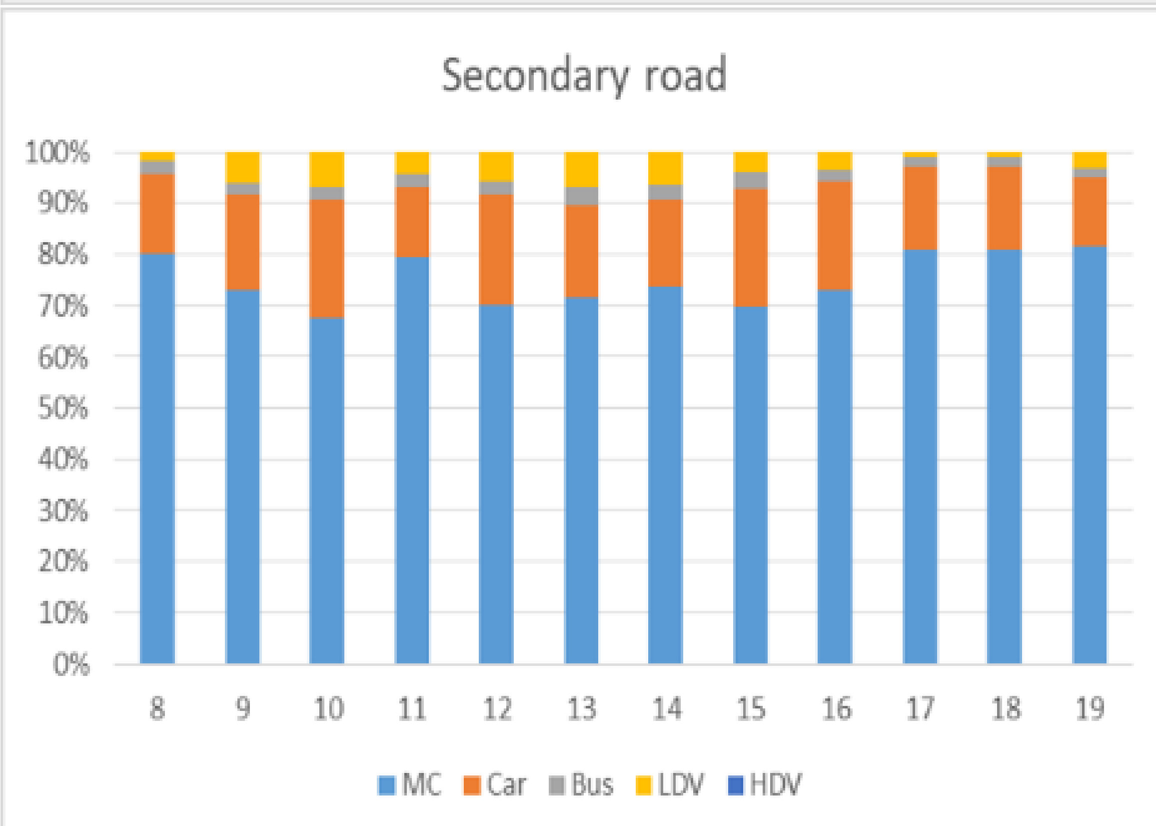
MC
Car
Bus
LDV
HDV


Secondary road
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
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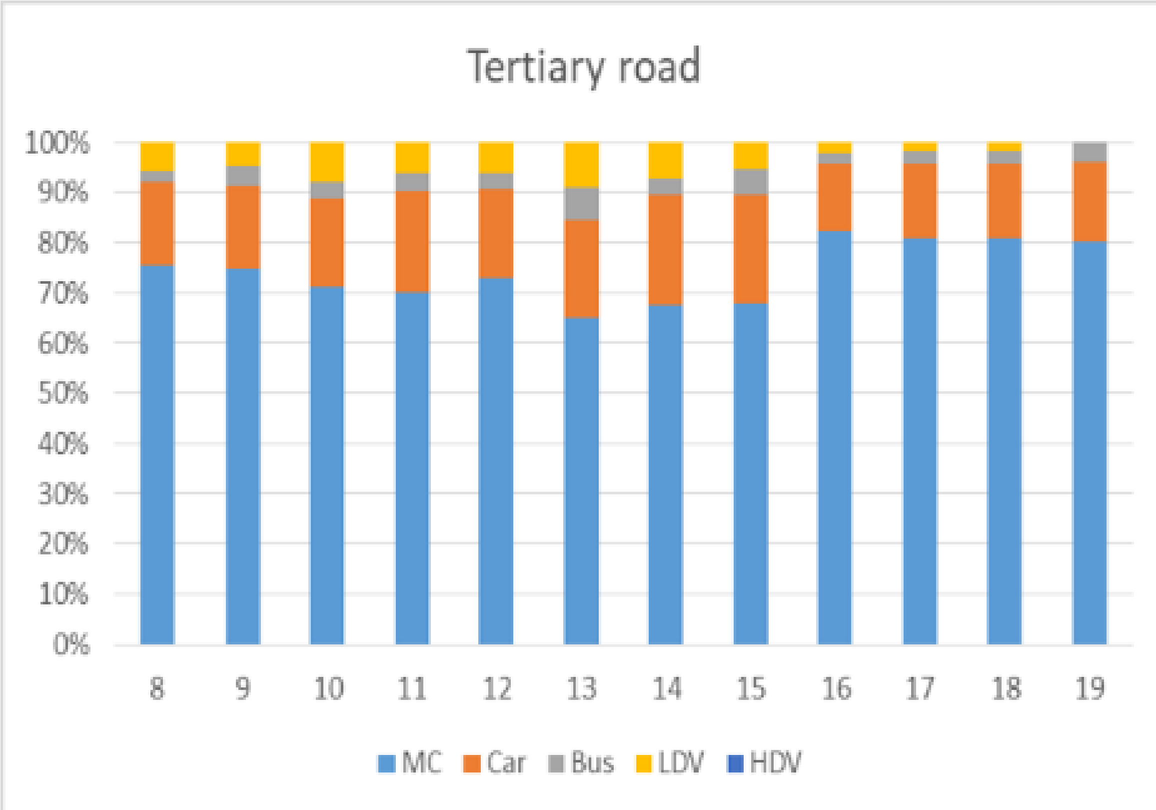


Figure 4.3 Vehicle mixing along time in three road categories in HCMC

MC is the most dominated vehicle type, accounting for over 50% and 65% in Primary road and two other road types, respectively. This proportion is followed by personal cars, which contribute more than 10%-20% in all categories of road. HDVs mainly contribute to vehicle fleet in primary road only. In compare with previous studies, MC shared lower ratio in our observations, while personal cars have higher percentage (Fig 4.4) For example, according to study of T.T.Trang et al, 2015 in Hanoi, MC had the predominant proportion, a share of 93-97%, in the operating traffic fleet in Hanoi. However, when comparing with increment trends of MCs and personal cars provided by HCMC Department of Transportation (Fig 4.5), our result makes sense. The growth rate of MC in HCMC is still high but decreasing slowly. The personal car fleet inclined in the years of 2012 and 2013 but grew rapidly since 2014, approximately 20% in 2014 only.

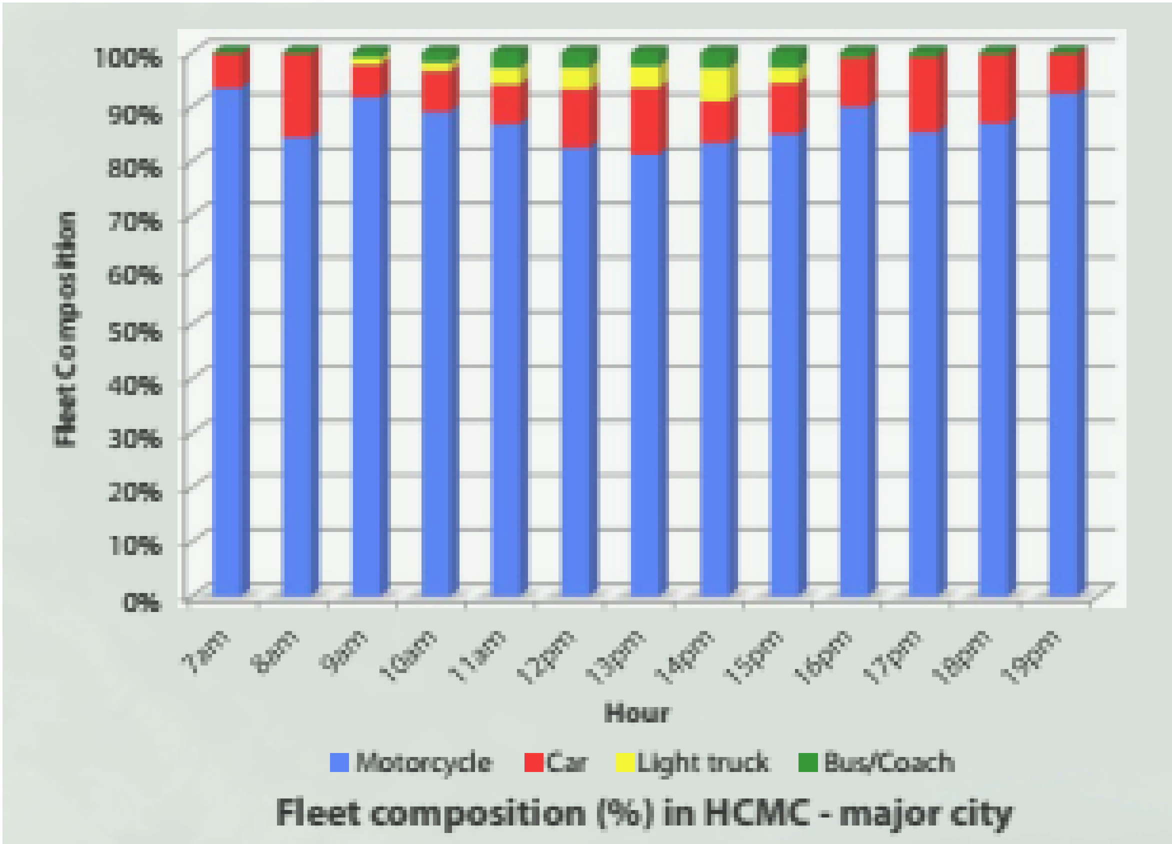
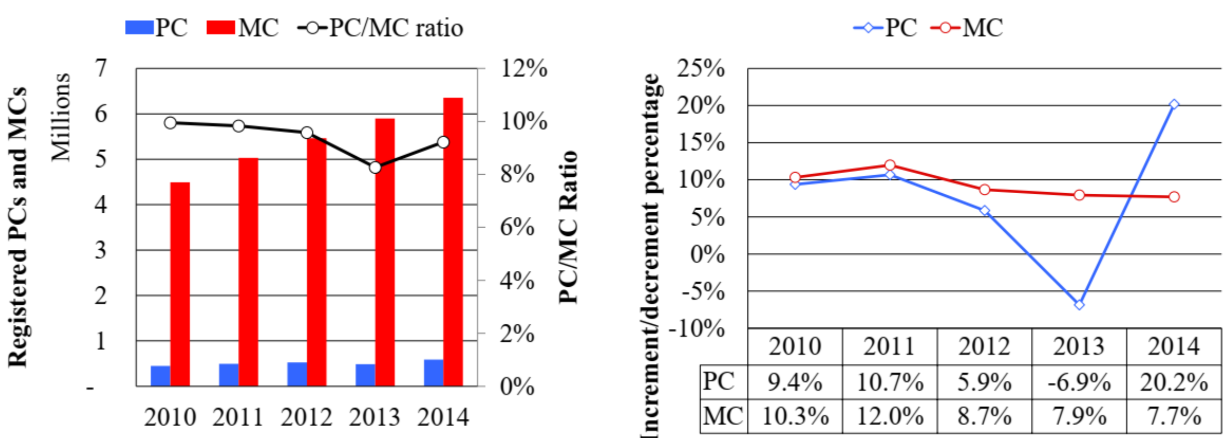


Figure 4.4 Fleet composition in HCMC from study of L.T.P.Linh, 2018.



(a) Registered PCs/MCs and their ratio (b) Increment trends of MCs and PCs

Figure 4.5 Registered PC and MC in HCMC from 2010 to 2014 (HCMC Department of Transportation)

Regarding age, fuel type, engine standard sharing among vehicles, previous studies in Hanoi and HCMC were reviewed. Accordingly, diesel and gasoline were the main two fuel types used for on-road transportation. Other types of cleaner fuels, such as compressed natural gas (CNG) and liquefied petroleum gas (LPG), share very low proportion, so they are neglected in this study. The main fuel used by motorcycles is gasoline. Only a small portion of the personal car fleet and LDVs used diesel. 98% cars use the gasoline for fuel and the rest of cars use the diesel oil (H.Q.Bang, 2010) The bus fleet and HDVs was 100% diesel powered (Tab. 4.1)

The cars and MCs that have less than 4 years old are commonly observed in the fleet in HCMC (Fig 4.6) The PCs and MCs less than 5 years old share about 66% and 74%, respectively. Approximately 49% of the motorcycle and 44% of the car were purchased 3 years or less. The ones with higher 15 years old are seldom found in the fleet for both PCs and MCs (C.T.Dung et al, 2015)

The study of C.T.Dung et al, 2015 showed that more than a half of total personal cars in HCMC use EURO 2, EURO 3 and EURO 4 engines. However, substantial shares of pre-EURO and EURO 1 MCs were still observed in these fleets

Table 4.1 Fleet composition in terms of fuel type, age, engine standard and daily VKT of vehicle fleet in HCMC from literature review

	MC	**Personal car**	**Bus**	**LDV**	**HDV**
Fuel	100% gasoline (a)	75% gasoline (a)	Diesel (b)	95% gasoline (b)	Diesel (b)
Age (years)	4.15 (a)	4.84 (a)	6.3 (b)		11.7(c)
Engine standard	Pre Euro: 60.34% Euro 2: 19.45% Euro 3: 15.51% (a)	Pre Euro: 28.48% Euro 2: 21.82% Euro 3: 26.67% (a)	Euro 2: 53% (b)		Euro 2: 75% (c)
Daily VKT (km)	25.98 (a)	35.92(a) 52(b)	239 (b)		31(c)

(a) Study in HCMC, 2014 (C.T.Dung et al, 2015)
(b) Study in Hanoi, 2010 (T.T.Trang et al, 2015)
(c) Study in HCMC, 2013 (H.H.Van et al, 2014)

4.2.3 Emission factors

Because MC and Car are accounted for the highest shares of vehicle fleet in HCMC and because of the availability of data, the detail emission factors equivalent with different engine standard levels were considered only for MC and Car in this chapter. Also, Euro 2 is the most common emission control technology for Bus and HDV, according to previous study (Tab. 4.1), so the emission factor of Euro 2 was assigned for Bus, LDV and HDV. These emission factors were extracted from EMEP/EEA air pollutant emission inventory guidebook 2016.

Table 4.2 The emission factors (g.km-1.vehicle-1) from EMEP/EEA air pollutant emission inventory guidebook 2016

Unit (g.km-1.vehicle-1)	**MC**			**Car**			**Bus**	**LDV**	**HDV**
	Pre Euro	Euro 2	Euro 3	Pre Euro	Euro 2	Euro 3	Euro2	(Euro2)	Euro2
CO	32.8	7.17	3.03	13.4	2.04	1.82	2.44	5.89	0.902
NOx	0.225	0.317	0.194	2.66	0.255	0.097	10.7	0.23	5.5
PM2.5	0.014	0.0035	0.0035	0.0022	0.0022	0.0011	0.22	0.0023	0.104

4.2.4 Traffic flow

High-resolution mapping of vehicle emissions of atmospheric pollutants based on large-scale, real-world traffic datasets. To map traffic flow along time in HCMC, Macroscopic Fundamental Diagram model was applied. Traffic flow fundamental diagram that relates space-mean flow, density and speed of an entire network. The fundamental diagram relates two of the three variables average speed (v), flow (q) and density (k) to each other (Fig. 4.6) If two of these variables are known, the third can be derived using the relation q = kv. Therefore, if only one variable is known, and the fundamental diagram is known, the traffic state (i.e. combination of speed, density and flow) can be determined. In the fundamental diagram, the relationship between flow q and density k is linear in congestion (Fig. 4.6) Data used to estimate this relationship are usually obtained from loop detectors at a specific location.

There are three types of Macroscopic Fundamental Diagram model: Single regime model; Two regime model (uses separate equations for free flow and congested flow) and Three regime model (uses 3 separate equations for free flow, congested flow and transition flow. The most common single regime models are Greenshields model (Greenshields, 1935), Greenberg model (Greenberg, 1959), Underwood model (Underwood, 1961) and Northwestern Univ. model, 1967. Linear relationship between speed and density was assumed in these models, although the speed density relationship tends to be nonlinear at low density and very high density. They require free flow speed and optimum density (depends on road type) as the boundary values. The Two regime model can use Underwood model for free flow conditions and Greenberg model for congested conditions. However, the most difficult part of Two and Three regime model is define transition point between free flow and congested condition.

In this study, traffic flow is calculated basing single regime models. Accordingly, traffic flow is a function of speed, jam density and free flow speed. Where prior knowledge about jam density and free flow speed in each road type is needed:

$q = \frac{k_j}{u_f}\left(u_f - u\right)u = k_j\left(u - \frac{u^2}{u_f}\right)$ (8) (Greenshields et al,1935)

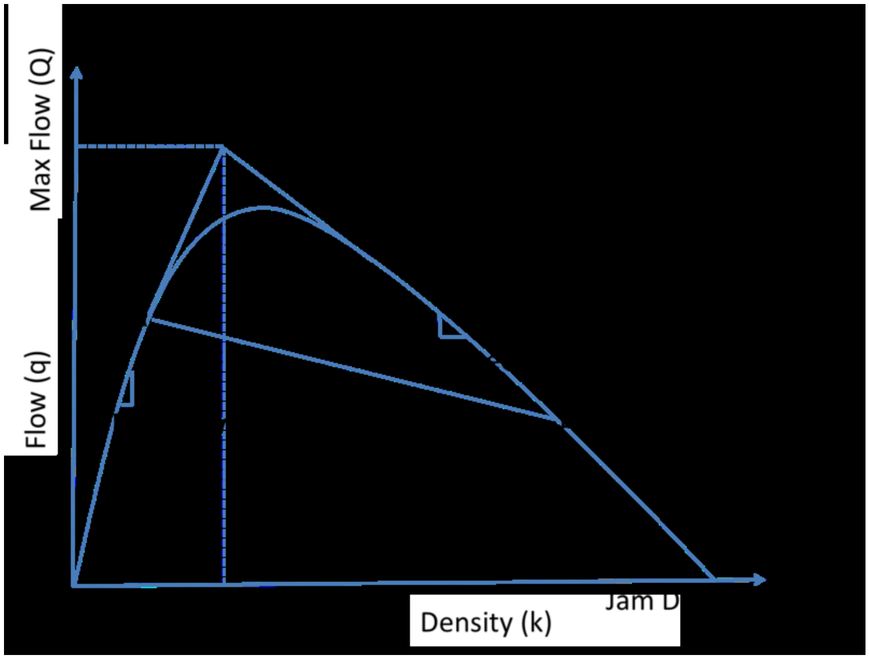


Figure 4.6. Flow density relationship

Where q is hourly traffic flow (veh./hour), k_j is jam density (veh./km), u is speed (km/h), u_f is free flow speed.

4.2.4.1 Speed map

Basing Google typical traffic map, three Level of Service (LOS) types, corresponding with three colors (green-free flow; orange-delayed traffic; red-congested traffic) can be seen, dark red – serious congestion condition account for very low proportion. So we will neglect the highest LOS – dark red in this study. 16 LOS maps in HCMC for weekend and weekdays, from 8.00 to 20.00, with 2 hour interval can be generated (Fig 4.7) Those colors of different LOS will be assigned with detail speed rank to make speed maps. To create these speed ranks, a survey basing on Google traffic data was carried out. Accordingly, the distance between the originate point and destination point is divided by approximate traveled time to calculate average speed of traffic flow (Fig 4.8)

It is easy to see that Free flow condition with green color has the highest speed, with the mean values of speed are 43, 25, 22 km/h for Primary road, Secondary and Tertiary road, respectively. And the traffic condition in Primary road is much better than other road types. When congestion occurs, the speed drops to 10 and below 10 km/h in all sorts of road, and speed ranks show much less variations than free flow and delayed conditions, also. Comparing with other studies using in situ measurements in HCMC (Fig. 4.9 and Tab. 4.3, Tab 4.4), the finding from Google traffic data is reasonable.

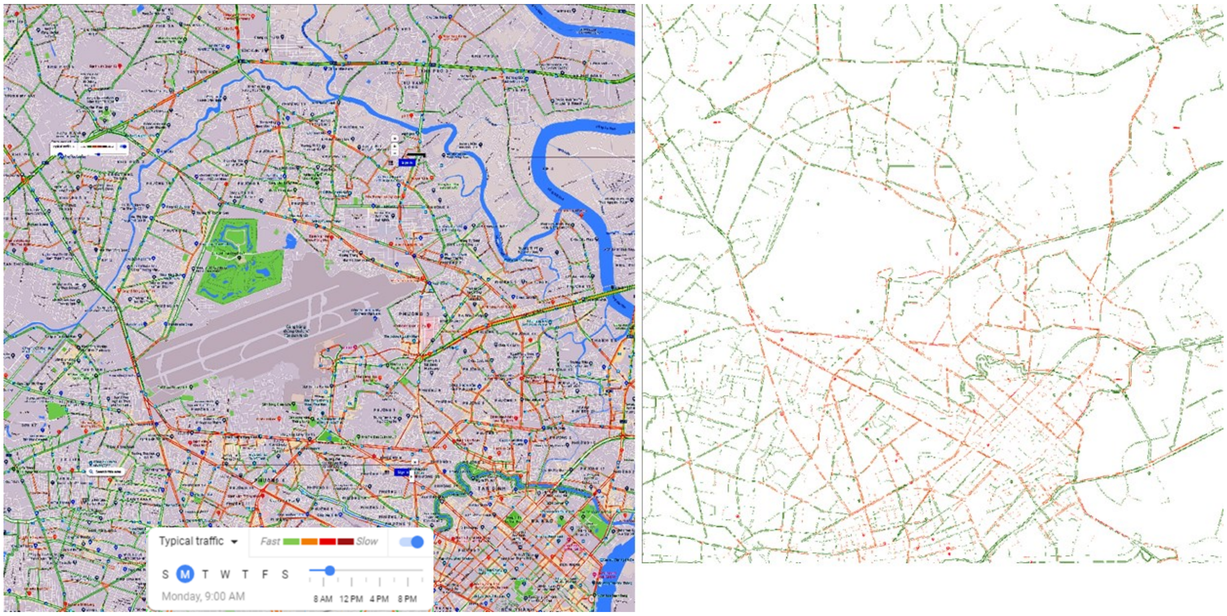


Figure 4.7 Typical traffic condition map from Google and traffic condition map after digitalizing and classification basing on colors

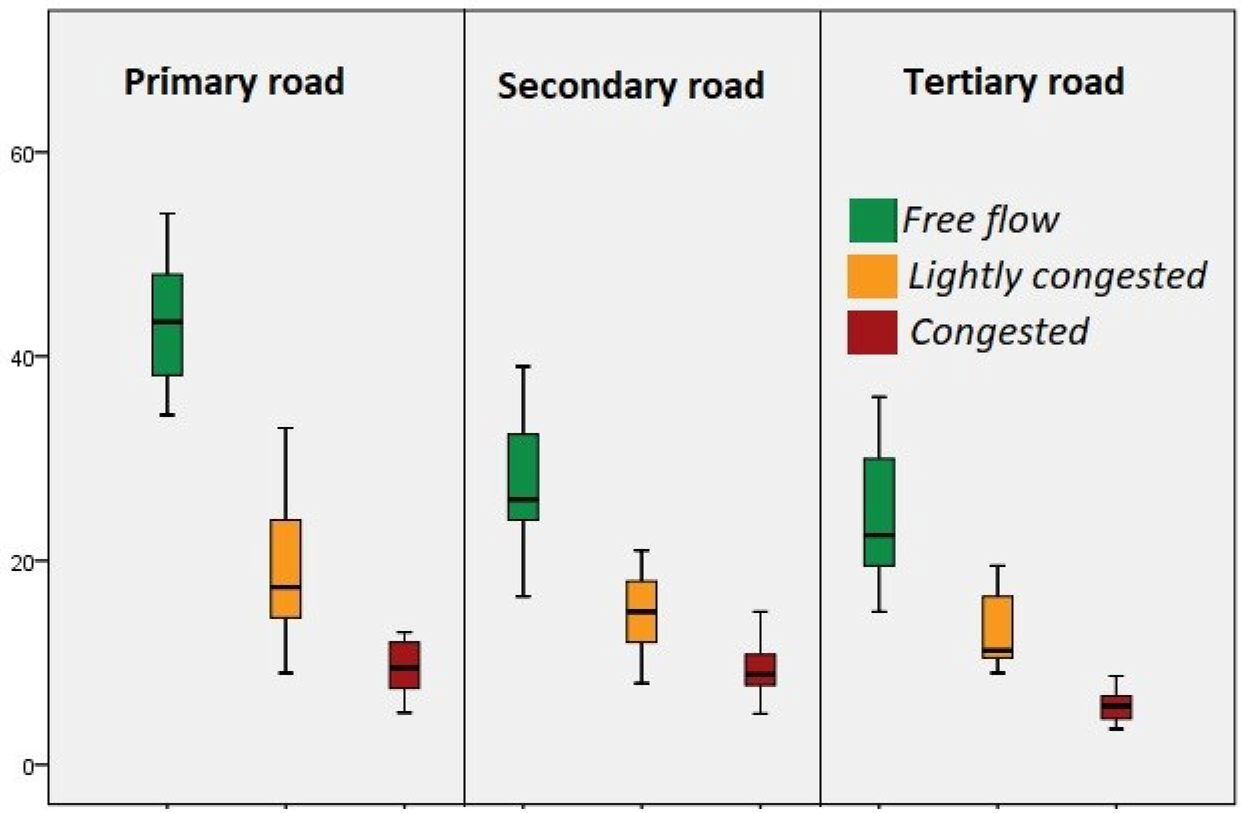


Figure 4.8 Average speed rank (km/h) equivalent with three Levels of Service in three road categories

Table 4.3 Speed rank (km/h) (mean values and standard deviations) equivalent with three Levels of Service in three road categories

	LOS =1	LOS =2	LOS =3
Primary road	36.0377 ± 1.4	18.7035 ± 1.08	10.05 ± 0.49
Secondary road	27.0827 ± 0.91	15.5813 ± 0.67	8.7661 ± 0.51
Tertiary road	23.3 ± 1.06	11.9437 ± 0.51	5.6536 ± 0.32

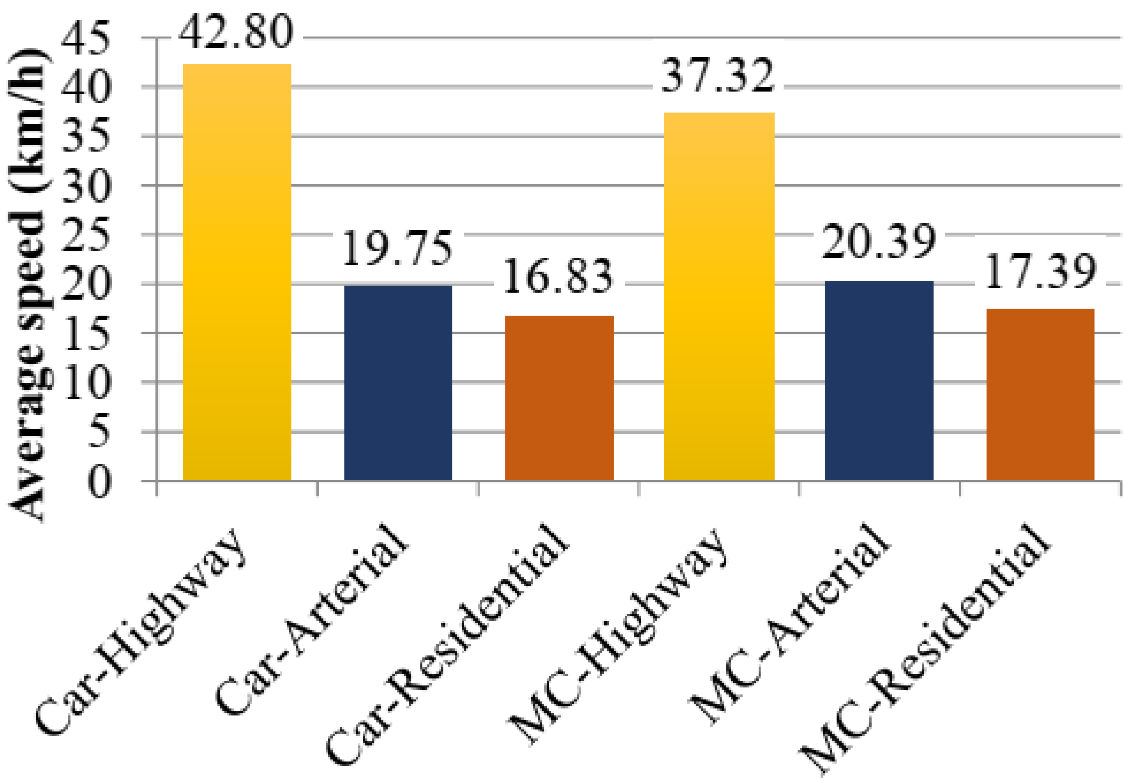


Figure 4.9 Average speeds of PCs and MCs on different streets from study of C.T.Dung, 2015 in HCMC

Table 4.4 Motorcycle speed data from study of C.C. Minh, 2005 in HCMC

Location	Motorcycle Volume	Number of Sampling	Observed Speed				
			Mean (Km/h)	Max (Km/h)	Min (Km/h)	St. dev.	
						(Km/h)	%
1	3,240	582	32.3	55.2	14.3	5.7	17
2	2,621	270	32.7	56.3	20.9	5.2	15
3	5,074	322	21.3	44.8	9.5	5.1	23
4	2,706	579	22.8	43.6	9.7	4.6	20

4.2.4.2 Free flow speed and jam density

Being one of two boundary values in traffic flow model, jam density should be prior estimated for each road category. From Greenshield's model, it is possible to use road capacity and free flow speed to calculate Jam density:

$$q_{max} = v_f \frac{k_j}{2} - \frac{v_f}{k_j} . \left[\frac{k_j}{2}\right]^2 = v_f \frac{k_j}{2} - v_f . \frac{k_j}{4} = \frac{v_f}{4} . k_j \quad (9)$$

This method is based on Greenshields equation (2) and the assumption that optimal density k_{cap} is equal with a half jam density k_j (Fig 4.10)

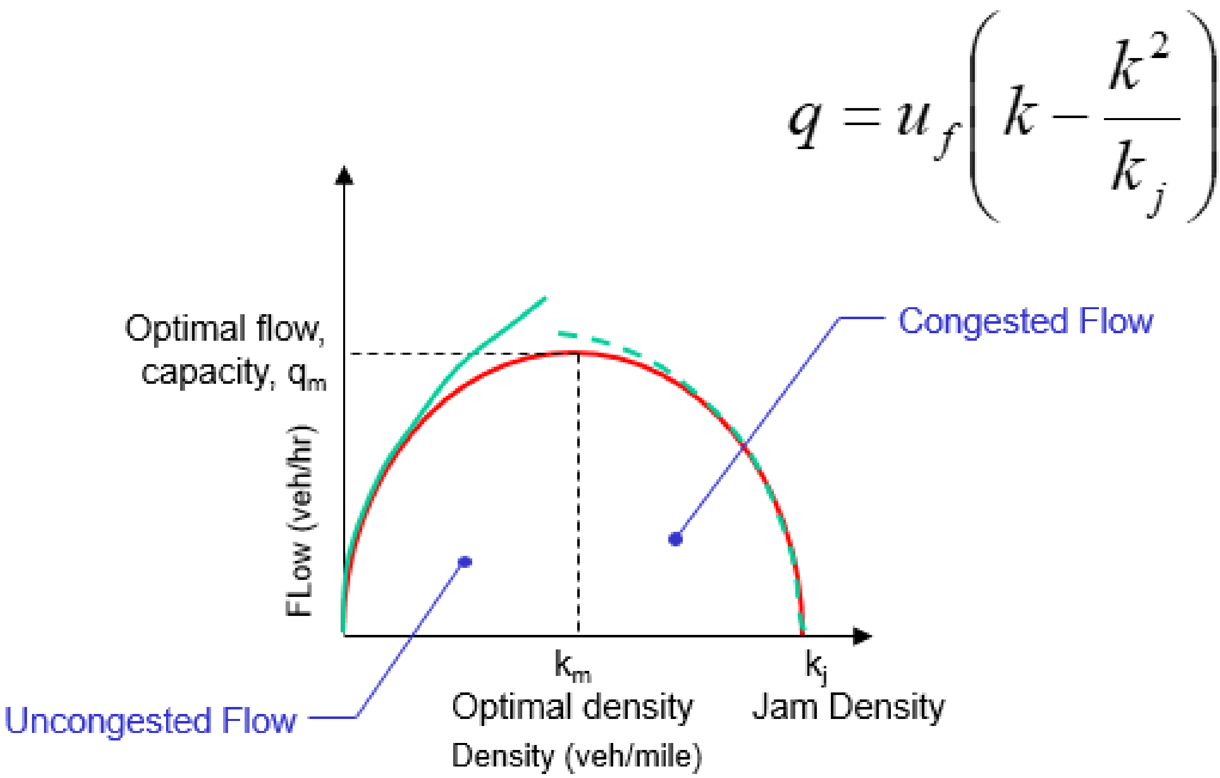


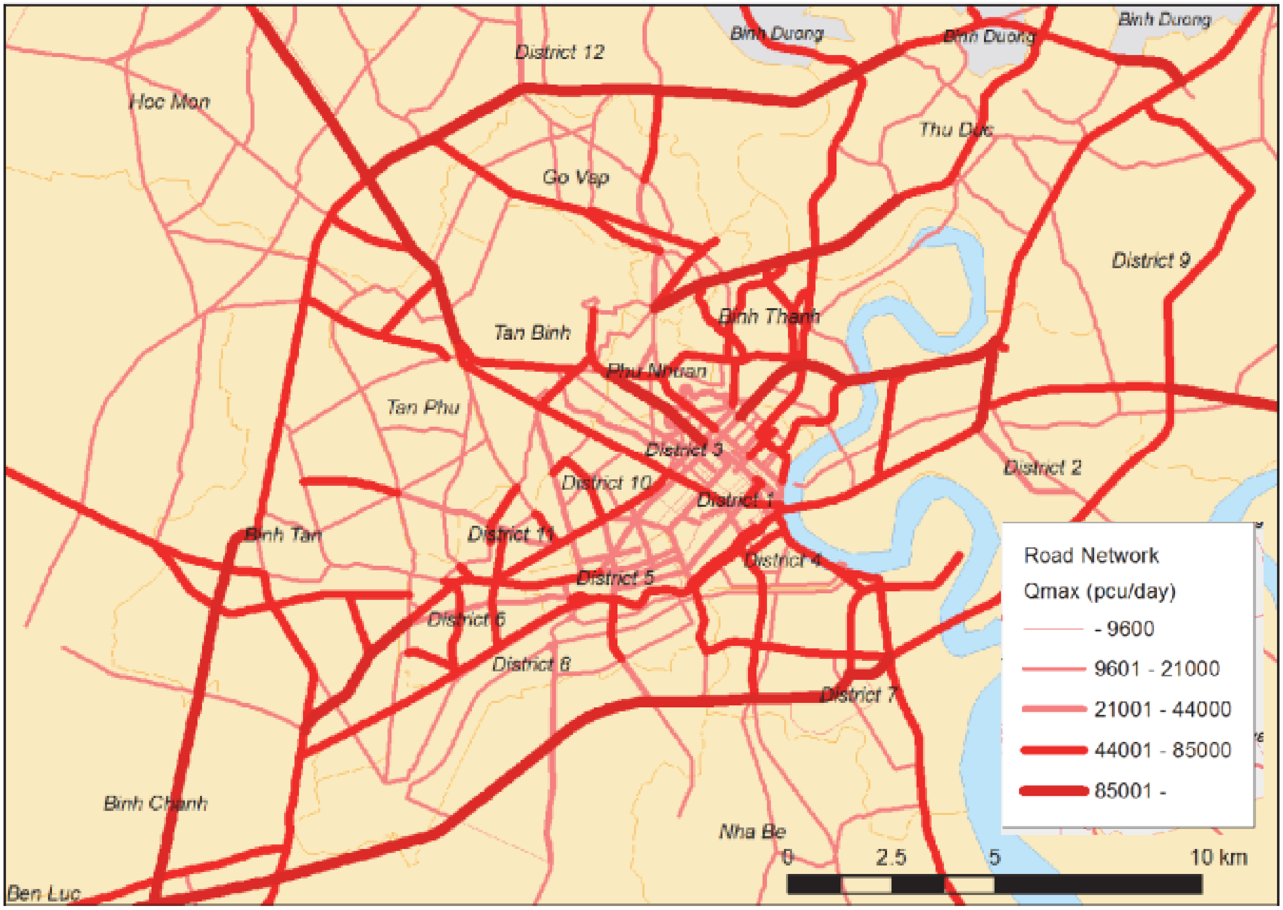
Figure 4.10. Flow-density relationship diagram.

Road capacity (q_{max}) can be exploited from a work of JICA, 2004 in HCMC that estimated traffic flow max for different road types, equivalent with three LOS (Tab. 4.5 and Fig. 4.14). Deriving from this literature and my speed data extracted from Google, various parameters of equations (8) and (9) – free flow speeds, road capacities and jam densities were defined as Tab. 4.6. In addition, the detail numbers of five vehicle types per hour in each road type were estimated from Personal Car Unit (PCU) equivalent parameters (Tab. 4.7), calculated flows in PCU and fleet composition data mentioned in 4.2.2.

Table 4.5 Road capacity in HCMC by HOUTRANS project, JICA, 2004

	Urban/		Carriage-way		Qmax pcu/day		
Class	**Rural**	**Vmax**	**Min**	**Max**	**Service Level1**	**Service Level2**	**Service Level3**
Car Exclusive	Urban	80			26,000		
		100			88,000		
		100			132,000		
	Rural	70			20,000		
		80			70,000		
		80			106,000		
Primary	Urban	30		<6m	16,250	17,500	20,000
		35	7m	<12m	16,250	17,500	20,000
		40	13m	<20m	56,250	63,750	70,000
		45	21m	<28m	85,000	95,000	105,000
		50	29m		112,500	126,250	141,250
	Rural	40		<6m	17,000	19,000	23,000
		45	7m	<12m	17,000	19,000	23,000
		50	13m	<20m	59,000	67,000	79,000
		55	21m	<28m	89,000	101,000	119,000
		60	29m		119,000	135,000	158,000
Secondary	Urban	30		<6m	13,750	16,250	17,500
		35	7m	<12m	13,750	16,250	17,500
		40	13m	<20m	48,750	55,000	61,250
		45	21m	<28m	73,750	83,750	92,500
		50	29m		98,750	111,250	123,750
	Rural	40		<6m	13,000	15,000	18,000
		45	7m	<12m	13,000	15,000	18,000
		50	13m	<20m	46,000	52,000	62,000
		55	21m	<28m	69,000	79,000	92,000
		60	29m		92,000	105,000	123,000
Tertiary	Urban	25		<6m	13,750	15,000	17,500
		30	7m	<12m	13,750	15,000	17,500
		35	13m	<20m	47,500	53,750	60,000
	Rural	35		<6m	9,000	11,000	13,000
		40	7m	<12m	9,000	11,000	13,000
		45	13m	<20m	33,000	37,000	44,000

Source: HOUTRANS



Source: JICA Survey Team

Figure 4.11. Modeled road capacity in HCMC in 2016 by HOUTRANS project, JICA, 2004

Table 4.6. Free flow speeds, Jam densities (Kj) and Road capacities (Q_{max}) of three road types used in this study

	Free flow Speed (km/h)	**Q max (PCU/day)**	**Kj (PCU/km)**
Primary road	50	85000	400
Secondary road	40	48750	300
Tertiary road	35	13750	98

Table 4.7. PCU equivalents of different vehicle types (S. Chandra et al, 2000)

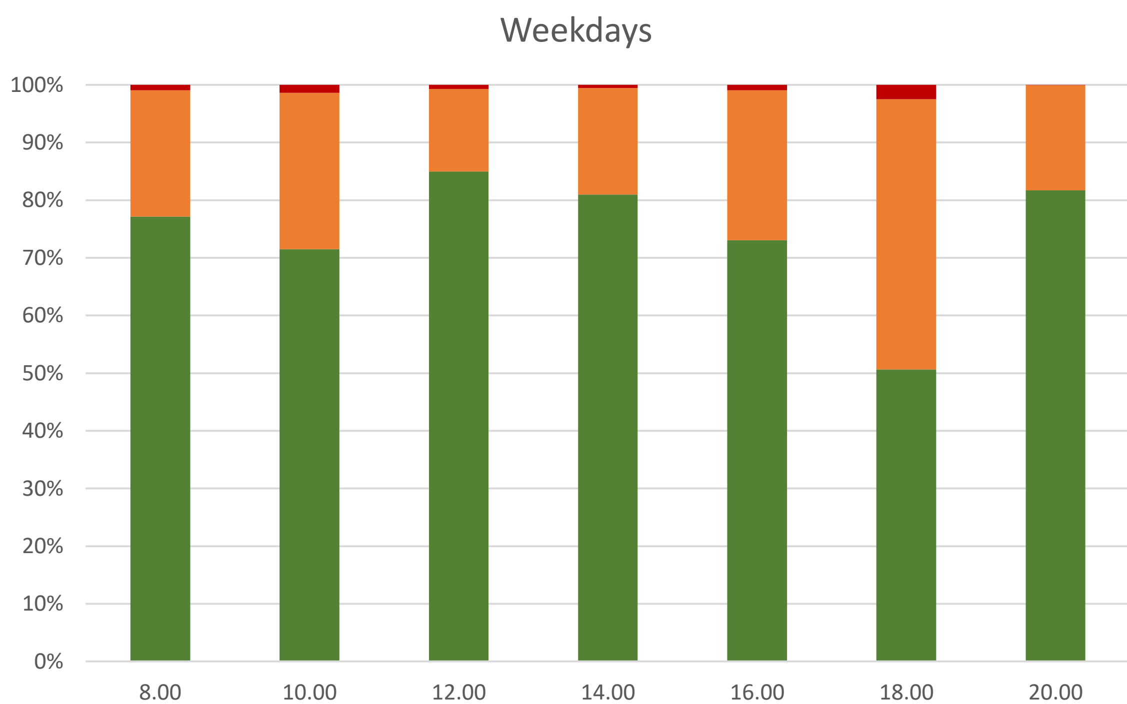
Vehicle type	**PCU**
MC	0.5
Car	1
Bus	1.74
LDV	1.88
HDV	5.86

The results of this chapter is 500 m resolution grid net of transportation emission with hourly interval for in the central part of HCMC from 8.00 to 19.00, separate for weekdays and weekend.

4.3. Results

4.3.1. Temporal distribution

Firstly, the diurnal variation of three Levels of service in weekdays and weekend derived from the classification results of Google traffic maps is shown in Fig 4.12. Generally speaking, Free flow traffic condition is accounted for the highest percentage, followed by lightly congested condition. Real congested flow shares a tiny fraction, under 10% in all cases. Also, it is apparently seen that the traffic in weekend is better than weekdays. The higher ratios of Free flow condition on Sunday and Saturday proved that. However, it is worth noticing that the diurnal variation of sharing percentages among three traffic conditions are similar between weekdays and weekend. The most unfavorable traffic flow is observed around rush hour – 18.00. In weekdays, 50% of road system becomes lightly congested and congested during this time slot. This fraction reduces to 32% in weekend. The most favorable time slots for traffic in HCMC are 12.00 and 14.00 - noon time, when over 80-90% of road network show free flow condition. To conclude, on weekdays, the percentage of lightly congested road increases to 45% in peak hours from 15% recorded in non – peak hours. In weekend, this number rises from 6% to 31% in rush hours.



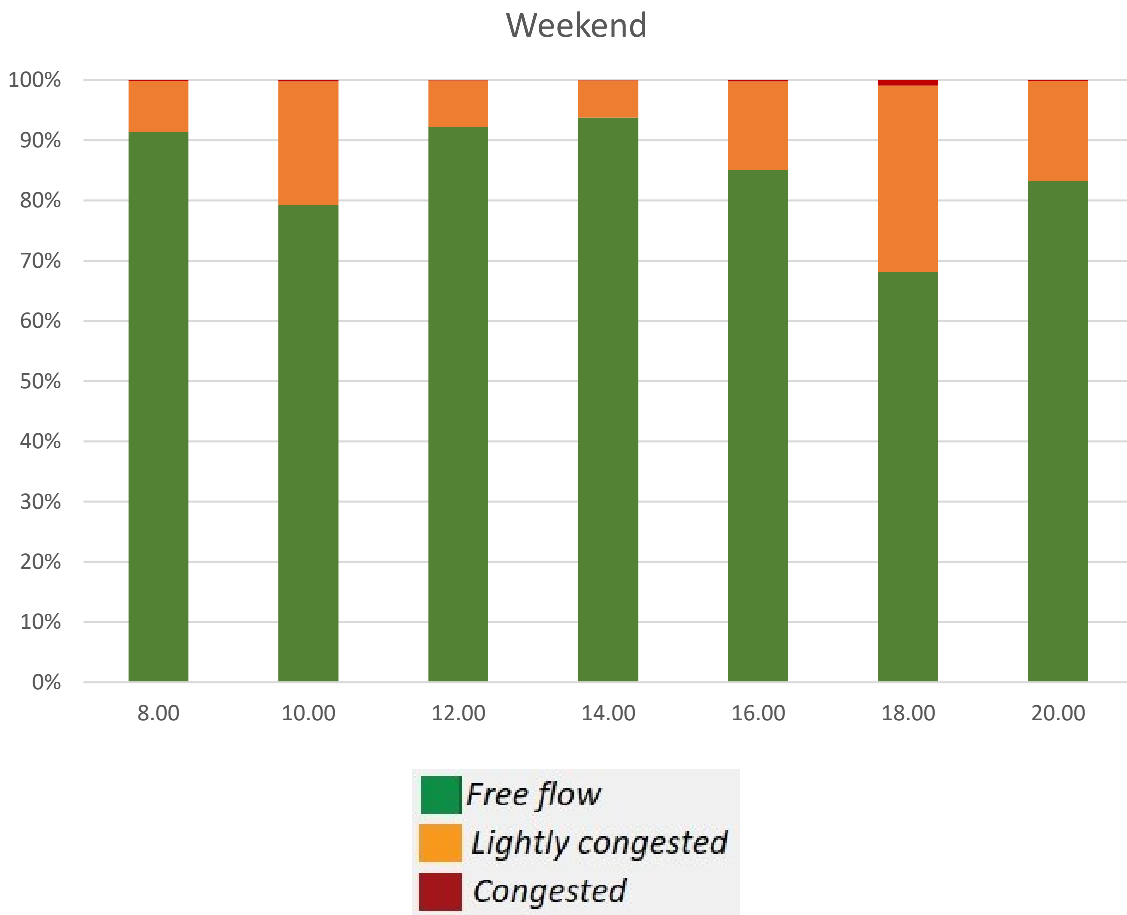
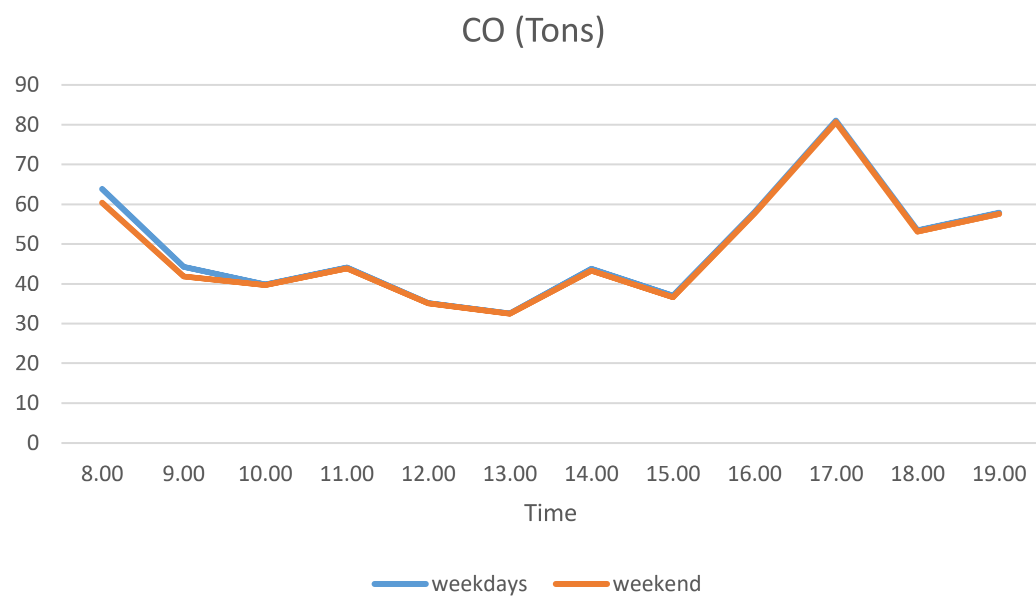
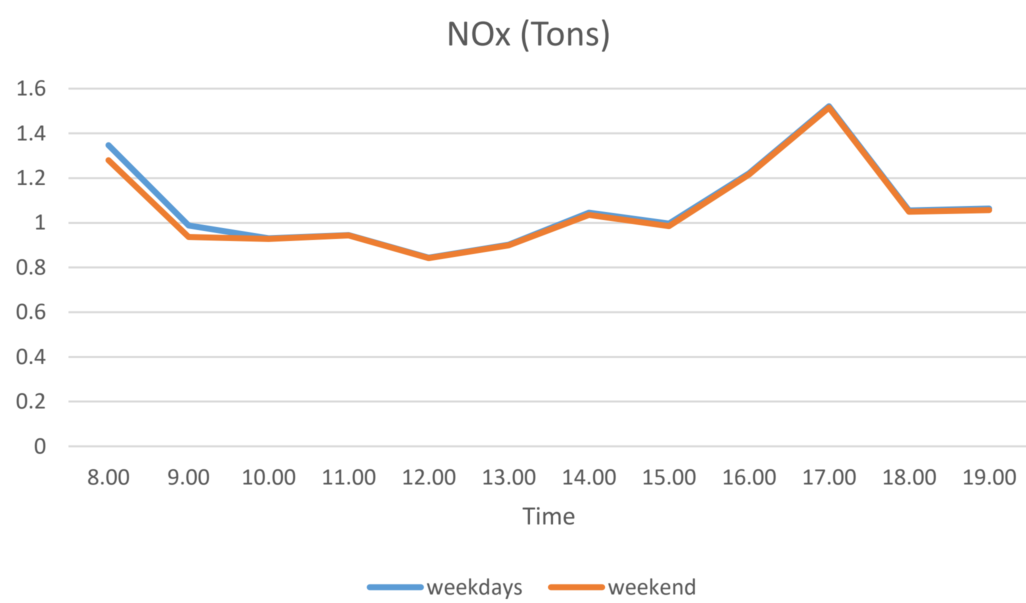


Figure 4.12. Diurnal variation of three Levels of service in weekdays and weekend in central area of HCMC

Combining with Jam density, Free flow speed parameters as mentioned in previous part, the diurnal variation of traffic density can be seen in Fig 4.13. Traffic density is expressed by number of PCUs per one km road segment over one hour and it is output of traffic flow model. On the whole, Secondary road is the busiest road type, while the lowest traffic densities are recorded in Tertiary road. Besides, the gap between Primary road and Secondary one is not significant, particularly in rush hour – 17.00. It is obvious that the average numbers of vehicles on all three road types reach the climax in 17.00. In Primary and Secondary road, over 4000 PCUs were estimated for traffic density in this time slot. In the smallest road type, the number of vehicle hits 2600 PCUs during rush hour, also. The density in 8 am is ranked second with 3200, 2900 and 2000 PCUs were calculated for Primary, Secondary and Tertiary roads, respectively. The graph shows the oscillations of the traffic flow from 8.00 to 17.00. After 17.00, the numbers of vehicle travelling in all road types drop dramatically, making the minimum densities observed around 19.00. Apart from that, it is worth noticing that the temporal variation in traffic densities in weekdays and weekend are quite similar. The rationale is that the sharing ratios among three traffic conditions in weekdays and weekend are not much different, as shown in Fig 4.15. The second cause is there was no distinction in fleet composition data between weekdays and weekend. To conclude, on weekdays, the traffic densities increase by 130% and 150% in secondary – primary roads and tertiary roads, respectively. On weekend, the growth by 127% and 145% of traffic densities in secondary – primary roads and tertiary roads are observed, respectively.

Figure 4.13. Diurnal variation of hourly traffic density on three road types


CO (Tons)
90
80
70
60
50
40
30
20
10
0
8.00
9.00
10.00
11.00
12.00
13.00
14.00
15.00
16.00
17.00
18.00
19.00
Time
weekdays
weekend


NOx (Tons)
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
8.00
9.00
10.00
11.00
12.00
13.00
14.00
15.00
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19.00
Time
weekdays
weekend

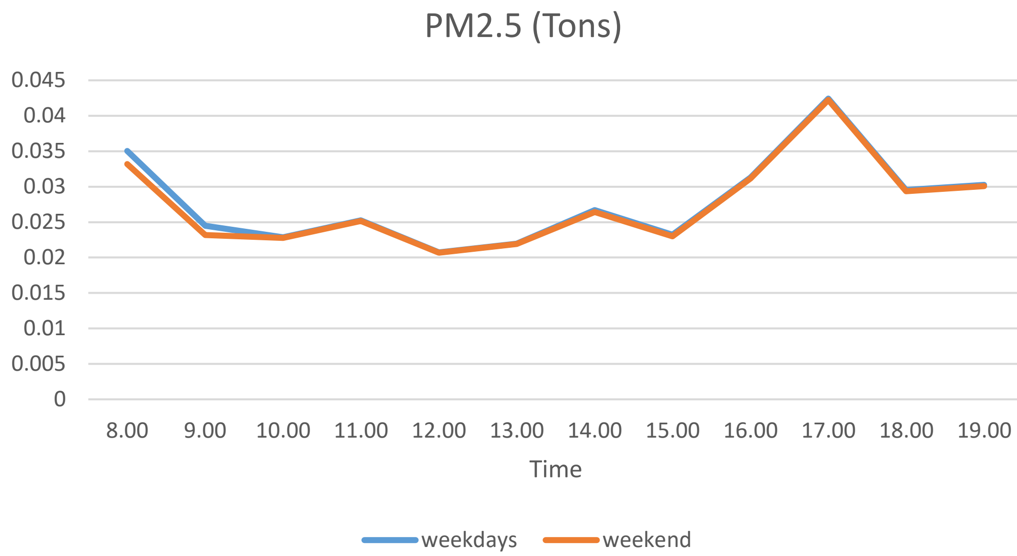
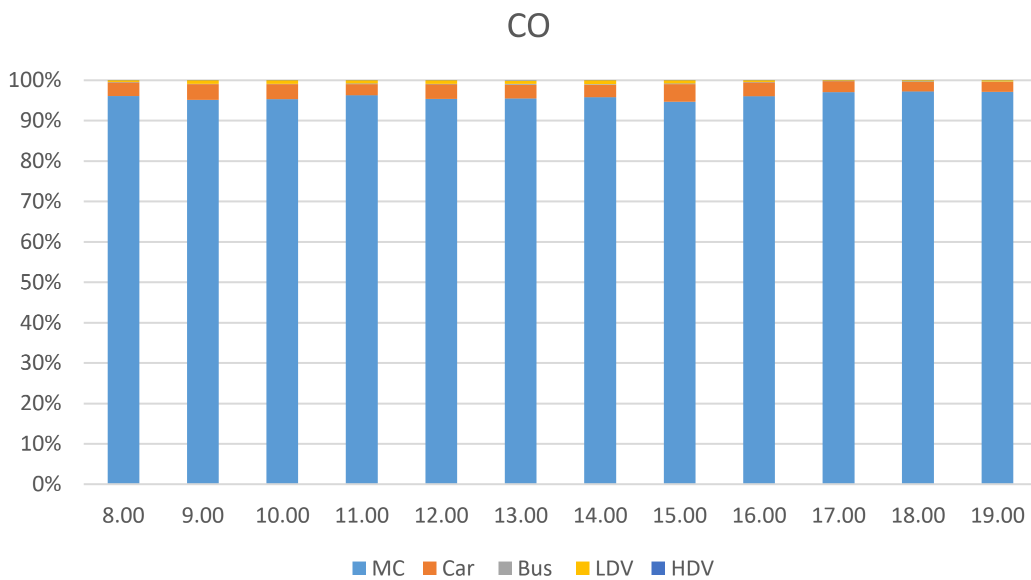


Figure 4.14 Diurnal variation of total CO, NOx and PM2.5 emission from vehicle fleet on weekdays and weekend in HCMC

The diurnal variation of total CO, NOx and PM2.5 emissions from transportation was shown in Fig 4.14. At a first glance, all three pollution species demonstrate the same pattern with traffic densities as seen in Fig 4.13. The “cleanest” time slot is around noon – 12.00. Meanwhile, in rush hours, the highest emissions were estimated. The vehicle fleet within boundary of study area emits over 80 Tons of CO, 1.5 Tons of NOx and 0.043 Tons of PM2.5 in 17.00 time slot. It means the emissions significantly increase by 49 tons of CO (153%), 0.69 tons of NOx (84%) and 0.023 tons of PM2.5 (115%) in rush hour, in compare with the “cleanest” time slots. It is equivalent with the growth by 130% and 150% in secondary – primary roads and tertiary roads on weekdays, respectively and the growth by 127% and 145% of traffic densities in secondary – primary roads and tertiary roads observed in weekend. Again, the distinction between weekend and weekdays here is not obvious, because of similar temporal trend of traffic condition and the same fleet composition data applied in two cases.


CO
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
8.00
9.00
10.00
11.00
12.00
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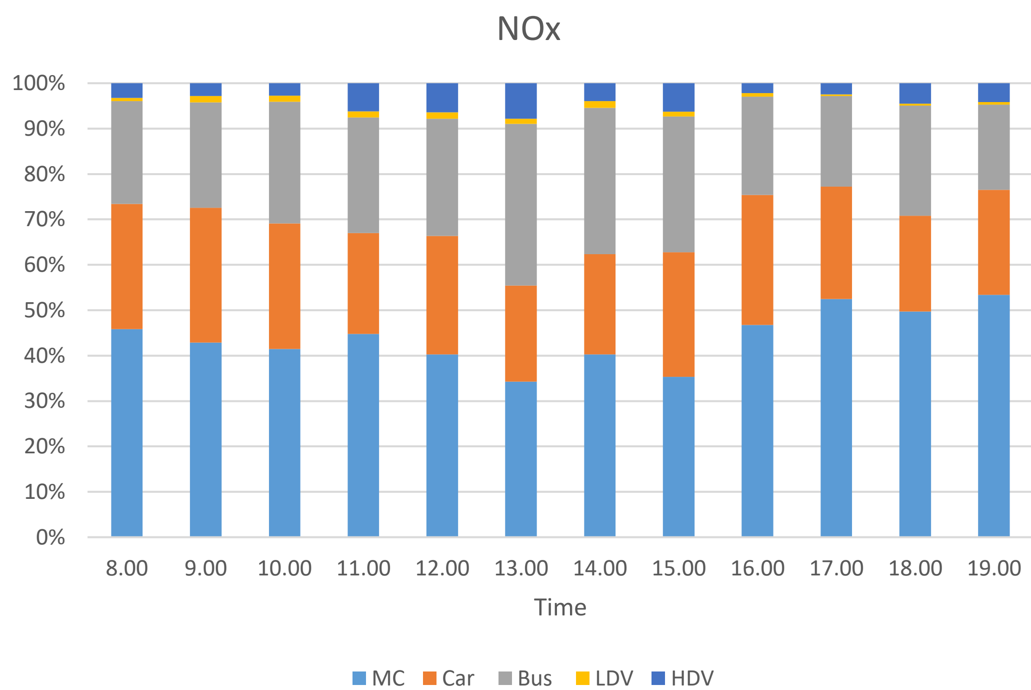
MC
Car
Bus
LDV
HDV


NOx
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
8.00
9.00
10.00
11.00
12.00
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MC
Car
Bus
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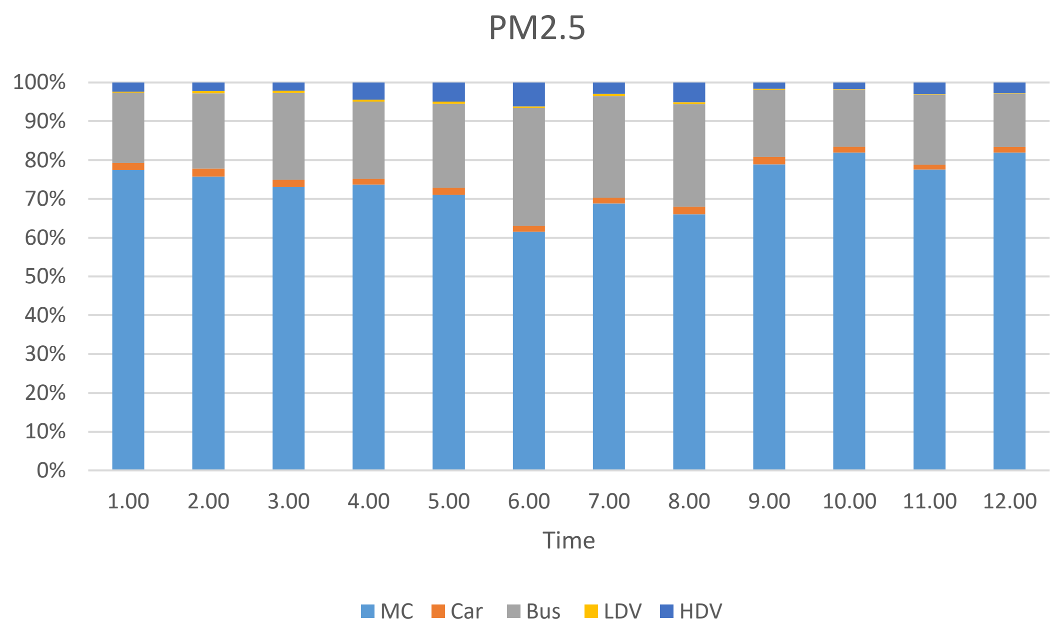


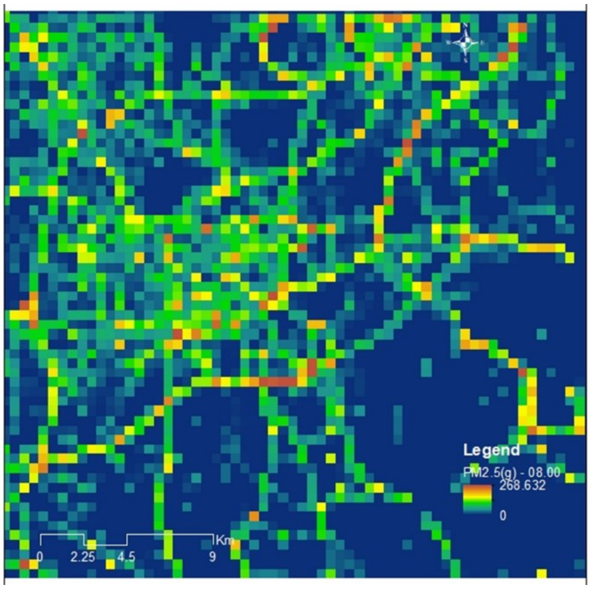
Figure 4.15 Diurnal variation of sharing ratios of five vehicle types regarding the contributions to emissions of CO, NOx and PM2.5 in HCMC.

Besides, the sharing fraction of five vehicle types regarding the contributions to emissions varies during day, also (Fig 4.15) At the onset, MC contributes most for CO emission, over 95% of CO pollution emitted by this vehicle type. Regarding NOx, the fraction of MC varies between 35-52%, depending on time slot, followed by personal car and bus. In case of PM2.5, MC and bus are considered as primary emission sources. Over 60% PM2.5 emission comes from MC, and bus contribute 19-24 % of total PM emission, too.

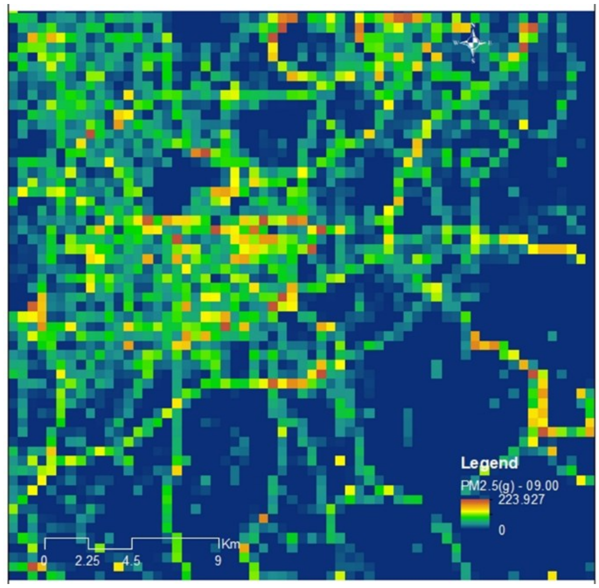
4.3.2. Spatial distribution

The final outputs of this chapter are hourly emission maps with 500m resolution for CO, NOx, PM2.5 during 12 hours, from 8.00 to 19.00. Fig 4.16 demonstrated the spatial distribution along time of PM2.5 within study area. The similar spatial patterns of NOx and CO are expected because they were all derived from the same model traffic flow data set. In the morning, before noon, the high emission levels are recorded in ring roads and primary roads. After 14.00, the pollution hot spots are shifted to central part, where road density is highest. In compare with earlier time slots, 13 and 14.00, the high emission area in rush hour – 17.00 is less scattered, forming quite clear elevated emission zone. It should be noted that the min and max values of PM2.5 emission in each time slots are difference. These emission maps can be useful material for studies on human exposure to air pollution during commuting time.

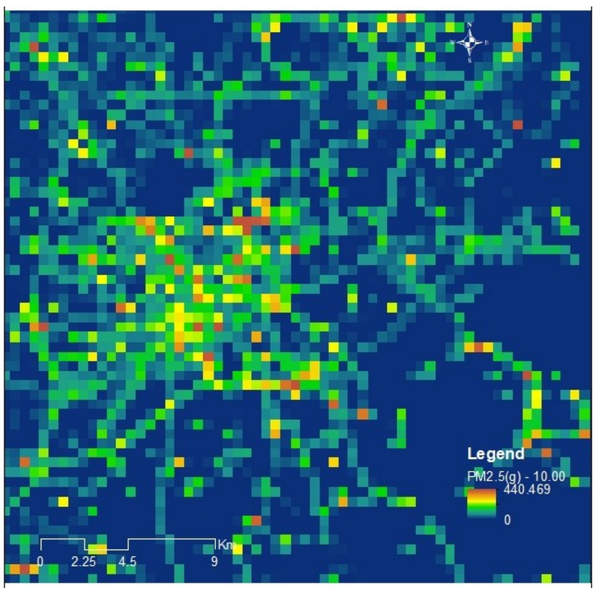
8.00



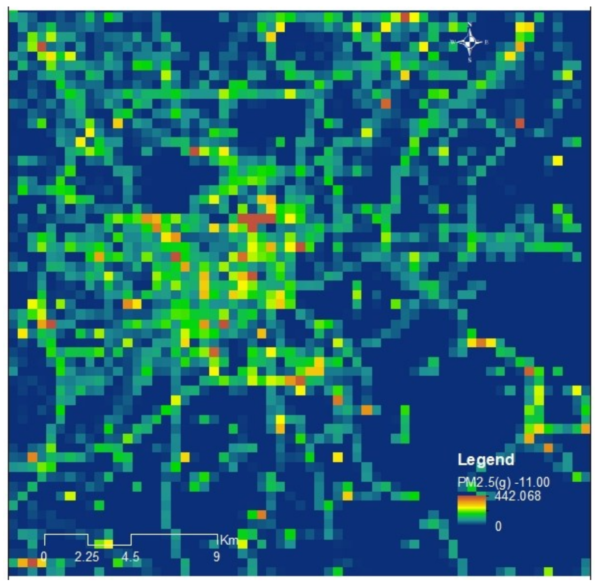
9.00



10.00

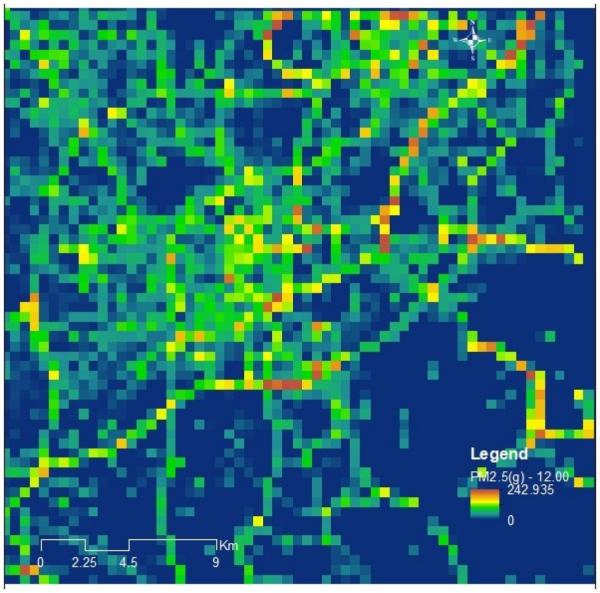


11.00

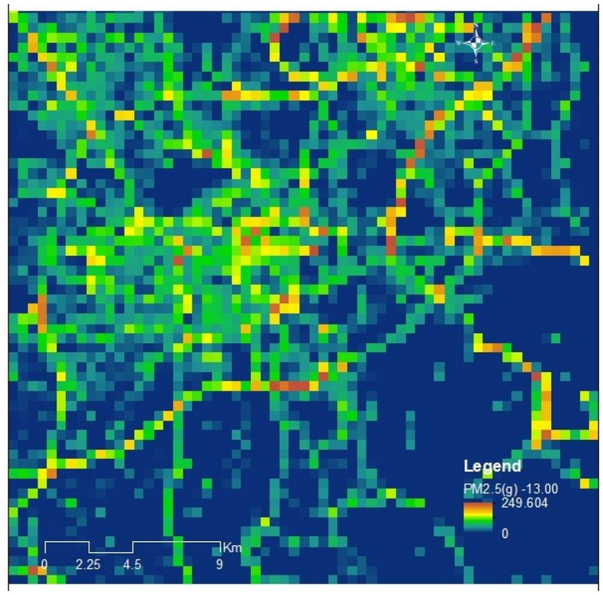


12.00

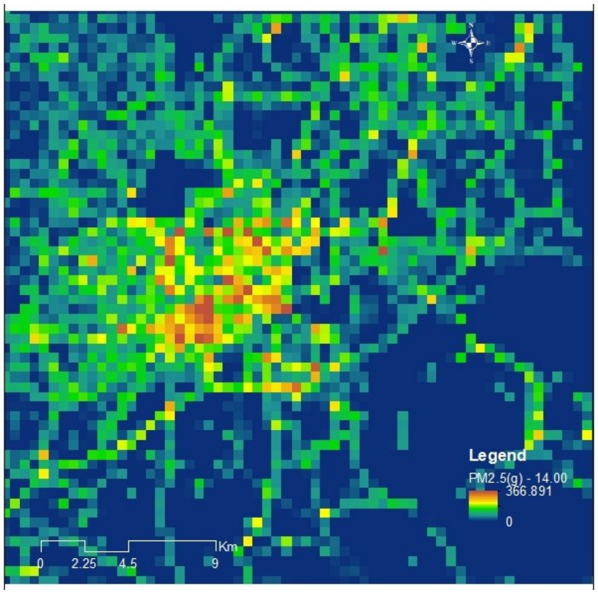
13.00



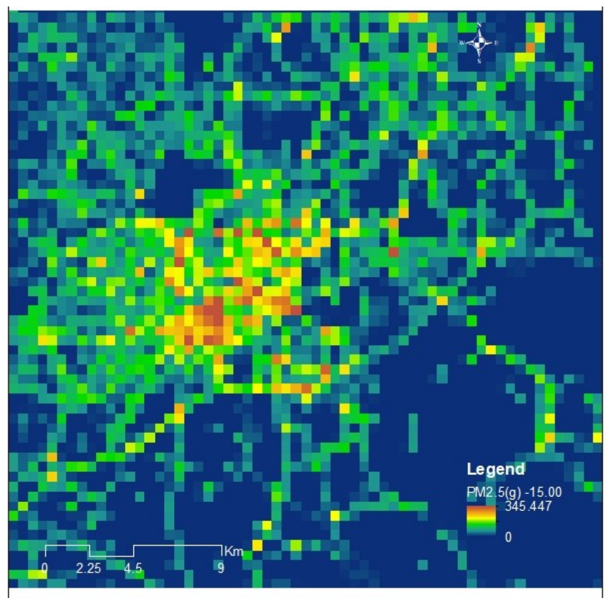
14.00



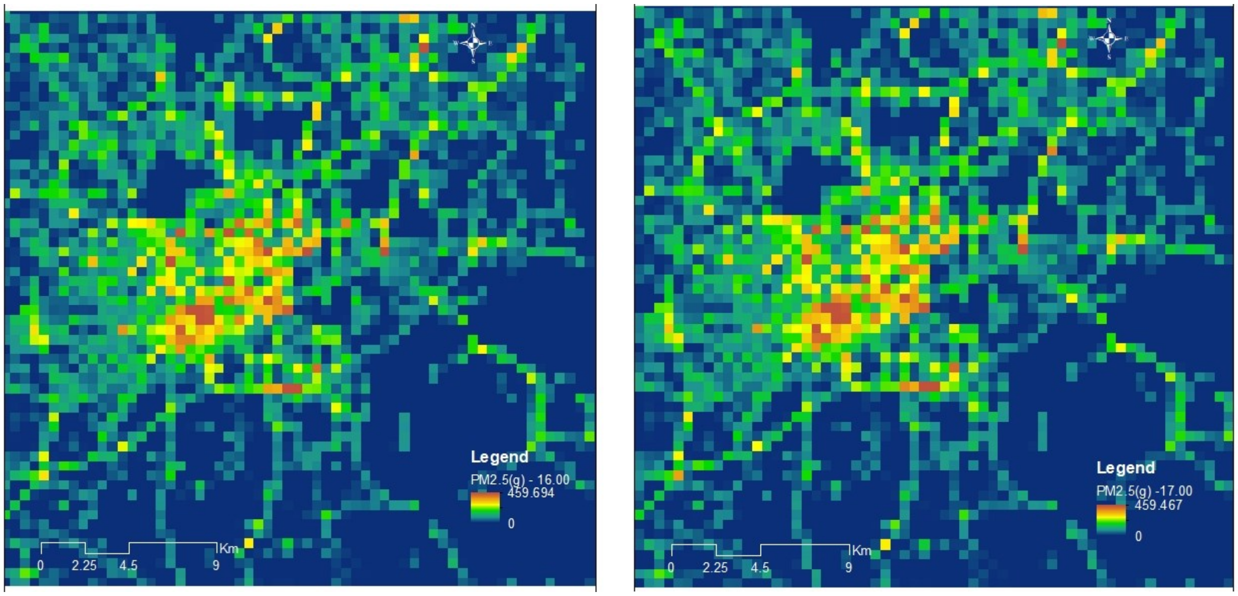
15.00



16.00



17.00



18.00 19.00

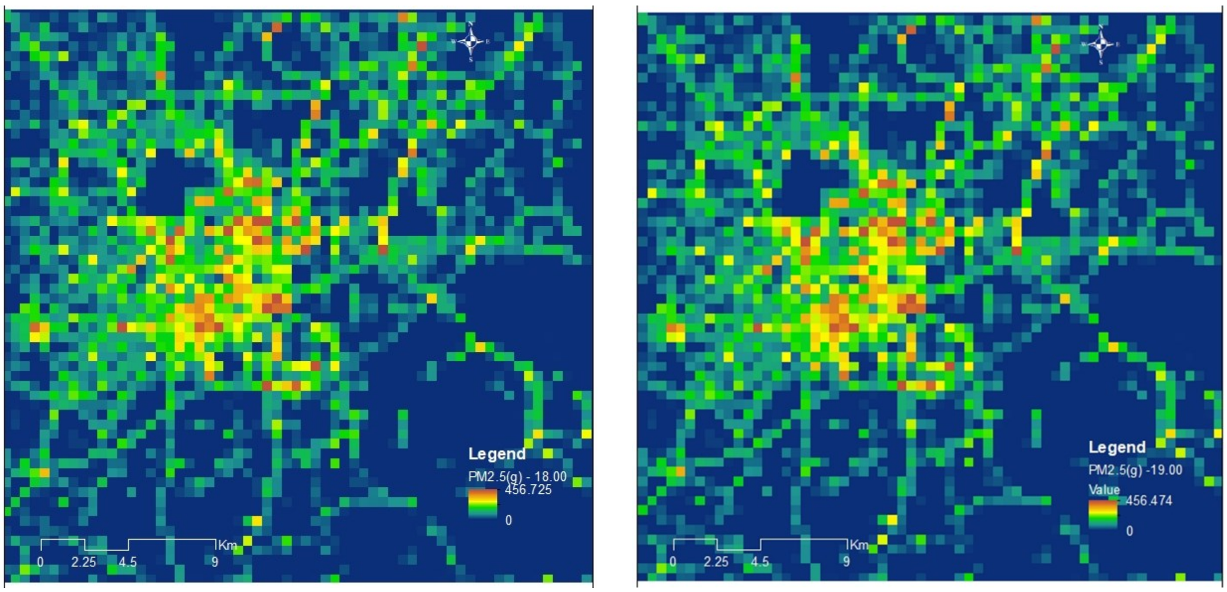


Figure 4.16. Hourly PM2.5 emission maps in weekdays from 8.00 to 19.00 in HCMC

4.3.3 Comparison with other studies

In this part my estimations are compared with two previous hourly traffic emission studies. A traffic emission inventory in Hanoi in 2010 was conducted by T.T.Trang et al, 2015 (Fig 4.17), using data from questionnaire survey and vehicle counting at nine selected roads. Also, in HCMC, H.Q.Bang applied EMISENS model to calculate hourly emission from vehicle fleet in 2010.

Firstly, according to the EI in Hanoi, the peak hours of traffic emission are 7.00-8.00 and 17.00-18.00 for the cases of CO, VOC and PM. The highest emission level of whole vehicle fleet could reach 55 tons CO, almost 3 tons NOx and 0.8 tons PM per hour. My estimations for central area in HCMC show higher amount of CO emission – over 80 tons at 17.00 but lower NOx emission – 1.5 tons and much lower PM level – only 0.043 tons in peak hour (Fig 4.14) In fact, the study in

Hanoi consider PM10, my estimation was for PM2.5 so the significant gap in PM case is reasonable. The study in Hanoi applied International Vehicle Emissions (IVE) model to produce detail EFs which are separated by road types, speed and acceleration ranges (Tab 4.8) Meanwhile, my model use EFs separated by engine technology types only (Tab 4.2) In my estimation, 60.34% MC had Pre Euro engine, equivalent with 32.8g CO and 0.225g NOx per km per vehicle. It is obvious that my EF of CO is much higher than their EF, making the higher hourly CO emission. A relative agreement in EF of NOx can be seen, so the difference in NOx emission is likely come from estimated traffic flow in two cities.

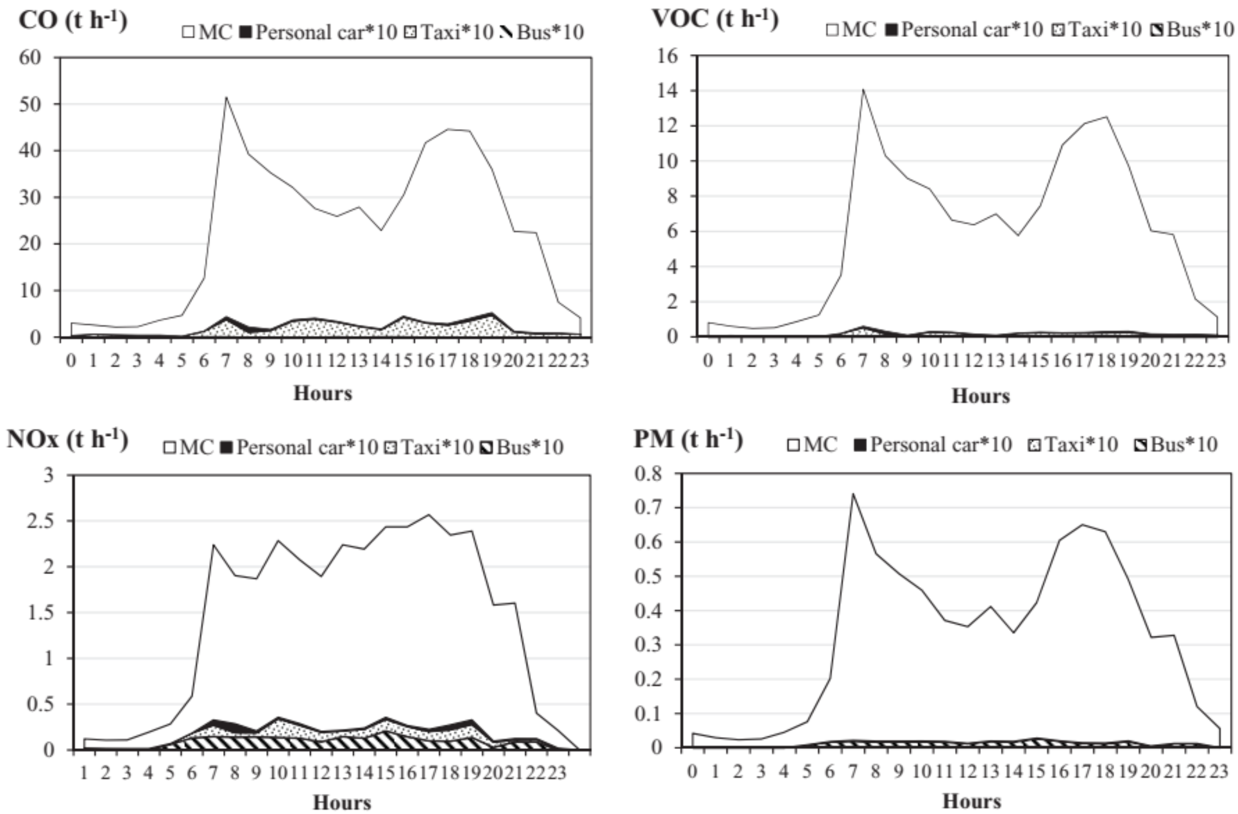


Figure 4.17 Diurnal emissions of vehicle fleet in Hanoi, 2008 for MC, personal cars, taxi and buses by T.T.Trang et al, 2015

Table 4.8 Motorcycle running emission factors by road Type and start emission factors in Hanoi by T.T.Trang et al, 2015

(g/ km)	CO	NOx
Highways	3.801 ± 0.429	0.137 ± 0.043
Arterials	5.960 ± 1.066	0.210 ± 0.064
Residential streets	7.499 ± 1.601	0.268 ± 0.083
Composite running	5.491 ± 1.971	0.195 ± 0.114
Start	18.121 ± 5.463	1.663 ± 0.453

According to the study of H.Q.Bang in 2010, the peak traffic time in HCMC are 7.00-8.00 and 17.00-18.00. The hourly emissions from traffic in central area of HCMC were 3.44 tons NOx and

331.4 ton CO. His estimations were 4 times and 2 times of my calculations for CO and NOx, respectively. This study used the counted traffic flow on 170 streets and the same fleet composition in all road types. In compare with my EFs shown in Tab 4.2, their EFs of CO and NOx are much higher in cases of bus, personal car, LDV and HDV. However, motorcycle EFs of both two pollutants from this research are lower than mine, 1.5 times and 4 times for CO and NOx, respectively. In fact, my estimations were based on traffic maps provided by Google. In the zoom level that can cover central area of HCMC, a number of tertiary roads and residential streets were missed. This fact leads to the possibility of underestimation in my calculated hourly traffic flow and the total emission from vehicle fleet.

Table 4.9 Emission factors were used in study of H.Q.Bang, 2010 in HCMC

(g/ km)	CO	NOx
Motorcycle	21.8±8.67	0.05±0.02
Bus	11.1±5.3	19.7±5.2
LDV	34.8±15.5	1.9±0.9
HDV	11.1±5.3	19.7±5.2
Car	34.8±15.5	1.9±0.9

Also, according to this study, MC shares 94% of total CO emission and 29% of NOx. HDV is the most dominated emission source of NOx. These findings have agreement with my sharing ratios of MC regarding emission of CO and NOx (Fig 4.15) My output expressed that 95% of CO emission come from MC. Regarding NOx, the fraction of MC varies between 35-52%. However, the sharing percentages of HDV in NOx case in my calculation are much lower (2-8 %) This gap is explained by much smaller NOx EF used in my model.

In previous chapter, my estimations for annual Transportation emission demonstrate over 95% CO emission and 5-10% NOx emission every year derived from MC. Truck was accounted for 50-60% of the total NOx emission, similar with study of H.Q.Bang, 2010. These comparisons sketch out the high confidence level of my hourly CO emission inventory. The calculation for NOx has higher uncertainty range because of the inconsistencies in EFs and the estimated traffic flow.

4.4 Conclusion

In conclusion, the objective of this chapter is to compile hourly emission inventory for Transportation sector in Central part of HCMC. The vehicle EI was calculated basing emission factors, vehicle mixing data, road network and traffic flow. Among these four factors, traffic flow is the most fluctuating factor over time. So apart from emission factors, road network derived from various sources, this study calculated vehicle emission basing on modeled hourly traffic flows in three road types. It is the first work taking advantages of Google traffic condition maps combining with other traffic parameters provided by previous studies to derive hourly traffic flows in HCMC.

The diurnal traffic flow demonstrates clearly the peak hours in study area – 17.00 with traffic densities estimated for Secondary, Primary road and Tertiary road are over 4000 PCUs and 2600 PCUs respectively. Morning rush hour – 08.00 expressed high traffic flow levels, but still lower than 17.00. In rush hours, the percentage of lightly congested road increases to 45% from 15% in case of weekdays and rises to 31% from 6% in weekends. The outputs of my model also demonstrate the growth by 130% and 150% of traffic densities in secondary – primary roads and tertiary roads, respectively in peak hours on weekdays and the growth by 127% and 145% in secondary – primary roads and tertiary roads in weekend. As a result, the emissions significantly increase by 49 tons of CO (153%), 0.69 tons of NOx (84%) and 0.023 tons of PM2.5 (115%) in rush hour, in compare with the "cleanest" time slots. On the whole, because of traffic jam in peak hours, the total hourly vehicle emission can uplift 2 - 2.5 times, in compare with non-busy time slots. These findings indicate if the traffic jam situation in HCMC is controlled by reducing traffic densities, local air quality will be improved considerably.

Regarding the sharing fraction of five vehicle types regarding the contributions to emissions varies during day, MC is responsible for over 95%, 35-52%, 60-80% of CO, NOx and PM2.5, respectively. The fractions of personal car in terms of NOx is 20-30%, but its contributions to CO and PM is insignificant.

The spatial distribution of emission varies along time, also. In the morning, high emission level is seen mainly in ring road. Afterward, the emission hot spot shifts to central area, making the remarkable change in spatial allocation. From 15.00, the most elevated emission was recorded in central business districted where road density is highest.

Although the agreement between my estimations and findings of previous study in some extent was found, few limitations in my model was noted. Firstly, the Google traffic map can omit the small roads like residential streets and service roads, according to the categories of Open Street map. To cover my study area in one frame, the highest zoom level of Google could not be chosen, so a number of tertiary roads were omitted. My hypothesis is the traffic flows in those streets are negligible but the model can underestimate the real emissions from traffic in HCMC. Secondly, the same fleet composition data set was applied for both weekdays and weekend. It leads to quite small distinctions in emission and temporal trend between two cases. As a result, the vehicle mixing ratio should be calculated for weekend to improve the emission model. Thirdly, constant EF values were applied in my model. The change of EFs due to a change in speed and acceleration of vehicles should be considered to improve the accuracy of estimated emissions. In addition to that, the uncertainties of emission inventory is recommended to be estimated in future work. The biases can come from every factors in model. And in both policy purposes and scientific purposes, understanding the uncertainties is an important issue. Moreover, the estimations of traffic flow model is recommended to be validated by other reference sources, such as origin-destination data or call detail record data that can be used to calculate the network traffic density. These data is likely derived from traffic studies of JICA or ADB who often conduct large scale traffic survey campaigns in Asian cities like HCMC.

Chapter 5.

Conclusion and future work

5.1. Conclusion

In this thesis the objective was to compile and update key emission sectors in HCMC to develop a comprehensive, comparable and consistent EI, with inherent EIs modelled for HCMC, Vietnam, and Southeast Asia. Using various data sources, like statistical data, and remote sensing data, the local emission inventories were updated with annual interval and hourly interval for the most dominated sector. Based on the analysis, the following conclusions can be drawn.

To achieve above objectives, local statistical data, several remote sensing datasets, global emission inventories, and an air dispersion model were used in this research. Firstly, the impact of biomass burning (BB) emission in the vicinity on air quality in Ho Chi Minh city was assessed using the Weather Research and Forecasting model coupled with Chemistry – WRF Chem and remote sensing data as complementary approach. The simulations showed little influence of BB on local air quality in HCMC. However, when comparing with in situ data and AOD product from MODIS, the uncertainties of WRF Chem output was revealed. So we supported our finding by satellite images analysis, including FRP data, burn area product, AOD, and simulations of HYSPLIT Trajectory Model. The conclusion of this part is BB is not key emission sector that can strongly impact on air pollution in HCMC.

In chapter 3, basing on the outputs of previous part and literature review, the dominant anthropogenic emission sectors in HCMC were defined: vehicle emission, residential buildings, and manufacturing industrial sector. In terms of Transportation, vehicle fleet in HCMC emitted over 682 Gg CO, 84.8 Gg NOx, 20.4 Gg PM10 and 22000Gg CO2 in 2016, which are were 1.8, 2.6, 2.5 and 2.03 times of the ones in 2009, respectively. This significant increase mainly due to the sharp rise in vehicle population Among five vehicle types, MC contributed around 94% to total CO emission, 14 % to total NOx emission and 50- 60% to CO2 emission. Regarding NOx and PM, truck is claimed as the biggest emission source and the sharing of personal car was considerable in terms of SO2, NMVOC and CO2. The emissions of Manufacturing industry and Residential sectors include both fuel consumption and electricity consumption. Electricity consumption is the most dominated emission source. In 2016, the electricity consumption of Manufacturing industry and Residential sectors in HCMC emitted 6985 Gg and 6691 Gg of CO2, respectively, increasing by 87% and 45% in compare with 2009, respectively. Considering fuel consumption only, both these two sectors account for a very small percentage in compare with Transportation. Regarding spatial allocation of final emission, Transportation is by far the highest emission source, in terms of all species, so the spatial distribution of all pollutions are similar with Transportation emission map. The central business districts like Quan 1, Quan 4 and Quan 7 express the highest emission intensities, which can be over 1900 times of the ones in outskirt area.

In chapter 4, high detailed vehicle emission inventory was compiled based on modelled traffic flow data. The vehicle EI was calculated basing emission factors, vehicle mixing data, road network, and traffic flow. This part take advantages of Google traffic condition maps combined with other traffic parameters provided by previous studies in HCMC to derive hourly traffic flows. The diurnal traffic flow demonstrates clearly the peak hours in study area – 17.00 with traffic densities estimated for Secondary, Primary road, and Tertiary road are over 4000 PCUs and 2600 PCUs respectively. In rush hours, the percentage of congested road increases to 45% from 15% in case of weekdays and rises to 31% from 6% in weekends. The outputs of my model also demonstrate the growth by 130% and 150% of traffic densities in secondary – primary roads and tertiary roads, respectively in the busiest hours on weekdays and the growth by 127% and 145% in secondary – primary roads and tertiary roads in weekend. As a result, the emissions significantly increase by 49 tons of CO (153%), 0.69 tons of NOx (84%) and 0.023 tons of PM2.5 (115%) during traffic jam time, in compare with the "cleanest" time slots. On the whole, because of high traffic flow in peak duration, the total hourly vehicle emission can be double to 2.5 times, in compare with non-busy time slots. It suggests that if traffic densities is reduced by the limitation of personal vehicles or road network expansion, local air quality in HCMC will be improved considerably.

5.2. Recommendation

In the first chapter, WRF Chem was run using FINNv1.5 biomass burning emission inventory for pre monsoon season in 2016, over the southern part of Vietnam. Firstly, FINNv1.5 emission files was updated till 2016 and FINNv1.6 files are no longer used, HTAP anthropogenic EI is out of date also. Therefore, it is recommended that emission inventories should be updated before being applied to the dispersion model, not only biomass burning EI. Secondly, WRF Chem is recommended to run over SEA region in southwest monsoon season to confirm the influenced area of dominated BB in Kalimantan and Sumatra during those months.

In chapter 2, the changes in VKT, EFs of vehicle fleet and road network in HCMC are recommended to be considered. Moreover, the updated annual grid EF could improve the accuracy of emission estimated for electricity consumption. Technology evolution regarding fuel consumption should be taken into account in order to enhance the reliability of EI for Manufacturing and residential sectors. Regarding urban morphology maps, the ground truth data of building height could improve the accuracy of land use map, because only one AW3D data in 2011 was applied over 8 years in this study.

In chapter 3, the separate fleet composition data should be applied for weekend. At this moment, very small distinctions in emission and temporal trends between weekdays or weekends was found in my estimation. Besides, the uncertainties of emission inventory is recommended to be estimated in future work and the output of traffic flow model could be validated and enhanced when in situ traffic data is available.

5.3. Future work

Even though I have been able to update emission inventories for dominant sectors, detailed EI was compiled for vehicle EI only. It is important to calculate EI in higher detail level for all primary emission sectors. Future studies can continue to develop high temporal and spatial resolution EI for residential buildings and manufacturing industrial sector.

Besides, the validation of updated local EI should be considered, although it normally is not a straightforward task. The common way to assess how realistic the results are is a comparison to independently derived data. In this case, remote sensing data, observed data provided by air quality monitoring network, or an application of updated EI as input of chemical transport model and comparing with in situ data can be the answers. In addition, other traffic data sources, such as origin-destination matrix data or call detail record data can be reference to assess the accuracy of traffic flow model.

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