The authors would like to thank Referee #1 and Anonymous Referee #2 for taking their time to review our manuscript and for giving very constructive and informative comments. These comments helped us improve the quality and clarity of the manuscript. We revised our manuscript based on them. Below are our responses to each comment.

The structure of this document is as follows:

(1) Comments, author's response, and author's changes in manuscript related to Referee #1

(2) Comments, author's response, and author's changes in manuscript related to Referee #2

(3) The revised main manuscript where changed parts were yellow highlighted

Author's response, and author's changes in manuscript related to Referee #1:

1. The abstract should mention how is the novel method developed (give an idea of the main parts). The abstract is focused on the local EI for the HCMC, it would be important to mention the two main points of the paper the local EI but also the novel method.

We revised the abstract with more information about the novel method: "Our originality is the use of satellite derived urban land-use morphological maps which allow spatial disaggregation of emissions. We investigated the possibility of using freely available coarse resolution satellite derived digital surface model (DSM) to estimate building height. Building height is combined with urban built-up area classified from Landsat images and nighttime light data to generate annual urban morphological maps. With outstanding advantages of these remote sensing data, our novel method is expected to make a major improvement in comparison with conventional allocation methodologies such as basing on population data."

2. In the introduction, the authors should explain deeper and in context with other methodologies (that already exist) the novel approach presented in this work, which is the main difference. For example, other methodologies focus only on the disaggregation of transport emissions. It is not enough to mention that they developed a novel approach. The introduction might have more about this aspect.

We revised the introduction with more information about our novel approach: "With respect to grid allocation, spatial distribution of emissions is a crucial step to fulfil the requirements of gridded EI as input data for air quality modelling. Top-down EIs are often being used as input data for modelling activities at urban scale after downscaling (Susana López-Aparicio et al., 2017). In conventional way, other methodologies focus only on the disaggregation of transport emissions using traffic counts and road network data (C.D. Gómez et al, 2018). The spatial allocation of area source emissions is mainly based on rural, urban and total population data (J. Kurokawa et al, 2013; J. Kurokawa et al, 2019). These approaches are not suitable for community scale EIs what demand higher detail levels of both activity data and spatial disaggregation. Especially, it is not rational to use population data for spatial disaggregation of Industrial sector. Using these methodologies without consideration could lead to underestimation of emissions in urban centre, industrial zones, as well as overestimation in residential zones (P.Saide et al, 2009). It is worth mentioning that these spatial proxies have a strong influence on simulations of air quality modelling, especially when the results are considered for policy making and planning options (M. Trombetti et al, 2018). J Kühlwein et al., 2002 made comparisons among spatial distribution of EIs computed with different levels of information and concluded that a big source of uncertainty is encountered when only considering disaggregation using population. M. Trombetti et al, 2018 also conducted an inter-comparison of the main top-down EIs currently used for air quality modelling studies at the European level regarding downscaling approaches and choice of spatial proxies. Their finding is that the traditional proxies used for gridding residential emissions (e.g. population density) would not be any more relevant. A few studies used land use map as a proxy for deriving spatial patterns of emissions (P.Saide et al, 2009). Nowadays, remote-sensing information is quite important source for land use/land cover modelling. The most prominent advantages of satellite images influencing the spatial allocation of emissions are the ability to collect information over large spatial areas and the ability to collect imagery of the same area of the earth's surface at different periods in time. By imaging on a continuous basis at different times it is possible to monitor the changes in land use in community scale if the resolution of data is high enough. Moreover, data collected through remote sensing is analyzed at the laboratory which minimizes the work that needs to be done on the field. Accordingly, in the context of spatial allocating emission at a finer scale, remote sensing data is quite promising approach that allows repetitive land use mapping in different study areas. In the case of HCMC, only a few attempts have been made to spatial disaggregate the emissions. Applying similar method with previous works, study of B.Q.Ho, 2010 provides the first emission maps for HCMC using road network as allocation factor for Transportation sector and population density as allocation factor for Industrial and Residential sectors."

3. The introduction is very focused on the EI from the city, but don't show the relevance of this study in comparison with other studies that propose allocation or disaggregation methodologies.
In the introduction, we explained that: "In the case of HCMC, only a few attempts have been made to spatial disaggregate the emissions. Applying similar method with previous works, study of B.Q.Ho, 2010 provides the first emission maps for HCMC using road network as allocation factor for Transportation sector and population density as allocation factor for Industrial and Residential sectors."

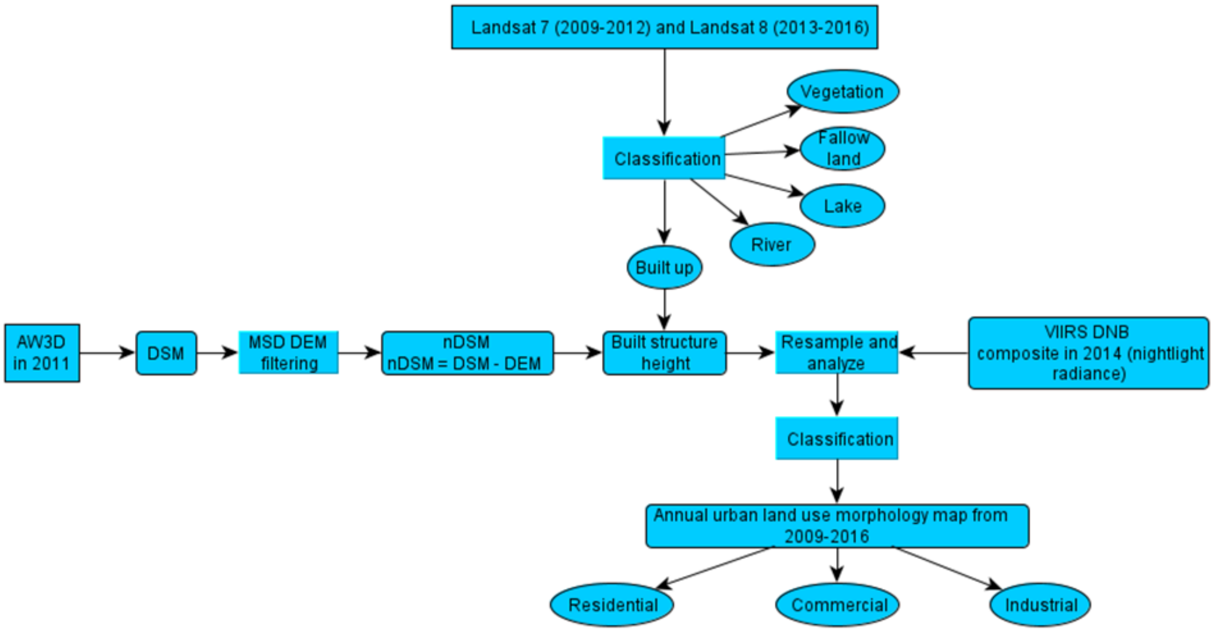
4. The title mention "using satellite..." but there is no information about the importance of these in the context of allocating EI that can help other cities to use this methodology.
We added this part in the introduction: "Nowadays, remote-sensing information is quite important source for land use/land cover modelling. The most prominent advantages of satellite images influencing the spatial allocation of emissions are the ability to collect information over large spatial areas and the ability to collect imagery of the same area of the earth's surface at different periods in time. By imaging on a continuous basis at different times it is possible to monitor the changes in land use in community scale if the resolution of data is high enough. Moreover, data collected through remote sensing is analyzed at the laboratory which minimizes the work that needs to be done on the field. Accordingly, in the context of spatial allocating emission at a finer scale, remote sensing data is quite promising approach that allows repetitive land use mapping in different study areas."

5. The authors mention (around 35) "Many atmospheric chemistry modelling researches in Asia have applied these EIs as input data but they are incoherent and not longer updated". Why are that EI incoherent? the authors should be more specific.
We realized that "incoherent" is improper word here, so this part was omitted already.

6. In Table 1, there is an updated inventory from 2019. In general, inventories depend on many factors, and determine which one is correct is not easy, how the authors establish which inventory is correct?
To determine which inventory is correct or how good the emission inventory is, the most common approach is using simulation models. For our next step, we plan to apply the EI calculated in this study as input of an air dispersion model to evaluate its reliability. In this study, we chose REASv2.1 as predecessor one. Because while other countries like China and Japan have their own EIs, at that moment, REASv2.1 is the only comprehensive one covering Vietnam. Previous studies had thus applied REASv2.1 in air quality simulations over Vietnam and big cities in Vietnam.

7. Please, include a figure that describes better the methodology for the spatial allocation (disaggregation), because that is the novel part. The authors can improve Figure 1 and 2, or include a new figure focus on the allocation part. Figures 1 and 2, only showed a box mention spatial allocation and the *resolution. The methodology for spatial allocation is not available. I also consider Figure 1 and 2 should be improved.*

We added a Figure about spatial allocation in Figure 2:



8. Methodology. I consider some equations are without references, please check these. For example, Eq. 1 and 2, they are taking from specific methods to calculate EIs that are well known.

We added the citations for equations:

$E_{hot} = \sum_i VP_i * DailyVKT_i * 365 * EF_i$ (1) (Creutzig et al., 2011)

$E_{cold} = E_{hot} * \beta_i * F_i$ (2) (Ahlvik P.et al, 1997)

$E_{Fuel} = \sum_i A_i * EF_i * (1 - R_i)$ (3) (IPCC, 1996)

$EF_{SO2} = S_i * (1 - SR_i)$ (4) (IPCC, 1996)

9. The authors mention (around 170) "Fuel consumption in 2013, 2014, 2015 were provided by GHG emission inventory compiled by JICA, 2017 (Tab. 4) The fuel consumptions in other years were inferred using population provided by HCMC Statistical Yearbook (Tab.8)". Which correlation/statistic do the authors use for the years 2009, 2010, etc? How the information is "inferred"? The authors again mention "So, electricity consumptions in other years were inferred using the same parameters used in Fuel consumption part". I consider the authors should establish clear the correlation (which parameter? this is not mentioned) because when EIs are calculated this information can affect the results.

We wrote more for the explanation of this part in Methodology: "The fuel consumptions of Manufacturing industrial sector in five other years (2009 to 2012 and 2016) were proportional calculated using annual Gross output of industry at current prices by industry activity in HCMC, provided by HCMC Statistical Yearbook (Tab.8) with the assumption that there is linear relationship between Fuel consumption of Manufacturing industrial sector and Gross output of industry"

And

"Fuel consumption in 2013, 2014, 2015 were provided by GHG EI compiled by JICA, 2017 (Tab. 6) The fuel consumptions in other years were proportional calculated using population provided by HCMC Statistical Yearbook (Tab.8) with the assumption that there is linear relationship between Fuel consumption of Residential sector and population of city."

And

"electricity consumptions in other years were proportional calculated using the same proxies applied in Fuel consumption part:

- Manufacturing Industries and Construction sector: used Annual Gross output of industry at current prices by industry activity with the assumption that there is linear relationship between electricity consumption of Manufacturing industrial sector and Gross output of industry.
- Residential: used Annual population of HCMC with the assumption that there is linear relationship between electricity consumption of Residential sector and population of city."

10. Section 2.3.5 Spatial allocation, the authors explained how to allocate EI for each source: transport, point sources (residential, industrial, commercial), however, it is not clear how the total EI is integrated.

We wrote more for the explanation of this part in Methodology: "These land use maps were used for spatial distribution of Manufacturing industrial and Residential emissions into the same grid net – 1 km resolution with Transportation sector. Basing on the spatial matching, total emission of three key sectors is simply sum of grid nets of Manufacturing industrial, Residential and Transportation emissions."

11. It is not clear which is the step in the integration of urban morphological maps, DSM, DEM in the case of point sources.

We explained in the Spatial allocation part: "Noteworthy, in this study industrial emission sector is considered as area source instead of point source like previous studies."

12. Additionally, the authors stated "The composite Landsat (Landsat 7 for 4 years: 2009 to 2012 and Landsat 8 for other four years: 2013 to 2016) was classified in a supervised manner using Mahalanobis distance into 7 classes (including class built-up)", which are the 7 classes used? Since this is the novel methodology, I consider this should be presented in a more organized way.

We revised this part with more detailed explanations: "A time-series of Landsat imagery (Landsat 7 for 4 years: 2009 to 2012 and Landsat 8 for other four years: 2013 to 2016) was classified to generate the urban built-up extent for 2009 to 2016. A Mahalanobis distance based supervised classification was performed to identify 5 classes (including built up, vegetation, fallow land, lake and river)."

13. In the last part of the section Summary and discussions (around line 515), the authors said "We relied on only one building height data (extracted from AW3D30) in 2011 to prepare land use maps for 8 years. The assumption of constant building height neglects vertical growth and land-use transitions, causing inevitable uncertainty in the spatial allocation of emission. Also, this approach assumes that all constituents of the field data of building height and land use could improve the reliability of annual urban morphology maps". That details should be in the methodology about the approximation to use land maps, etc. Additionally, how do the authors "assume" that?

The objective of urban morphology mapping is to classify annual land use into three classes: residential, commercial and industrial. The assumption of constant building height is valid as long as the change in building heights does not impact the transitions among those three land use types. Our simple random resampling in Google earth proved that the land use change occurring in HCMC mainly is urban expansion (95%) The transitions among residential- commercial – industrial barely happen. So neglecting vertical growth of city will cause inevitable uncertainty in the spatial allocation of emission.

14. For the sections Results, conclusions, I would recommend an analysis that clearly establishes how the new methodology makes a difference from the previous EIs available for the city. For example, if the transport is the main source as the author mentioned and the methodology implemented in the present work is similar for the spatial disaggregation of transport, how the allocation of point sources using *satellite for urban land-use morphological maps improved the resolution and the information (comparing with the previous study of "H.Q.Bang, 2010, the first emission maps were developed for HCMC using road network as allocation factor for Transportation sector, population density as allocation factor for Industrial and Residential sectors")*

We wrote more explanations for this in Conclusion part: "The previous emission maps available for HCMC include works of B.Q.Ho, 2010, B.Q.Ho et al, 2019 and REAS inventories. Those studies used road network and population density data for spatial allocation. The novelty of this study is that the disaggregation of transportation emission based on road density combining with different weights for three types of roads that are their traffic volumes, while residential and commercial sectors were allocated by urban morphology maps. In conventional way, field-work based data are labor consuming and cannot be performed frequently. Also, the use of those existing spatial distribution surrogates neglects the effects of urban sprawl that is evident in big cities. It is desirable to have access to revised spatial allocation factors that may be more representative of spatial distributions in community scale and more available. And even if statistical data is inaccessible in other cities remote sensing data can be used. Remote sensing data can be updated frequently, too. Thus, the use of satellite images makes spatial disaggregation updating quite simple and efficient. Besides, it is the best tool to represent urban expansion and land use change, so it ensures the accuracy of grid allocation when closely related spatial activity surrogate is needed to compile EI in local scale"

A comprehensive analysis of the improvement of our EIs will be conducted in our future study that uses these EIs as input data of atmospheric chemistry models and conduct the comparison to independently derived data.

15. Technical corrections:

We revised the manuscript according to these corrections as shown in *The revised main manuscript.*

Author's response, and author's changes in manuscript related to Referee 2:

1. Abstract: The authors should talk more about the novel methodology they use, rather than the EI results of the city.

We revised the abstract with more information about the novel method: "Our originality is the use of satellite derived urban land-use morphological maps which allow spatial disaggregation of emissions. We investigated the possibility of using freely available coarse resolution satellite derived digital surface model (DSM) to estimate building height. Building height is combined with urban built-up area classified from Landsat images and nighttime light data to generate annual urban morphological maps. With outstanding advantages of these remote sensing data, our novel method is expected to make a major improvement in comparison with conventional allocation methodologies such as basing on population data."

2. Introduction Line 44: Please remove Taiwan from the list. It is NOT a country.

We omitted Taiwan in this line.

3. The authors compare the difference among previous EIs, which is quite helpful. But they should also talk more about the major improvements of their novel methodology in comparison with other studies that use different allocation methodologies. Higher detail level of activity data, local emission factors and a novel approach for grid allocation are used in this study. It is obvious the last one is their major originality. They should focus most on this point and provide more information. For example, what are the advantages of using satellite derived urban land-use morphological maps?

We added more information about the novel methodology and the advantages of using satellite derived urban land-use morphological maps in the Introduction: "With respect to grid allocation, spatial distribution of emissions is a crucial step to fulfil the requirements of gridded EI as input data for air quality modelling. Top-down EIs are often being used as input data for modelling activities at urban scale after downscaling (Susana López-Aparicio et al., 2017) In conventional way, other methodologies focus only on the disaggregation of transport emissions using traffic counts and road network data (C.D. Gómez et al, 2018). The spatial allocation of area source emissions is mainly based on rural, urban and total population data (J. Kurokawa et al, 2013; J. Kurokawa et al, 2019) These approaches are not suitable for community scale EIs what demand higher detail levels of both activity data and spatial disaggregation. Especially, it is not rational to use population data for spatial disaggregation of Industrial sector. Using these methodologies without consideration could lead to underestimation of emissions in urban centre, industrial zones, as well as overestimation in residential zones (P.Saide et al, 2009). It is worth mentioning that these spatial proxies have a strong influence on simulations of air quality modelling, especially when the results are considered for policy making and planning options (M. Trombetti et al, 2018). J Kühlwein et al., 2002 made comparisons among spatial distribution of EIs computed with different levels of information and concluded that a big source of uncertainty is encountered when only considering disaggregation using population. M. Trombetti et al, 2018 also conducted an inter-comparison of the main top-down EIs currently used for air quality modelling studies at the European level regarding downscaling approaches and choice of spatial proxies. Their finding is that the traditional proxies used for gridding residential emissions (e.g. population density) would not be any more relevant. A few studies used land use map as a proxy for deriving spatial patterns of emissions (P.Saide et al, 2009) Nowadays, remote-sensing information is quite important source for land use/land cover modelling. The most prominent advantages of satellite images influencing the spatial allocation of emissions are the ability to collect information over large spatial areas and the ability to collect imagery of the same area of the earth's surface at different periods in time. By imaging on a continuous basis at different times it is possible to monitor the changes in land use in community scale if the resolution of data is high enough. Moreover, data collected through remote sensing is analyzed at the laboratory which minimizes the work that needs to be done on the field. Accordingly, in the context of spatial allocating emission at a finer scale, remote sensing data is quite promising approach that allows repetitive land use mapping in different study areas. In the case of HCMC, only a few attempts have been made to spatial disaggregate the emissions. Applying similar method with previous works, study of B.Q.Ho, 2010 provides the first emission maps for HCMC using road network as allocation factor for Transportation sector and population density as allocation factor for Industrial and Residential sectors."

4. Table 1: The table should also include a comparison of the time resolutions of these EIs.

We revised Table 1 according to this comment:

Table 1. General information on Asia emission inventories

Emission inventories	References	Species	Years	Area covered	Spatial resolution	Time resolution
	Kato and Akimoto (1992)	SO2 and NOx	1975, 1980, 1985, 1986 and 1987	East Asian, Southeast Asian and South Asian countries	1◦×1◦	Annual
TRACE-P	Jacob et al., 2003	CO2, CH4, N2O, O3, CFC, CO, SO2	2000	Over western Pacific		
INTEX-B	Zhang et al., 2009	CO2, CH4, N2O, O3, CFC, CO, SO2	2006	Over western Pacific		

REASv1.1	T. Ohara et al, 2007	SO2, NOx, CO, NMVOC, BC, OC, CO2, NH3, CH4 and N2O	From 1980 to 2020	East, Southeast and South Asia	$0.5^\circ \times 0.5^\circ$	Monthly
REASv2.1	J. Kurokawa et al, 2013	SO2, NOx, CO, NMVOC, PM2.5, PM10, BC, OC, CO2, NH3, CH4 and N2O	From 2000 to 2008	East, Southeast, South Asia, Central Asia and Russia Asia	$0.25^\circ \times 0.25^\circ$	Monthly
REASv3.1	J. Kurokawa et al, 2019	SO2, NOx, CO, NMVOC, PM2.5, PM10, BC, OC, CO2, NH3, CH4 and N2O	During 1950-1955 and from 2010-2015	East, Southeast, South Asia, Central Asia and Russia Asia	$0.25^\circ \times 0.25^\circ$	Monthly
MIX	Tsinghua University (Zhang et al., 2009; Li et al., 2014; Zheng et al., 2014)	SO2, NOx, CO, NMVOC, NH3, PM10, PM2.5, BC, OC and CO2	2008 and 2010	East, Southeast, South Asia, Central Asia and Russia Asia	$0.25^\circ \times 0.25^\circ$	Monthly

5. As mentioned in Introduction, the time resolution of previous EIs can be one year or one month. Why annual emissions (a coarse resolution) are estimated in this study if emissions exhibit strong seasonality?
In this study, we estimated annual emissions in Ho Chi Minh city because the emissions here do not exhibit strong seasonality as ones in Hanoi. Besides, HCMC is located in tropical region, so the significant monthly variations in fuel consumption and electricity consumption of stationary energy sectors is not expected.

6. Methodology: There is no need to talk about Hanoi. Local emissions are important in all big cities even they are greatly influenced by adjacent sources.
We omitted Hanoi part and revised this part: "HCMC is the most populous city in Vietnam with a population of 9 million as of 2019. Air quality in this city is mainly influenced by anthropogenic emission occurring inside the city. In other words, the relative independence of situation in this city on other adjacent sources facilitates the compiling local EI. Also, the local emissions are dominant sources of pollution (GreenID, 2018)"

7. Figure 1: The boundary of Ho Chi Minh City is not very clear in the right figure.
We revised Figure 1 according to this comment:

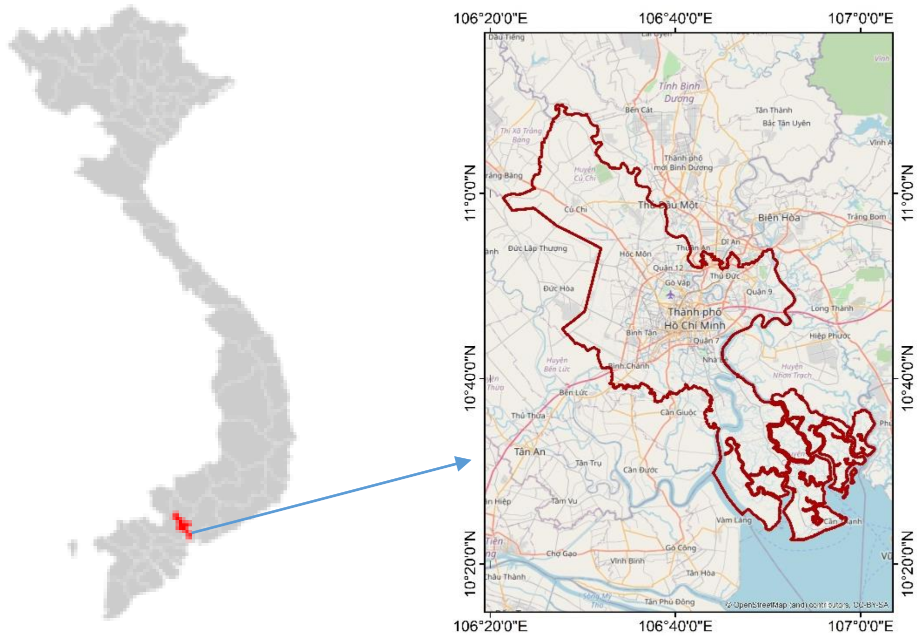
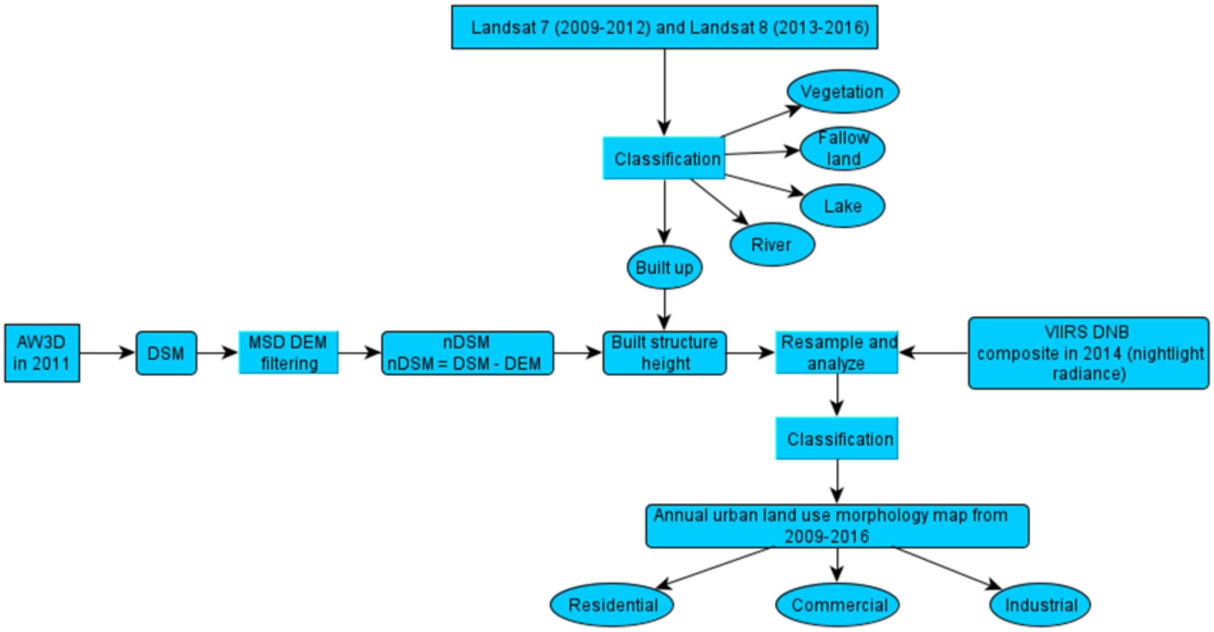


Figure 1. Ho Chi Minh city – inventory domain of our EI (© OpenStreetMap contributors 2019. Distributed under a Creative Commons BY-SA License.)

8. As mentioned in Introduction, a study by B.Q.Ho et al.., 2019 (Line 69-72) calculate emissions of many pollutants in Ho Chi Minh City in 2017 and also allocate emissions from area sources to grid cells. Why the authors choose 2009 to 2016 as their target year? What is the difference between these two studies?
We chose 2009 to 2016 as target year to continue the REASv2.1, which is the first inventory to integrate time series of emission data for Asia on the basis of a consistent methodology. A study by B.Q.Ho et al.., 2019 estimated emissions in Ho Chi Minh city in a single year – 2017 and they used road network and population density data as proxies for spatial allocation.

9. Figure 2 is not clear enough to show how spatial allocation is achieved. A detailed figure that illustrate the complete spatial allocation process is needed in this part.
We added a Figure about spatial allocation in Figure 2:



10. Line 123: Daily VKT can be influenced by many factors. Please justify the assumption that VKT is constant over years.

First of all, although VKT in this study is assumed to be constant, its uncertainty is discussed in Sect. 3.5 with Monte Carlo simulation. Secondly, because the traffic situation in Ho Chi Minh city is specific with the domination of motorcycles, it poses a great challenge to adopt VKTs from previous research conducted in other cities. More deeper studies are needed to consider the impact of urban expansion on the annual changes in VKTs of all vehicle types in Ho Chi Minh city.

11. The spatial allocation results should be validated by field measurement data.

For accuracy assessment, we chose 100 random samples from Google earth image in 2016, including 60 samples for Residential area, 20 samples for Industry and 20 samples for Commercial area. The total accuracy is 77%. The user's accuracy and producer's accuracy of Residential class are 88% and 75% respectively. The user's accuracy and producer's accuracy of Industrial class are 58% and 67% respectively. Meanwhile, Commercial area shown 57% and 80% for user's accuracy and producer's accuracy respectively.

12. Results Discussions Line 394: A Study of N.T.K.Oanh et al, 2015 applied the same method with this study. Does it mean the methodology used in this study is not a novel one?

A Study of N.T.K.Oanh et al, 2015 estimated Transportation emission in Ho Chi Minh city in a single year – 2013 and they did not conduct the spatial allocation of emission.

13. Line 440-441: why not use the same year to compare the results between two versions? I think it is more useful to show the improvements of the novel method.

Because our target years (2009-2016) is different from the target year of REASv2.1 (2000-2008)

14. As many assumptions and average values are used in this study (for example Line 125-130, Line 157-160 and elsewhere), the authors should try their best to justify these assumptions and discuss the uncertainties associated with these assumptions and average values. I recommend a Monte Carlo

simulation or other methods to be used in this study to quantify the uncertainty of each estimation process and the overall uncertainty.
We added the Uncertainty part using Monte Carlo simulation in Sect. 3.5

15. Technical corrections:
We revised the manuscript according to these corrections as shown in *The revised main manuscript.*

The revised main manuscript where changed parts were yellow highlighted:

Technical note: Emission mapping of key sectors in Ho Chi Minh city, Vietnam using satellite derived urban land-use data.

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Abstract. Emission inventories are important for both simulating pollutant concentrations and designing emission mitigation policies. Ho Chi Minh city (HCMC) is the biggest city in Vietnam but lacks of an updated spatial emission inventory (EI). In this study, we propose a new approach to update and improve a comprehensive spatial EI for major Short lived climate pollutants (SLCP) and Green house gases (GHG) (SO_2, NO_x, CO, NMVOC, PM_{10}, $PM_{2.5}$, BC, OC, NH_3, CH_4, N_2O, and CO_2). Our originality is the use of satellite derived urban land-use morphological maps which allow spatial disaggregation of emissions. We investigated the possibility of using freely available coarse resolution satellite derived digital surface model (DSM) to estimate building height. Building height is combined with urban built-up area classified from Landsat images and night time light data to generate annual urban morphological maps. With outstanding advantages of these remote sensing data, our novel method is expected to make a major improvement in comparison with conventional allocation methodologies such as basing on population data. A comparable and consistent local emission inventory (EI) for HCMC has been prepared, including three key sectors as a successor of previous EIs. It provides annual emissions of transportation, manufacturing industries and construction and residential sectors at 1km resolution. The target years are from 2009 to 2016. We consider both Scope 1 - all direct emissions from the activities occurring within the city and Scope 2 that is indirect emissions from electricity purchased. Transportation sector was found to be the most dominant emission sector in HCMC followed by manufacturing industries, and residential area, responsible for over 682 Gg CO, 84.8 Gg NO_x, 20.4 Gg PM_{10} and 22000Gg CO_2 emitted in 2016. Due to sharp rise in vehicle population, CO, NO_x, SO_2 and CO_2 traffic emissions show increases of 80%, 160%, 150% and 103% respectively between 2009 and 2016. Among five vehicle types, motorcycle contributed around 95% to total CO emission, 14% to total NO_x emission and 50-60% to CO_2 emission. Heavy vehicles are the biggest emission source of NO_x, SO_2 and PM while personal cars are the largest contributors to NMVOC and CO_2. Electricity consumption accounts for the majority of emissions from Manufacturing industry

and Residential sectors. We also found that Scope 2 emissions from manufacturing industry and residential areas in 2016 increased by 87% and 45% respectively in comparison with 2009. Spatial emission disaggregation reveals that emission hotspots are found in central business districts like Quan 1, Quan 4 and Quan 7, where emissions can be over 1900 times of ones estimated for sub urban HCMC. Our estimates show relative 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 REASv2.1, a regional EI, which mainly applied national statistical data. This publication provides not only the approach for updating and improving local EI but also the novel method of spatial allocation of emissions in city scale using available data sources.

1. Introduction

Emission inventories (EI) are key for identifying the source of pollutants. This is particularly true in South East Asia, where the rise of energy demands results in significant air quality and human health issues. A number of regional anthropogenic EIs exist to be used as input for atmospheric chemistry models and also to understand the long-term trends of emission level in this area (Tab. 1). But only a few attempts have been made to understand the annual evolution of Asian emissions. REAS (Regional Emission inventory in ASia) is the first inventory to integrate time series of emission data for Asia on the basis of a consistent methodology. REASv2.1 was developed from REASv1.1 with the spatial resolution of gridded data improved to $0.25^\circ \times 0.25^\circ$, and temporal resolution increased to monthly (J. Kurokawa et al., 2013). REASv3.1 was updated to 2015 and covers the longer historical time span from 1950-2015 (J. Kurokawa et al., 2019). These inventories were compiled in regional scale with coarse resolutions and are not longer updated. They mainly applied national energy consumption data as activity data. Apart from countries having their own database of emission factors (EF) like China and Japan, EFs of the rest of Asian countries were extracted from many sources, including previous Asian EIs and recent studies.

According to global protocol for community-scale Greenhouse gas emission inventories (GPC), urban areas are responsible for more than 70 percent of global energy-related carbon dioxide emissions and the achievement of emission reduction of the economy in the upcoming decades will depend mainly on cities. Thus, it is very important to develop an EI in city scale. At the same time, a continuous historical EI could show the long-term evolution of emissions as a consequence of socio-economic development in cities. In response to these needs, the GPC establishes credible emissions accounting and reporting practices that help cities to calculate and report on community scale greenhouse gases and develop their own historical EI.

A research study by Yale University found that Vietnam's PM2.5 index ranked 170th out of 180 surveyed countries and this is considered as one of the ten most polluted countries in the world in terms of air quality (Yale Univ.,2012). In urban area like Hanoi and Ho Chi Minh city (HCMC), the situation has become worse because of high intensity of anthropogenic activities. In 1st quarter 2018, the average PM 2.5 concentrations measured in Hanoi and HCMC reached 63.2 and 37.2 ug/m3, respectively (GreenID, 2018). However, while air pollution level in Hanoi exhibits strong seasonality and the dependence of meteorological factors, air quality in HCMC in mainly influenced by anthropogenic emission occurring inside the city (GreenID, 2018). For these reasons, in this study, we focus on the annual emissions of HCMC, Vietnam.

In 2017, the first comprehensive Green house gases (GHG) Inventory of HCMC was prepared for 2013, 2014 and 2015 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). According to their calculation, among five main anthropogenic sectors, transportation and stationary energy are two most prominent emission sectors in HCMC, comprising 45% and 46% of the total respectively. Within stationary energy sector, manufacturing industries accounts for the highest portion (46%), followed by residential buildings (33%) (JICA, 2017). Another EI by B.Q.Ho et al., 2019 was compiled to calculate emissions in HCMC in 2017 and forecast for 2025 and 2030. This EI includes on-road emission sources, non-road mobile sources, area source and biogenic sources. In addition to these comprehensive studies, a several of EIs were developed for HCMC but mainly focused on road traffic emission (L.C. Belalcazar, 2009, B.Q.Ho, 2010; N.T.K.Oanh et al., 2015; L.T.P.Le et al., 2018). These studies have low level of consistency and inheritance from previous EIs. Also, with the rapid economic development in HCMC, the significant evolution of various emission sources is expected. As a result, it is important to compile a detail and continuous local EI for this city.

With respect to grid allocation, spatial distribution of emissions is a crucial step to fulfil the requirements of gridded EI as input data for air quality modelling. Top-down EIs are often being used as input data for modelling activities at urban scale after downscaling (Susana López-Aparicio et al., 2017). In conventional way, other methodologies focus only on the disaggregation of transport emissions using traffic counts and road network data (C.D. Gómez et al, 2018). The spatial allocation of area source emissions is mainly based on rural, urban and total population data (J. Kurokawa et al, 2013; J. Kurokawa et al, 2019) These approaches are not suitable for community scale EIs what demand higher detail levels of both activity data and spatial disaggregation. Especially, it is not rational to use population data for spatial disaggregation of industrial sector. Using these methodologies without consideration could lead to underestimation of emissions in urban centre, industrial zones, as well as overestimation in residential zones (P.Saide et al, 2009). It is worth mentioning that these spatial proxies have a strong influence on simulations of air quality modelling, especially when the results are considered for policy making and planning options (M. Trombetti et al, 2018). J Kühlwein et al., 2002 made comparisons among spatial distribution of EIs computed with different levels of information and concluded that a big source of uncertainty is encountered when only considering disaggregation using population. M. Trombetti et al, 2018 also conducted an inter-comparison of the main top-down EIs currently used for air quality modelling studies at the European level regarding downscaling approaches and choice of spatial proxies. Their finding is that the traditional proxies used for gridding residential emissions (e.g. population density) would not be any more relevant. A few studies used land use map as a proxy for deriving spatial patterns of emissions (P.Saide et al, 2009). Nowadays, remote-sensing information is quite important source for land use/land cover modelling. The most prominent advantages of satellite images influencing the spatial allocation of emissions are the ability to collect information over large spatial areas and the ability to collect imagery of the same area of the earth's surface at different periods in time. By imaging on a continuous basis at different times it is possible to monitor the changes in land use in community scale if the resolution of data is high enough. Moreover, data collected through remote sensing is analyzed at the laboratory which minimizes the work that needs to be done on the field. Accordingly, in the context of spatial allocating emission at a finer scale, remote sensing data is quite promising approach that allows repetitive land use mapping in different study areas. In the case of HCMC, only a few attempts have been made to spatial disaggregate the emissions. Applying similar method with previous works, study of B.Q.Ho, 2010 provides the first emission maps for HCMC using road network as allocation factor for Transportation sector and population density as allocation factor for Industrial and Residential sectors.

In response to these needs, we developed an annual inventory, focusing on three key sectors: (1) transportation, (2) manufacturing industries and (3) residential building, using higher detail level of activity data, local EFs for HCMC and a novel approach for grid allocation using remote sensing data. This local EI covers from 2009 to 2016 and includes emissions of following species: SO2, NOx, CO, non-methane volatile organic compounds (NMVOC), black carbon (BC), organic carbon (OC), CO2, NH3, CH4, and N2O, PM10 and PM2.5 as successor of REASv2.1 that provides Asian anthropogenic emissions from 2000 to 2008. Moreover, this study inherits the statistics used in GHG emission inventory provided by JICA for 2013, 2014 and 2015. Both Scope 1 - direct emissions from the activities occurring within the city and Scope 2 that is indirect emissions from electricity purchased are considered. Accordingly, this EI is successor of REASv2.1 and GHG emission inventory provided by JICA. In this study, only annual emissions are considered because air pollution level in HCMC does not exhibit strong seasonality and the dependence of meteorological factors like one in Hanoi (GreenID, 2018). The novelty of our work is the use of satellite derived urban land-use morphological maps which allow spatial disaggregation of emissions. Section 2 describes the methodology used in our EI to estimate emissions, including activity data, emission factors and spatial distribution of EI. Section 3, the results and discussion, covers four topics: (1) emissions from each sectors; (2) Scope 1 and Scope 2 emissions; (3) spatial distribution; and (4) comparison with other inventories. Finally, the Monte Carlo method was applied to perform uncertainty analysis of estimated EIs. A summary and conclusion are given in Sect. 4 and 5.

2. Methodology

2.1. Study location

HCMC is the most populous city in Vietnam with a population of 9 million as of 2019. Air quality in this city is mainly influenced by anthropogenic emission occurring inside the city. In other words, the relative independence of situation in this city on other adjacent sources facilitates the compiling local EI. Also, the local emissions are dominant sources of pollution (GreenID, 2018). Figure 1 shows the inventory domain of our EI.

2.2. General description

Table 2 summarizes the general information of our EI that includes nine major air pollutants and three greenhouse gases, as a successor of REASv2.1: SO2, NOx, CO, non-methane volatile organic compounds (NMVOC), black carbon (BC), organic carbon (OC), CO2, NH3, CH4, N2O, PM10 and PM2.5. The target years are from 2009 to 2016, to continue the period covered by REASv2.1. Source categories considered in this inventory are basically the same with GHG EI that compiled basing on the guideline of GPC. But here we focus on only three dominated sectors defined by GHG EI developed by JICA: (1) transportation, (2) manufacturing industries and (3) residential building. The spatial resolution is improved to 1km to provide detailed grid nets for atmospheric chemistry models and emission maps for local government and decision makers. Besides, we collected more city-specific activity data and local emission factors (EF) from recent studies of EIs for Asian countries (see Sect. 2.3)

2.3. Basic methodology

2.3.1. Transportation emission

Figure 2a shows the flow of diagram for estimating emissions from road transport. On road vehicles were classified as motorcycle (MC), taxi, car, bus and heavy duty vehicle – truck, each of which includes gasoline and diesel vehicles. We calculated annual hot emissions based on annual number of registered vehicles, average daily vehicle mileage traveled, and emission factors for each vehicle type with the following equation:

$E_{hot} = \sum_i VP_i * DailyVKT_i * 365 * EF_i$ (1) (Creutzig et al., 2011)

Where i represents vehicles types; daily VKT is the average daily vehicle kilometre travelled of vehicle type i (km/day); VP_i is the population of vehicle type i; EF_i is hot emission factor of vehicle type i. The daily VKTs of each vehicle type in HCMC, 2013 were extracted from study of N.T.K. Oanh, 2015 and were assumed to be constant over years (Tab. 3)

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 vehicles in some types were missing, such as population of truck and bus over years. The number of trucks was calculated basing on the data in 2013 (N.T.K.Oanh 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. 4)

Cold emissions from road transport were included for NOx, CO, PM10, PM2.5, BC, OC, and NMVOC by the following equation:

$E_{cold} = E_{hot} * \beta_i * F_i$ (2) (Ahlvik P.et al, 1997)

Cold emissions were adjusted according to hot emissions using the fraction of distance travelled driven with a cold engine or with the catalyst operating below the light-off temperature (β_i) and the correction factor of EF_{hot} for cold start emissions (F_i) The parameter β and F are functions of average monthly temperature. Equations for β and F and related parameters were taken from the EMEP/EEA EI guidebook 2009 (EEA, 2009). Monthly average surface temperatures in HCMC were adopted from https://www.weather-atlas.com/

The EFs were extracted from seven different studies conducted in Hanoi, China (Tab. 5), covering 12 pollutant species. In Eq. (1), EFs and daily VKTs of each vehicle type were assumed to be constant over years. This usage of constant EFs and daily VKT is a result of limited availability of public data. Therefore, the annual emission was mainly driven by vehicle populations.

2.3.2 Manufacturing industries emission

Figure 2b shows the basic procedure to estimate emissions from Manufacturing industry sector. It focuses on fuel-consumption based emission which is considered as Scope 1 emission. Scope 1 refers to all direct emissions from sources located within the city boundary. Besides, this study will calculate Scope 2 - consumption-based emission separately, which originates from electricity consumption (Sect. 2.3.4). Emissions from fuel combustion were calculated from the following equation, similar with the one applied in REASv2.1 (J. Kurokawa et al., 2013):

$E_{Fuel} = \sum_i A_i * EF_i * (1 - R_i)$ (3) (IPCC, 1996)

Where E is emission from fuel consumption of manufacturing industrial activities, i is fuel type, A is fuel consumption, EF_i is unabated emission factor of each combustion species; R_i is reduction efficiency of control device. In the case of SO2, emission factor was estimated from the following equation:

$EF_{SO2} = S_i * (1 - SR_i)$ (4) (IPCC, 1996)

Where EF_{SO2} is emission of SO2 for each fuel type, S_i is sulfur content of fuel, SR is sulfur retention in ash. The total fuel consumption in HCMC in 2013, 2014 and 2015 with ratio of final fuel consumption by sub-sector and fuel type (Tab. 6) were provided in the GHG EI compiled by JICA, 2017. Basing on this GHG EI, the annual 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, 2014 and 2015. The fuel consumptions of manufacturing industrial sector in five other years (2009 to 2012 and 2016) were proportional calculated using annual gross output of industry at current prices by industry activity in HCMC, provided by HCMC statistical yearbook (Tab.8) with the assumption that there is linear relationship between fuel consumption of manufacturing industrial sector and gross output of industry. Unabated emission factors, reduction efficiencies of each pollutant species, sulfur content of fuel, sulfur retention in ash were adopted 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 (Tab. 7)

2.3.3 Residential emission

Figure 2b shows the flow of diagram for estimating emissions from residential sector. This sector covers all fuel combustion activities in households, including domestic cooking and use of fireplaces. 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. Similar to manufacturing industry sector, the annual emission from residential sector was calculated using Eq. 3 and 4. Fuel consumption in 2013, 2014, 2015 were provided by GHG EI compiled by JICA, 2017 (Tab. 6). The fuel consumptions in other years were proportional calculated using population provided by HCMC statistical yearbook (Tab.8) with the assumption that there is linear relationship between fuel consumption of residential sector and population of city.

The uncontrolled emission factors and reduction efficiencies for residential sector, sulfur content of fuel and sulfur retention in ash were adopted from ABCEIM by Shrestha et al. 2013 (Tab.7)

2.3.4 Emission from electricity consumption

Apart from Scope 1 emission, this study also considered CO2 Scope 2 emission that is 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. Local governments often include Scope 2 emissions when they do not have electric generating plants within their boundaries but still wish to evaluate the impacts of electricity use in the community. CO2 emission from electricity consumptions of Manufacturing industries and Residential sectors were calculated from the simple equation:

$E_{Electricity} = \sum \ A \times EF_{electricity}$ (5)

Where E is emissions from electricity consumption, A is activity data, here is amount of electricity consumption from each sector, $EF_{electricity}$ is grid emission factor, specific for each region. In GHG EI compiled by JICA, the electricity consumption in 2013, 2014, 2015 by sub-sectors was 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) (Tab. 9). This value includes emissions from both consumption of grid supplied energy consumed within the city boundary and transmission and distribution loss from grid supplied energy.

The significant linear relationships during 2013-2015 between electricity consumption of industry sector and residential sector with annual gross output of industry and annual population, respectively were found (Fig. S1). So, electricity consumptions in other years were proportional calculated using the same proxies applied in fuel consumption part:

- Manufacturing Industries and Construction sector: used Annual Gross output of industry at current prices by industry activity with the assumption that there is linear relationship between electricity consumption of Manufacturing industrial sector and Gross output of industry.
- Residential: used Annual population of HCMC with the assumption that there is linear relationship between electricity consumption of Residential sector and population of city.

The EF on electricity consumption varies every year. This EF depends on: combustion technology; emission source category; fuel type; combustion technology type and emission control technology. In GHG EI of JICA, grid emission factor on electricity consumption in Vietnam were provided for 2013, 2014 and 2015 (Tab. 9). 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.

2.3.5. Spatial allocation

Figure 2c shows the methodology for spatial allocation applied in this study. Current EIs like REASv2.1 use population datasets to allocate their emissions from area source to grid cells. Similarly, in study of H.Q.Bang, 2010 and H.Q.Bang et al, 2019, the spatial distribution of industrial and residential emission sources are estimated by using the population density in each cell with the justification that the industry in HCMC is mainly located in residential area. However, the level of detail required by local emissions inventories cannot be met sufficiently if these approaches are applied. To overcome such limitations, we prepared original datasets that allowed spatial allocation at 1 km grid nets. This advantageous method, as summarized below, can benefit the compilation of other community scale EIs in future.

In order to make gridded emissions from the road transportation sector, the road density from road network downloaded from Open Street Map (OpenStreetMap contributors 2019. Distributed under a Creative Commons BY-SA License) was applied for spatial disaggregation. In which, a gridded network was created whereby road density was estimated for each “grid 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 modelled road capacity in HCMC in 2016 by the HOUTRANS project, JICA, 2004. In which, the assigned traffic volume in primary road is over 85,000 passenger car unit (PCU) per day, in secondary roads is 44,000 to 85,000 and the smallest road have under 44,000 PCU per day (JICA, 2004)

Scope 1 urban emissions from manufacturing industries, commercial places and residences was allocated spatially based on the urban land-use morphology. As spatial distribution of land-use is not available for HCM, annual urban land-use maps were created with the help of remote sensing datasets for the period 2009 - 2016 in HCMC following Misra P. et al. (2019). Urban morphology maps include three land use types most commonly associated with urban emissions: residential, commercial and industrial land. In this study, industrial emission sector is considered as area source instead of point source like previous studies. Identification of the three land-use type areas (residential, commercial and industrial) was based on the hypothesis that each land-use typology generally follows a distinct morphology with regards to the height of structures and nighttime artificial lighting. Therefore, urban morphological maps were prepared at 30-meter spatial resolution by classifying digital building heights and night time light over each pixel into the three land-use types.

Digital building heights were extracted from publicly available ALOS World 3D (AW3D30) digital surface model (DSM) data at 30-meter resolution. A DSM is a representation of visible geological earth terrain and any other features (tree and crop vegetation, built structures, etc.) occurring over the ground terrain. The AW3D DSM was generated using images acquired from PRISM’s (Panchromatic Remote-Sensing Instrument for Stereo Mapping) front, nadir, and backward-looking panchromatic bands aboard ALOS (Advanced Land Observing Satellite) between 2008 to 2011. It is publicly available at 1 second (30m) horizontal resolution from JAXA (http://www.eorc.jaxa.jp/ALOS/en/aw3d30/). The AW3D DSM generally meets the 5 m root mean square target height accuracy as per its producers (Tadono et al. 2015). To extract the height of features that do not form part of the terrain (known as normalized digital surface model or nDSM), first a continuous ground terrain (known as digital terrain model or DTM) needs to be constructed which can then be differenced from DSM (Eq. 6). A multidirectional processing and slope-dependent (MSD) filtering approach was used for DTM extraction and is further described in Misra et al. (2018). Accordingly, the MSD filtering technique requires four parameters to generate a DEM: the Gaussian smoothing kernel size, the scanline filter extent, the height threshold, and the slope threshold. Each DSM pixel was checked to determine whether it should be considered ground by comparing it with other pixels within the predefined neighbour hood scanline filter extending in eight directions. If the pixel was identified as a ground pixel in more than five directions, it was labelled as a terrain pixel by the majority voting method. To draw the comparison, a local reference terrain slope was first generated by 2D Gaussian smoothing. Then, the pixel’s height was compared with the lowest elevated pixel within the scanline filter extent. If this height difference was more than the height threshold parameter, the pixel was classified as a non-ground pixel. Then, if the slope difference between the current and the successive pixel in the scanline direction was greater than the slope threshold, it was labelled as a non-ground pixel. If the slope was positive and less than the slope threshold, then that pixel was given the same label as its previous pixel. Otherwise, that pixel was labelled as ground.

nDSM = DSM –DTM (6)

To ascertain that the height of the extracted features was indeed from the built-up structures and not features like trees, a built-up class binary mask was generated and multiplied with the corresponding pixels in the nDSM raster to generate nDSM for built-up area (subsequently referred to as digital building height). A time-series of Landsat imagery (Landsat 7 for 4 years: 2009 to 2012 and Landsat 8 for other four years: 2013 to 2016) was classified to generate the urban built-up extent for 2009 to 2016. A Mahalanobis distance based supervised classification was performed to identify 5 classes (including built up, vegetation, fallow land, lake and river).

Nighttime light was obtained using the VIIRS (Visible Infrared Imaging Radiometer Suite) DNB (Day-Night Band) monthly images for the year 2014. The VIIRS DNB was freely obtained from (https://ngdc.noaa.gov/eog/viirs/) its spatial resolution of approximately 15 seconds (450m) was resampled to 30 m. Annual DNB image was prepared by considering median radiance of monthly composites of DNB product. It consists of light from persistent sources but the original data has not been filtered for forest fires or any other activity that may generate light from natural sources. Thereafter training samples were collected for the digital building height and the nighttime light over the residential, commercial and industrial pixels they were classified using the random forest classifier.

In this study, we relied on only one building height data (extracted from AW3D30) in 2011 and calibrated VIIRS DNB night light radiance in 2014 to prepare land use maps for 8 years. This usage of constant building height is a result of limited availability of public DSM. Therefore, any land-use transitions among the residential, commercial and industrial land-use types were assumed to negligible. However, the changes in built-up land cover during 8 years as identified in Landsat images help in accounting for horizontal urban growth. Ultimately this resulted in eight annual urban morphological maps for HCMC from 2009 to 2016. These land use maps were used for spatial distribution of manufacturing industrial and residential emissions into the same grid net – 1 km resolution with transportation sector. Basing on the spatial matching, total emission of three key sectors is simply sum of grid nets of manufacturing industrial, residential and transportation emissions. Noteworthy, in this study industrial emission sector is considered as area source instead of point source like previous studies.

3. Results

3.1. Emissions from each sector

3.1.1. Transportation emission

Table 10 summarizes emissions for each species in HCMC from on road transportation during eight years, from 2009 to 2016. Figure 3 shows the relative contribution of vehicle types to total transportation emission. 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 was driven by the same data set of vehicle population, VKT and emission factors were assumed to be constant. However, the mix of contributions from different vehicle types were different for each pollutant species.

Total CO emissions in 2016 were 682 Gg, increasing by 312 Gg (+98%) compared to 2009. Over 95% of CO emission from transportation was accounted by MC. In HCMC, growth rate of MC reached 180% over 8 years (from over 4 mil. to over 7.2 mil. veh.). Although the increase rate of personal cars was higher (+130% from 2009 to 2016), MC had constantly shared around 90% of totally vehicle population during that period (Fig. 3). Furthermore, CO emission factor of MC by far the highest one among five types of vehicle (12.592 g.km-1.vehicle-1). This is almost 6 times higher than the one of personal car and taxi.

Over this period, NOx presented a different pattern, despite the same monotonically increasing trend with CO. Total NOx in 2016 was 84.8 Gg (+157.4%) for HCMC. The majority of NOx emission was from heavy duty vehicle (HDV) – truck (50% - 61.9% during the period 2009-2016), followed by personal car (19-21%). The fact is that HDVs use diesel engines which emit higher amount of PM and NOx (Reşitoğlu, İ.A. et al., 2015). 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) (N.T.K.Oanh et al., 2015). As a result, NOx emission factor of truck is the highest one among five types of vehicle. Although emission factors of truck (17 g.km-1.vehicle-1) and bus (16.954 g.km-1.vehicle-1) are roughly equal, the dominated population of trucks made it the largest contributor to total NOx emission from transportation.

Total SO2 emission from on road traffic in 2016 was 6.773 Gg. The emission values more than double from 2009 to 2016 (+155.78%). Again, contribution was dominated by fleet of truck (39-48%), followed by personal cars (38-42%). Different from CO emission, MC was not an important source for SO2. This common vehicle accounts for modest proportion (7.4 - 10.5%) compared to others. This trend reflects the highest SO2 emission factor of truck which use diesel engines (1.06 g.km-1.vehicle-1).

Total emissions of PM10/PM2.5 in 2016 from Transportation sector in HCMC were 20.4/5.07 Gg (+143/157%). Showing a similar pattern with NOx, truck made the highest contributions to emission of particle matter (38.4-49.5% and 54.7-66.9% for PM10 and PM2.5, respectively). The reason is that diesel engines emitted much more fine particles than gasoline engines that are mainly found in MC (Reşitoğlu, İ.A. et al., 2015). EFs of HDV used in this study are 3.28 and 1.1 g.km-1.vehicle-1 for PM10 and PM2.5 respectively, that are almost 35 and 61 times higher than those ones of MC. Consequently, although MC shared over 90% of total vehicle population, the dominated emission factors of vehicles using diesel engines made them to be the main emission sources of PM.

Emission of aerosols – BC and OC showed almost opposite tendencies. Total emissions BC and OC emissions in 2016 in HCMC were 0.222 and 0.982 Gg (+85%/+87%) respectively. MC made the most considerable contribution of these primary aerosol emissions (92% - 94%). The remaining transportation types accounted for very small shares (1%-5%) This is because we applied emission factors of BC and OC from Updated emission factors of air pollutants from vehicle operations in GREET (Green house gases, regulated emissions, and energy use in transportation) using MOVES (Motor vehicle emission simulator) (Hao Cai et al., 2013). According to this database, MC is the most common source of BC and OC emissions (0.004 and 0.0178 g.km-1.vehicle-1).

Regarding Green house gases, total emission of CO2, CH4 and N2O in 2016 in HCMC were 21999 Gg (+103%), 6.601 Gg (+100%) and 0.292 Gg (+ 92%), respectively. In the cases of CO2 and N2O, MC and personal car are considered as the main sources for emissions. 50-57 % of CO2 emissions were from MC and its proportion decreased by 7% over 8 years. Personal cars ranked second but its share of the total rose from 32 to 36.8% from 2009 to 2016. The similar trend was seen in N2O, although MC had larger share for this species than CO2 (74-79%). The contribution of personal car slowly grew from 18 to 22% of total N2O emission from transportation. In terms of CH4 which is responsible as an important measure to reduce Short-lived climate forcers, the share of MC was by far the highest (95-97%). Very small share of CH_4 emission in transportation sector were from other vehicle types. These estimations are in line with other previous studies who claimed diesel engines emit less CO_2 and Greenhouse Gases than similar gasoline ones (Reşitoğlu, İ.A. et al., 2015).

3.1.2. Manufacturing industries and Residential building emission

Table 11 presents annual emissions from fuel consumptions in two other key sectors: manufacturing industries and residential building. Figure 4 shows the comparison among three key sectors for each species in HCMC from 2009 to 2016. It should be noted that only Scope 1 emissions that occur within the boundary of city are considered in this sector. Generally speaking, both of these emission sources expressed much smaller amount of emissions and slower growth paces than transportation.

In terms of manufacturing industries in HCMC, total SO_2 emissions from this sector in HCMC increased monotonically from 1.092 to 2.36 Gg (+116%) over 8 years. However, these amounts are still modest compared to emissions from transport activities and the gap between two sectors increased along time. In 2009, emission of manufacturing industries was less than a half of traffic emission. Eight years later, this proportion reduced to 34.8%. Normally, the main source of sulfur dioxide in the air is industrial activity that processes materials that contain sulfur. However, the explosion of transport activities in HCMC led to the dominated contribution of this sector to SO_2 emission. SO_2 is one component of greatest concerns because controlling SO_2 emission may have the important co-benefit of reducing the formation of particulate sulfur pollutants, such as fine sulfate particles. NO_x emission from manufacturing industries in 2016 was 9.739 Gg, increased by 120% over 8 years. Similar to SO_2, this accounted for only a very small fraction (almost a ninth) of traffic emission. This is reasonable because NO_x is produced from the reaction of nitrogen and oxygen gases in the air during fuel combustion. In large cities, the highest amount of nitrogen oxide emitted into the atmosphere as air pollution is usually from road transport. This distance is even more profound in the case of CO. In 2016, CO emission from manufacturing industries was 4.152 Gg. Meanwhile, transportation sector emitted 682.613 Gg, around 160 times higher than manufacturing industries. Besides, emission of CO from manufacturing industries showed a moderate growth rate compared to NO_x and SO_2, 75% over 8 years.

Regarding primary particle matter, both PM_{10} and $PM_{2.5}$ emissions value almost double from 2009 to 2016. Total emissions of PM_{10}/$PM_{2.5}$ in 2016 were 0.6/0.33 Gg (+96%/93%). Again, these amounts of emission are relatively insignificant compared to emissions from transport activities. However, the sharing ratio among sectors changed for the case of BC. BC emission was still mainly from road transport but the contributions of manufacturing industries to total emission of this Short – lived climate pollutant cannot be neglected. In 2016, industry sector in HCMC emitted 0.14 Gg (+129%). BC into the atmosphere, which was equal as 63% of BC emission from transportation and this proportion was tending to increase. OC emissions differed from BC. The total OC emission from manufacturing industries in HCMC in 2016 was 0.0071 Gg (+86.8%), which was equal to only 7.2% of the emissions from transportation activities. Organic carbon has cooling effect as they are light reflecting. Meanwhile, black carbon is light absorbing. If the ratio of warming particles is higher, sources may have less cooling effect. It implied that apart from transportation, reducing Short lived climate forcers cannot disregard the share of manufacturing industries in HCMC.

Total CO_2 emission in 2016 from manufacturing industries in HCMC was 3861.89 Gg (+114.7%) CO_2 emissions generally reflects the energy consumption, infrastructure build up and economic growth. The dominance of energy consumption from traffic activities was confirmed again by the gap in CO_2 emission between manufacturing industries and transportation sector. Emission of CH_4 and N_2O from manufacturing industries in 2016 were 0.1512 Gg (+116%) and 0.03 Gg (+115%), respectively.

The fuel consumption of residential sector in big cities mainly includes heating, cooling, lighting, water heating, and consumer products. In GHG emission inventory prepared by JICA, the energy consumed by households in HCMC included only kerosene and liquefied petroleum gas (LPG). Because of tropical climate in HCMC, this energy consumption is generally for cooking/household stoves, the heating and water heating can be excluded. This explains for quite trivial shares from residential sector in total emissions of each pollutant species, although the population explosion in study area over 8 years (+27.1%). For example, CO emission from residential building in 2016 in HCMC was 0.4189 Gg, which is equivalent to a tenth of manufacturing industries emission. Besides, our estimation implied that the evolution of household emissions is much slower compared to other sectors. In parallel with 27% of the population growth in HCMC over 8 years is 34.5% increase in Green house gas emitted from residential sector. Meanwhile, CO_2 emission from transportation soared by 104% during the same period. In fact, the shares inside household energy consumption are incommensurate. Particularly in tropical region, where fuel consumption is mainly used for cooking purposes, the largest contributor is often household electricity consumption which belongs to Scope 2 emissions. The following section discusses this in more depth.

3.2 Scope 1 and Scope 2 emissions

According to GHG emission inventory prepared by JICA, 2017, electricity consumption shares the highest proportions in terms of manufacturing industry and residential sectors. Therefore, the pattern is quite different from Fuel consumption emission. The emission of Scope 2 considers Green house gas - CO_2 only.

Gradual increase trend in CO_2 emission from electricity consumption was recorded in both industry and residential sectors (Fig. 5 and Tab. 12) However, manufacturing industry showed stronger growth (+88% during 8 years). Consequently, by 2012, CO_2 emission from electricity consumption of industry had been lower than residential. But from 2013, the emission of this sector surpassed the one from household area. In 2016, the electricity consumptions from manufacturing industries and residential sectors in HCMC emitted 6985.29 Gg and 6691.43 Gg into the atmosphere, respectively. Besides, the dissimilarity in emissions between fuel consumption and electricity consumption were not the same for industry and household area. In terms of manufacturing industry, electricity consumption emitted almost double than fuel consumption. Meanwhile, the GHG emission from electricity consumption of households by far exceeded the fuel consumption of this sector.

The comparison of CO_2 emissions (both Scope 1 and Scope 2) among three key sectors was shown in Fig. 6. Transportation still contributed the highest ratio, its emission always valued double the one of manufacturing industry. However, the fastest growth was observed in manufacturing industry (+114.7%), followed by transportation sector (+104%). The lowest emission and the slowest evolution were observed in residential sector. Emission from this sector was equivalent to only a third of CO_2 emission from traffic in 2016. These findings implied that the mitigation of GHG in HCMC should consider transportation as the most important source.

3.3 Spatial distribution

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.

For accuracy assessment, we chose 100 random samples from Google earth image in 2016, including 60 samples for Residential area, 20 samples for Industry and 20 samples for Commercial area. The total accuracy is 77%. The user's accuracy and producer's accuracy of Residential class are 88% and 75% respectively. The user's accuracy and producer's accuracy of Industrial class are 58% and 67% respectively. Meanwhile, Commercial area shown 57% and 80% for user's accuracy and producer's accuracy respectively.

Fig. 7 revealed the spatial distribution of different pollutants as sum of three key sectors over study domain in 2016. It should be noted that these 1km resolution maps show only Scope 1 emissions which are the sum of transportation emission and emission from fuel consumption of two other sectors, not including emission from electricity consumption. According to Fig. 4, transportation emission is by far dominated than two other source types, in terms of all pollutant species. It explains for the similarity among emission maps of various pollutions shown in Fig. 7. Relatively high emission densities are found in the central business districts (CBD) like Quan 1, Quan 4 and Quan 7, because of high road densities in this area. 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. According to these maps, abatement strategies of emission in HCMC should focus on CBD to improve air quality. If regional EI like REAS is applied, the 0.25◦ resolution cannot show the spatial distribution within HCMC. Our originality is the use of satellite derived urban land-use morphological maps which allow spatial disaggregation of emissions in city scale. In previous study of H.Q.Bang, 2010, the first emission maps were developed for HCMC using road network as allocation factor for transportation sector, population density as allocation factor for industrial and residential sectors. Our finding about high emission intensities in CBD is in line with this research which stated that the highest emissions were found in the city centre, where has the highest density streets. Apart from this study, other works only provided the total emissions in HCMC, dismiss the spatial disaggregation. Thus, our approach is advantageous, it enables the mapping of emission with high reliability level in this city in future.

3.4 Comparison with other inventories

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. 13). Study of N.T.K.Oanh et al, 2015 applied the same equation to estimate emission of on road traffic 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 start up 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 N.T.K.Oanh et al, 2015. Their vehicle counts derived from field measurement and vehicle registry data. Regarding CO2 emission factor, they used country-specific EFs from COPERT model instead of EFs of 2006 IPCC guidelines. 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 type for each pollutant in this study was compared with the estimation in this study.

Our CO2 emission in 2013 was quite close with the calculation of JICA although they applied the different approach to estimate emission from Transportation. But our finding is higher than the estimation of N.T.K.Oanh et al, 2015, 2015 around 4000 Gg. We applied the same numbers of active vehicles and daily VKT used in research of N.T.K.Oanh et al, 2015 but they used EFs in much more detail levels. As a result, the different emission factors are likely the reason of this gap. In compare with the finding of L.T.P.Linh, 2018, our CO2 emission in 2016 is double. 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 our calculation.

In terms of other pollutants, estimations were lower by factors of 2 - 10 in compare with study of N.T.K.Oanh et al, 2015, 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 EF dataset used in the study of N.T.K.Oanh et al, 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 to produce the EFs that are relevant to the local driving conditions and local fleet composition and considers the engine technology distribution in vehicle fleet. Meanwhile, this study applied constant emission factors from different previous researches about transportation emissions in HCMC, Hanoi and China.

Regarding the sharing ratio of emission from MC and personal car (PC) in this study and previous studies for 2010 and 2013, our results is relatively consistent with research of H.Q.Bang (Tab. 14). MC is responsible for over 94% of CO emission from on-road traffic, 29% and 15.6 % of NOx emissions in study of H.Q.Bang, 2010 and in this study, respectively. In compare with the study of N.T.K.Oanh et al, 2015, the sharing proportion of MC from my estimation is higher but the contribution from personal cars 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 accounts 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, this study applied the same number of active vehicles, the same daily VKT data with study of N.T.K.Oanh et al, 2015 for emission in 2013. As a result, this gap is expected to come from inconsistent EF datasets between two studies.

3.4.2. Comparison with REAS v2.1 inventory

The general information of REASv2.1 and the data sources applied for three sectors: transportation, manufacturing industry and residential sectors are mentioned in Supplementary part (Tab. S1 and S2). 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. Table 15 shows the comparison between the estimations in this study for 2009 and the estimation of REAS 2.1 for three key sectors in HCMC in 2008. The transportation emissions from REAS for 2008 were much lower than our 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 travelled, and emission factors to estimate vehicle emission. Their vehicle population were national one then total emission was allocated to HCMC using road network, so it is likely that the calculation underestimated the emission from a traffic hot spot as HCMC. In addition, the gap between their annual VKT and our daily VKT could be a reason.

Conversely, the estimation of industry and residential emission of REASv2.1 surpassed the findings in this study by factors of 3-104. The difference for Residential sector is more significant than industry. In this comparison, only Scope 1 part of HCMC emission was compared with REAS emissions. So both of two studies applied fuel consumption as activity data. 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. Apart from different sources of activity data, Table 16 compares the EFs of fuel consumption in these two sectors that were applied in two research. Besides, for countries which do not have their own emission inventories, REAS adopted emission factors from 1980 to 2003 from many sources, including Asian emission inventories. Meanwhile, this study applied EFs provided by ABCEIM by Shrestha et al.. (2013). REAS 2.1 applied EFs of oil and gas only. In terms of industry sector, EFs of NOx and NMVOC were pretty similar. But EFs of CO and SO2 from REAS are much higher. 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 trivial consistency was seen in EFs used in residential sector as well.

The large discrepancies can be seen in sum of emissions from fuel consumptions of three key sectors also. The gap under 25% between our EI and REASv2.1 were recorded only in the cases of CO, NOx and CO2. According to the big gaps drawn from this analysis, the limitation when comparing a regional emission inventory with a local emission inventory can be implied. This inconsistency is expected due to the differences in activity data and EF databases. Again, the limitations of downscaling a regional EI into community scale can be seen here. Regional one is likely to underestimate the most profound emission sector like transportation and show the overestimation of other sectors when applying population as only spatial allocation index.

3.5. Uncertainty

In this study, in order to calculate the uncertainties of the estimated EI, the error range of each of the input, including activity data and emission factors is determined, computed or collected from different sources. Monte Carlo simulation is a common method for analyzing uncertainty propagation in air quality studies (H.Q.Bang, 2010). To calculate the uncertainty ranges of emissions of three key sectors in HCMC, Monte Carlo method is applied to select random values of EFs, activity data and other estimation parameters from within their individual probability density functions (PDF), and to calculate the corresponding emission values. This process is repeated many times and the results of each simulation contribute to an overall emission PDF. In fact, it is fundamentally hard to quantify the uncertainties of parameters and for most inputs, assessment of PDF is subjective. Accordingly, in previous studies and Good practice guidance and uncertainty management in national greenhouse gas inventories by IPCC, 2006, coefficient of variations for both activity data and EFs were determined based on expert judgment. When running Monte Carlo simulation, the activity data and EFs in this study are assumed to be independent. Regarding transportation sector, assuming a normal distribution, the relative uncertainties for vehicle population and daily VKT are 5% and 10% respectively. For activity data of stationary sources, we relied on fuel consumptions from 2013 to 2015 collected from HCMC Department of industry and trade (JICA, 2015); annual gross output of manufacturing industry and annual population in HCMC provided by HCMC statistical yearbook. So these activity data were assumed to be normally distributed with error range is 2%. EFs of transportation and fuel consumption of two other sectors are mainly based on detailed experiments so log normal distribution might be a reasonable assumption. Their uncertainties are adopted from previous research and Good practice guidance and uncertainty management in national greenhouse gas inventories by IPCC, 2006.

Table 18 presents the estimated uncertainties of emissions by sectors in HCMC in 2016. Uncertainties of total emissions from three key sectors are as follow: ±19% for CO, ±24% for NOx, ±22% for SO2, ±23% for CH4, ±31% for PM, ±25% for NMVOC, ±31% for BC, ±34% for OC, ±27% for NH3, ±31% for N2O and ±20% for CO2. In general, error ranges of CO2, CO and SO2 are the smallest. Meanwhile, those of PM, BC and OC are relatively large. The reason for a relatively high accuracy of SO2 and CO2 emissions is that their main emission sources are completed combustion. Whereas, those of PM species have larger uncertainties because they are emitted from the burning at low temperatures. In addition, the sensitivity analysis of Monte Carlo shows that the accuracy of transportation emissions is mainly impacted by the annual number of motorcycles and the number of trucks. The uncertainty of heavy oil consumption is the largest driver causing error range of resulting emissions from manufacturing industry sector. Meanwhile, the accuracy of residential emission is mostly decided by kerosene consumption. The activity data in this study were obtained directly from statistics, so their accuracy is higher than those applied in regional EI such as REAS. As a result, the uncertainties of local emissions from all three sectors are smaller than the ones provided by REAS.

4. Summary and discussions

We developed a consistent and continuous EI for three key sectors with local scale. Our objective is to fill the gap among inherent EIs developed for HCMC before. The activity data and EFs were synthesized from various sources. This local emission inventory includes most major air pollutants and greenhouse gases: SO2, NOx, CO, NMVOC,

PM_{10}, $PM_{2.5}$, BC, OC, NH_3, CH_4, N_2O, and CO_2. The target years are from 2009 to 2016. Emissions are estimated for area within the boundary of HCMC and are allocated to grids at a 1km resolution.

In terms of transportation, our results implied that the contribution of this sector to total emission in HCMC is the largest. Vehicle fleet in HCMC emitted over 682 Gg CO, 84.8 Gg NOx, 20.4 Gg PM_{10} and 22000Gg CO_2 in 2016. The overall emission of this sector increased significantly from 2009 to 2016, mainly because of the explosion of vehicle population. The emissions of CO, NOx, SO_2 and CO_2 from traffic in 2016 in HCMC were 80%, 160%, 150% and 103% 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 CO_2 emission. Regarding NOx, SO_2, and PM, truck is claimed as the biggest emission source and the sharing of personal cars was considerable in terms of NMVOC and CO_2.

The emissions of manufacturing industry and residential sectors include both fuel consumption and electricity consumption. Electricity consumption is the most profound contributor. In 2016, the electricity consumption of manufacturing industry and residential sectors in HCMC emitted 6985 Gg and 6691 Gg of CO_2, 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 compared to vehicle emission as well. The sum of CO_2 emission from fuel consumption and electricity consumption of these two stationary energy sectors still could not exceed transportation sector. In 2016, vehicle fleet emitted 22000 Gg CO_2, almost double manufacturing sector. Meanwhile, residential area contributed 7000 Gg CO_2 only. According to Monte Carlo analysis, uncertainties of total emissions from three key sectors are as follow: ±19% for CO, ±24% for NOx, ±22% for SO_2, ±23% for CH_4, ±31% for PM, ±25% for NMVOC, ±31% for BC, ±34% for OC, ±27% for NH_3, ±31% for N_2O and ±20% for CO_2.

Regarding spatial allocation of three key emission sectors, the CBDs 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. Thus, the policymakers must consider suitable future activities and regulations to control pollution in HCMC focusing on central regions. The estimations of this study showed the relative 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 REASv2.1. The different data sources of activity data and EFs database explained for this difference. 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 EIs like REAS.

Our study applied the activity data and EFs synthesized from various sources and a number of limitations and uncertainties were noted. Regarding transportation sector, this study assumed the constant VKTs, EFs of vehicle fleet and road network over 8 years. The technology standard distribution for each vehicle type 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, VKTs, EFs and road network is improved, the accuracy of total emission in HCMC can be enhanced considerably.

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 the administrative boundary of sale data provided by DOIT and EVN can impact on the accuracy of our 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 2013, 2014 and 2015. 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. Moreover, EFs of fuel consumption and removal efficiencies for both two stationary energy sectors were assumed to be constant during 8 years, meaning the technology evolution was not considered.

5. Conclusion

With updated methods and substantial new data on local emission sources, a city-scale emission inventory of twelve air pollutants has been developed for HCMC, Vietnam for 8 years, 2009–2016. Through statistical data, EFs adopted from previous studies in Asia and spatial emission distributions, the total emissions for three major sources (transportation, manufacturing industries and residential building sectors) are estimated and mapped. Emissions in the city are dominated by traffic activities, followed by manufacturing industries and household area. All these sector show the increases in emissions although the growth rates are not the same.

In future, to improve this local emission inventory, it is needed to include other sectors such as waste, industrial process and product use (IPPU) and agriculture, forestry, and other land use (AFOLU) for a comprehensive EI. Besides, although HCMC is located in tropical region, the significant monthly variations in fuel consumption and electricity consumption of stationary energy sectors is not expected, improving the level of detail of EI from annually to monthly is still required. The next step is using it as input data of atmospheric chemistry models and conduct the comparison to independently derived data. In this case, remote sensing data, observed data provided by air quality monitoring network can be the answers. In addition, with available local EIs, policy makers can see the quantitative improvement of air quality by atmospheric chemistry models using adjusted emission inventory according to mitigation solutions as input data. Besides, the improvement of local activity data and emission factors could enhance the reliability of this EI.

The continuous growth in emissions from all three sectors implies that substantial efforts should be undertaken to achieve targets in emission reduction in HCMC. According to our calculations, emission abatement should prioritize transportation activities. To decrease the total emission of this dominant sector, a number of air pollution control solutions are proposed: exhaust control policies for MC and truck to improve their emission factors, replacement the personal vehicles with public transport. It is a fact that the major of MC and trucks in HCMC use old technology standard engines as mentioned above, so the penetration of modern engines will lead to significant improvement of air quality in this city. In addition, because emissions from fuel consumption only account for small proportions, the reduction in grid emission factors of electricity consumption could have a remarkable impact on emissions from manufacturing industrial and residential building sectors. It can be achieved by the transition from coal-fired power to other forms of clean energy like hydroelectricity or solar power. According to our emission maps, the pollution control solutions should focus on central business districts where the traffic intensities are high. This area also has the highest population density. Thus, the emission mitigations for CBD will benefit not only the GHG reduction, but also the improvement of human exposure to air pollution.

Our originality is the use of satellite derived urban land-use morphological maps for spatial distribution of area emission sources. Conventionally, the existing regional inventories base on surrogate statistics such as fuel consumption, employment, population as spatial proxies of grid allocation. It can introduce a large uncertainty when downscaling to community scale EI because its assumption is based on linear relationship between the proxy value and the emission. Besides, these statistics are often adopted from field-work based inventories. Although field-work based data can be highly accurate, they are labor consuming and cannot be performed frequently. The use of those existing spatial distribution surrogates neglects the effects of urban sprawl that is evident in big cities, also. It is desirable to have access to revised spatial allocation factors that may be more representative of spatial distributions in community scale and more available. And even if statistical data is inaccessible in other cities remote sensing data can be used. Remote sensing data can be updated frequently. Thus, the use of satellite images makes spatial disaggregation updating quite simple and efficient. Besides, it is the best tool to represent urban expansion and land use change, so it ensures the accuracy of grid allocation when closely related spatial activity surrogate is needed to compile EI in local scale.

Data availability:

Gridded emission data sets at 1km resolution for three key sectors from 2009 to 2016 are available based on request from corresponding author.

Author contribution:

NTQT and WT conducted the study design. NTQT contributed to actual works for development of emission inventory such as collecting data and information, settings of parameters, calculating emissions and creating final data sets. PM conducted urban morphology mapping. NTQT prepared the manuscript with contributions from WT and PM.

Competing interest:

The authors declare that they have no conflict of interest.

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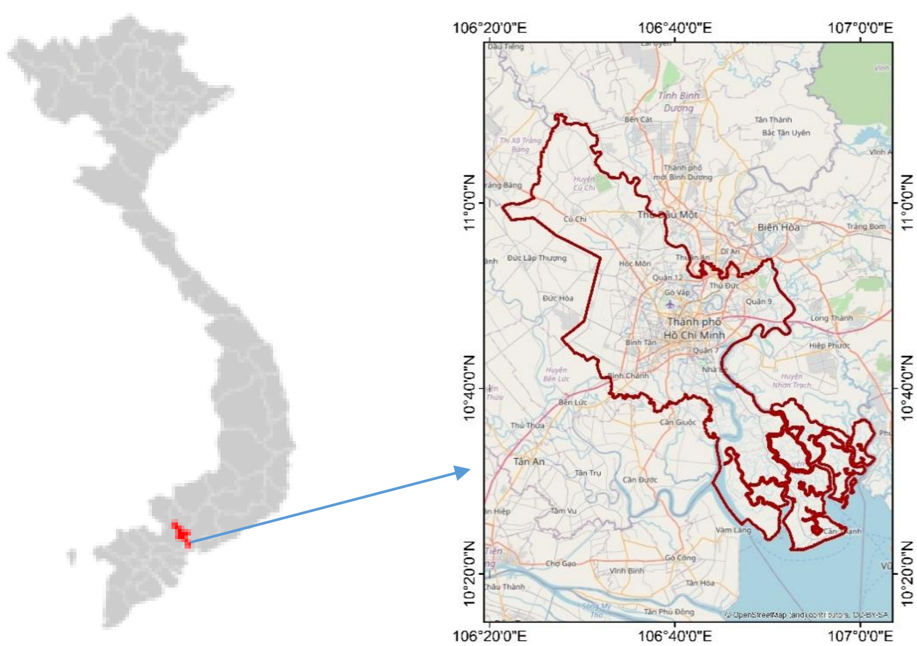
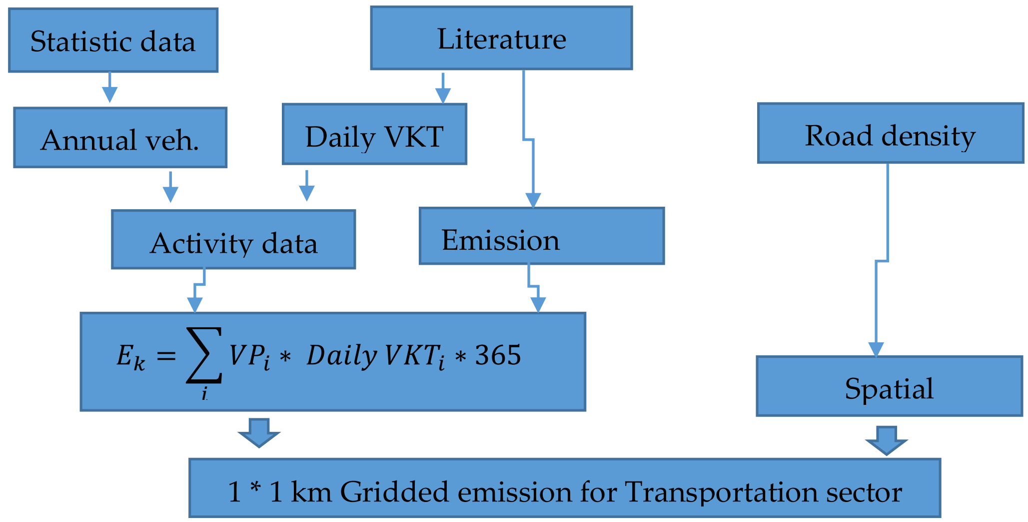
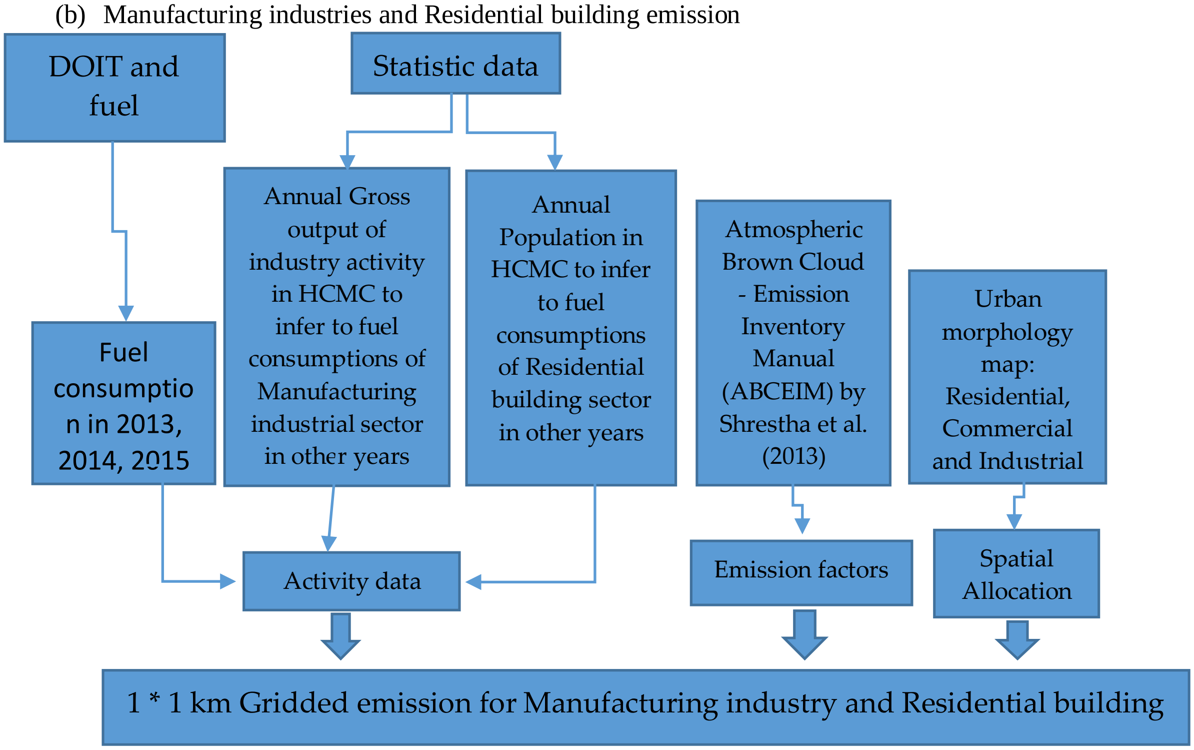


Figure 1. Ho Chi Minh city – inventory domain of our EI (© OpenStreetMap contributors 2019. Distributed under a Creative Commons BY-SA License.)

(a) Transportation emission



(b) Manufacturing industries and Residential building emission



(c) The spatial allocation process

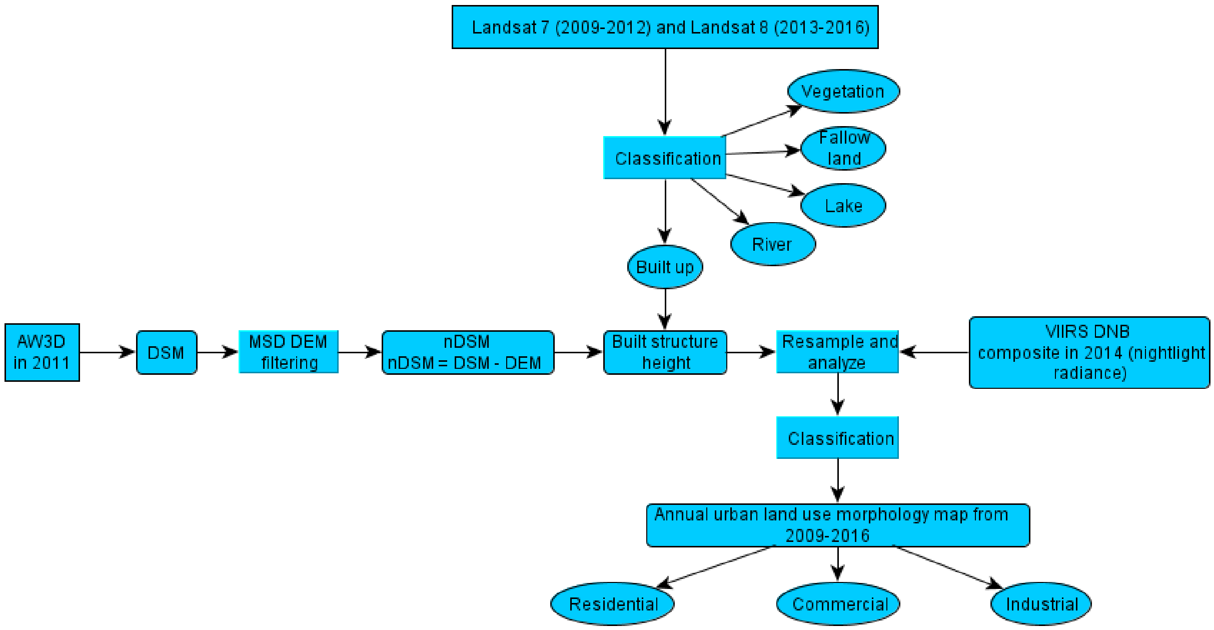
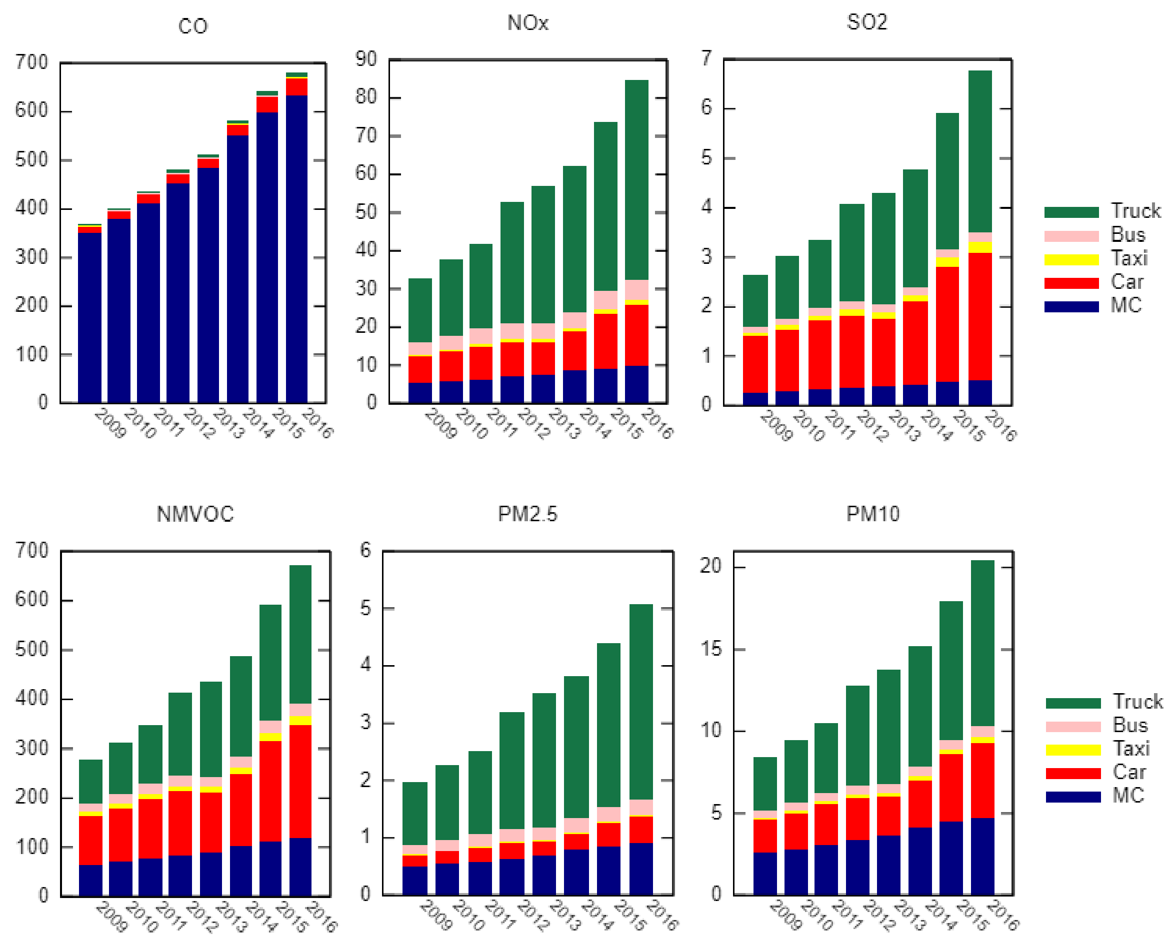


Figure 2. Schematic flow diagrams showing estimation of emissions from (a) transportation sources, (b) Manufacturing industrial source and Residential building sources and (c) the spatial allocation process



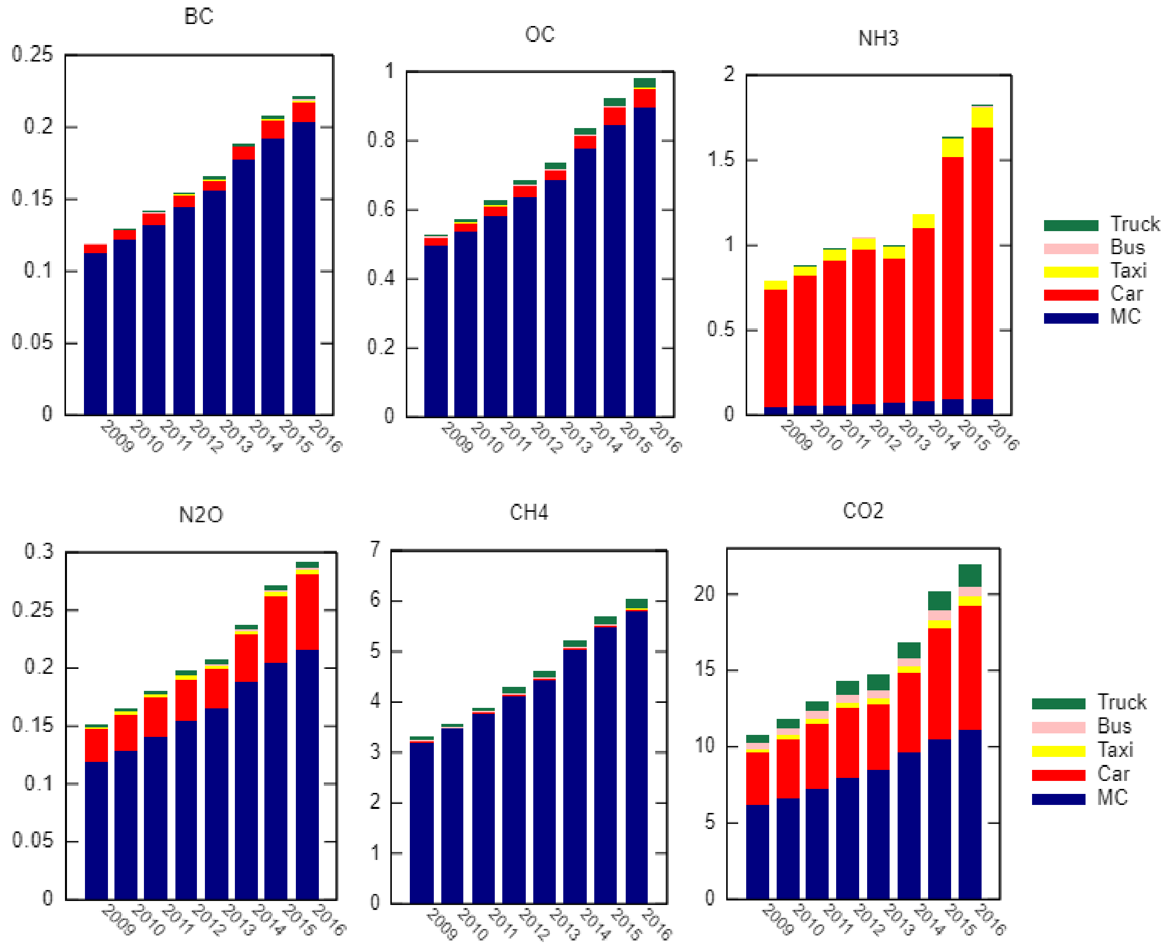
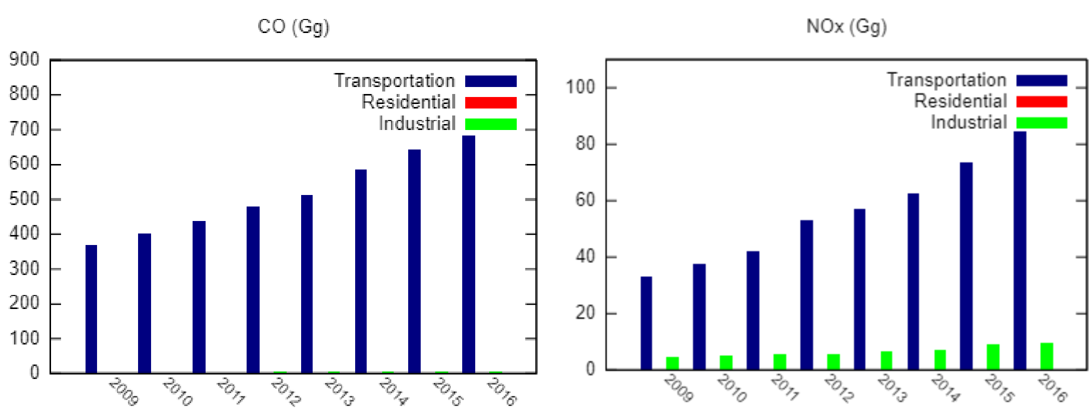
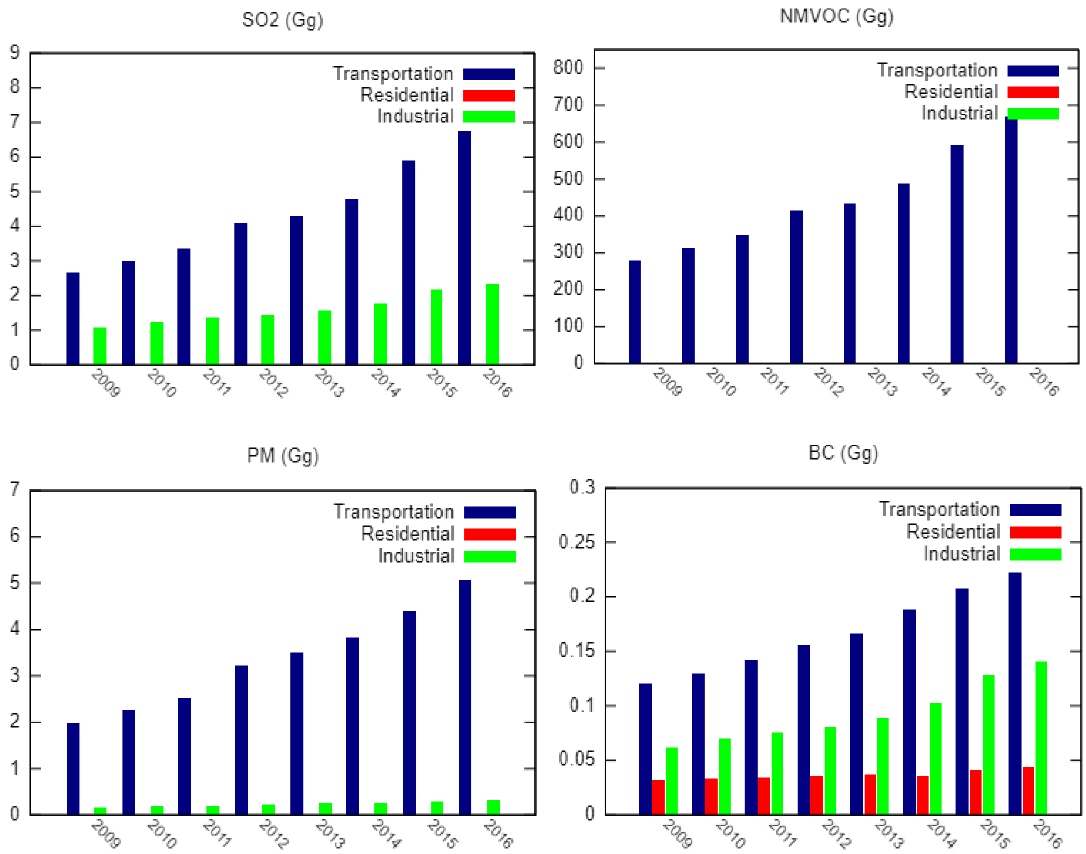


Figure 3. Annual emissions of twelve pollutant species in HCMC from 2009 to 2016 for each vehicle type (unit: Gg)




SO2 (Gg)
Transportation
Residential
Industrial
0
1
2
3
4
5
6
7
8
9
2009
2010
2011
2012
2013
2014
2015
2016
NMVOC (Gg)
Transportation
Residential
Industrial
0
100
200
300
400
500
600
700
800
2009
2010
2011
2012
2013
2014
2015
2016
PM (Gg)
Transportation
Residential
Industrial
0
1
2
3
4
5
6
7
2009
2010
2011
2012
2013
2014
2015
2016
BC (Gg)
Transportation
Residential
Industrial
0
0.05
0.1
0.15
0.2
0.25
0.3
2009
2010
2011
2012
2013
2014
2015
2016

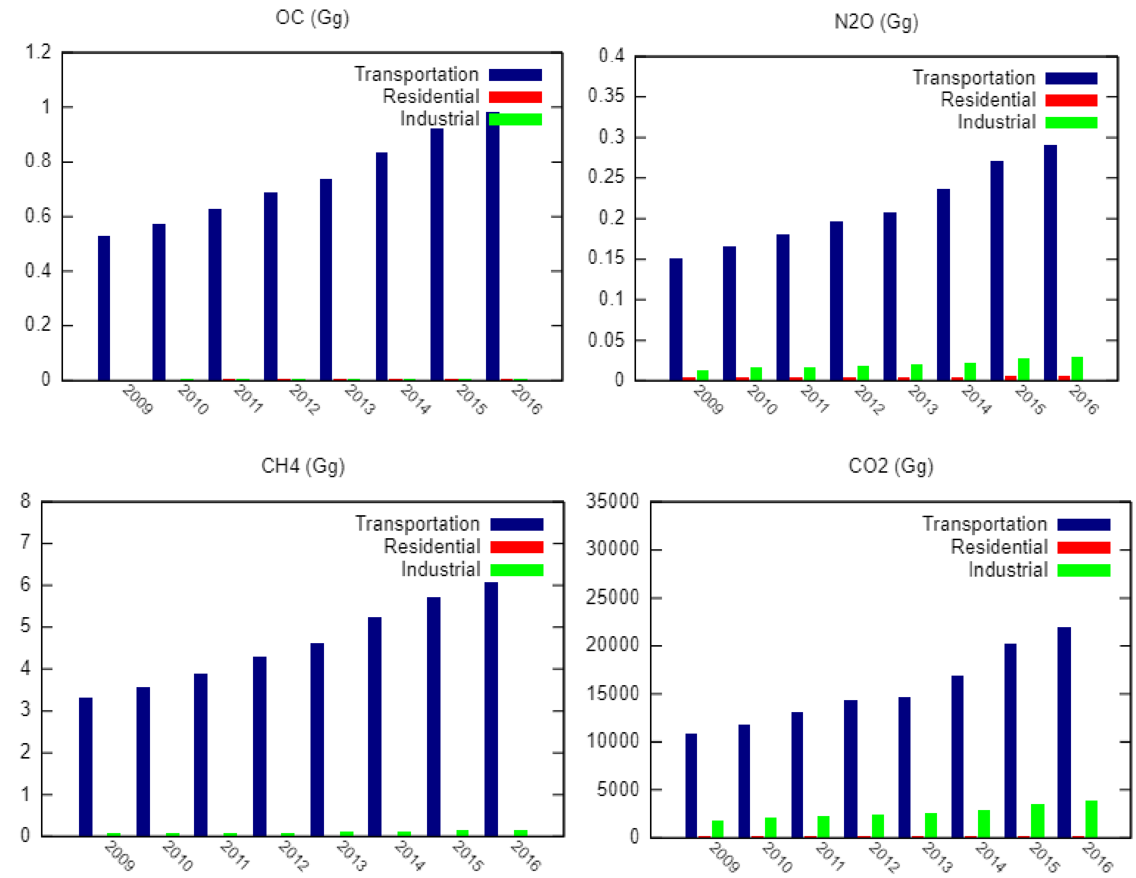


Figure 4. Annual emissions of each species in HCMC from 2009 to 2016 for three key sectors (Unit: Gg)

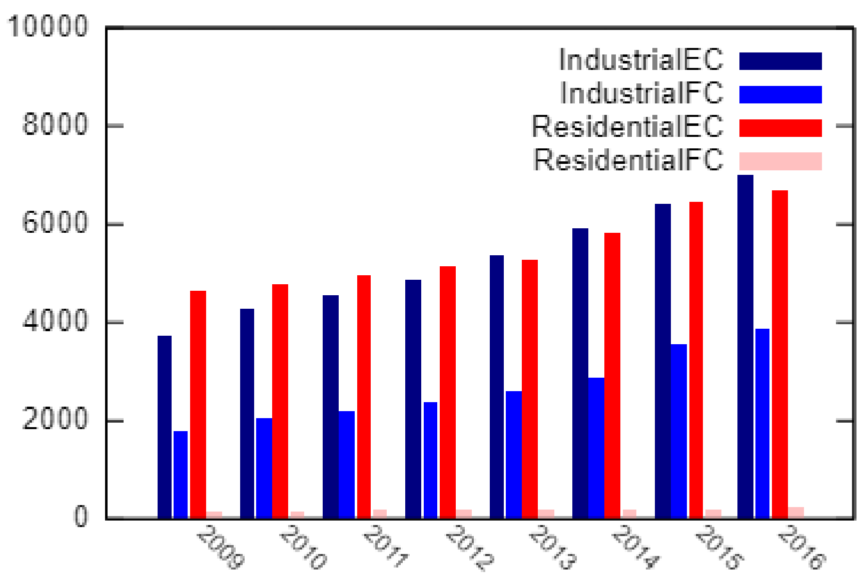


Figure 5. Annual CO2 emissions (Unit: Gg) of Electricity consumption (EC) and Fuel consumption (FC) of Manufacturing industry and Residential sector in HCMC from 2009 to 2016.

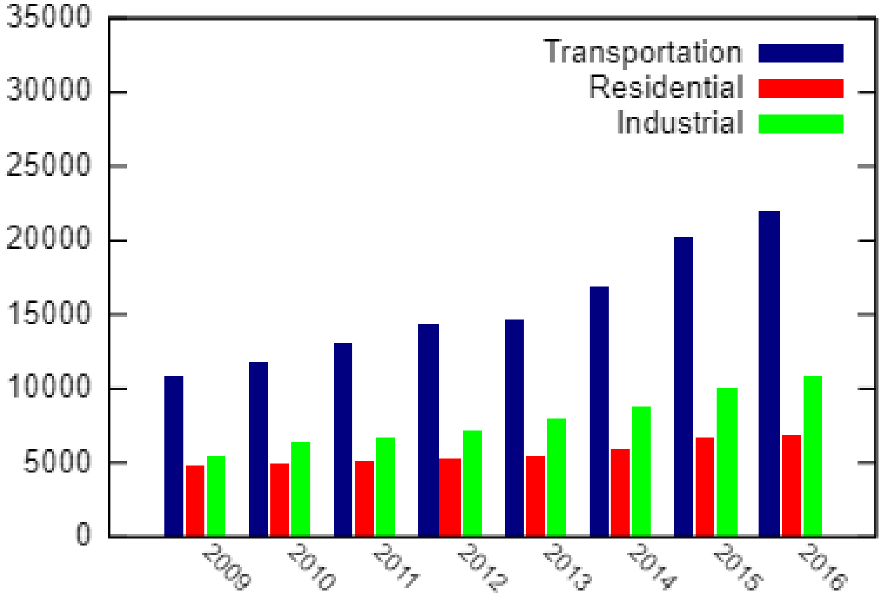
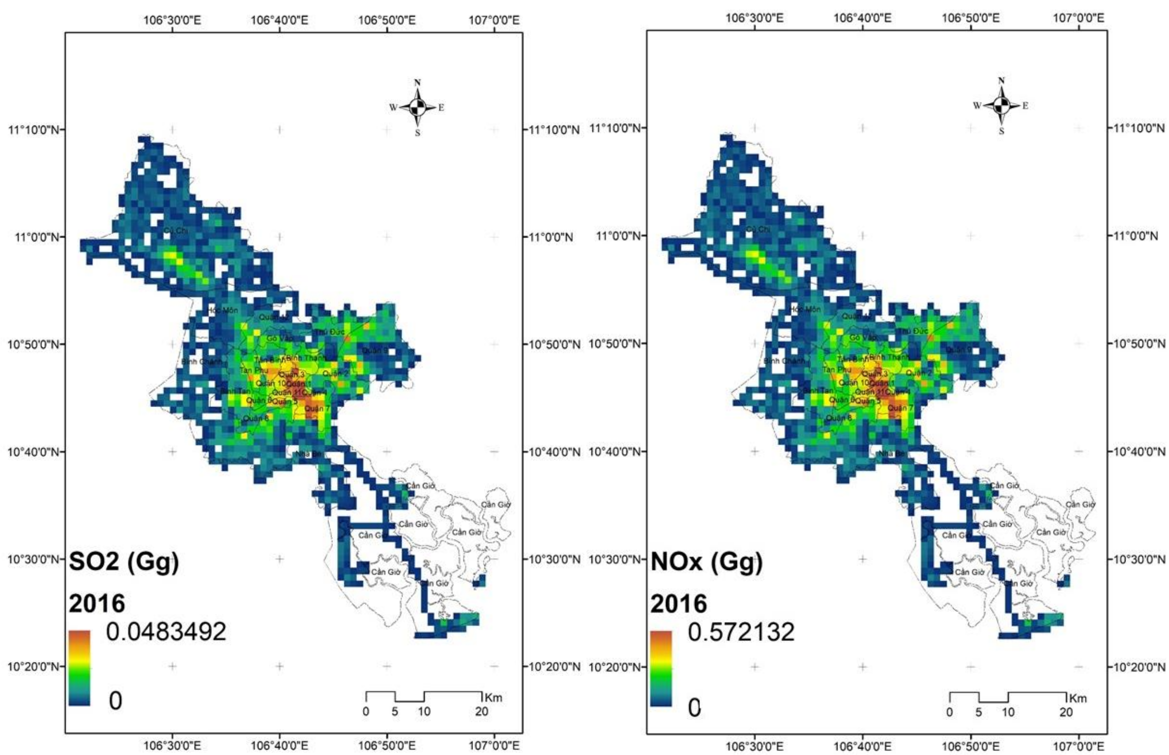


Figure 6. Annual CO2 emissions (Unit: Gg) of three key sectors: Transportation, Manufacturing industry and Residential sector in HCMC



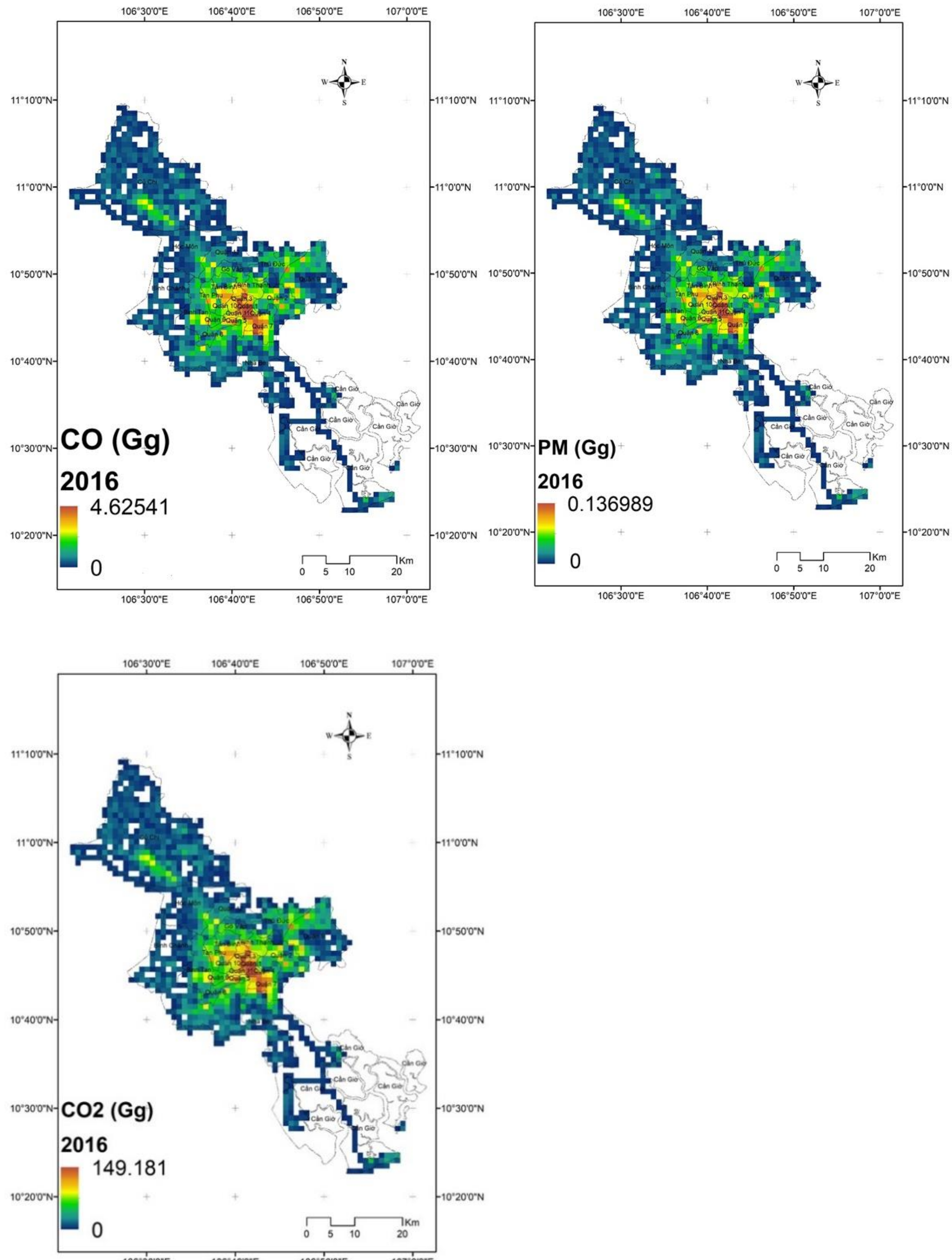


Figure 7. Emission maps of NOx, SO2, CO, PM and CO2 in 2016 in HCMC as sum of three key sectors: Transportation, Manufacturing industry and Residential Sectors.

Table 1. General information on Asia emission inventories

Emission inventories	References	Species	Years	Area covered	Spatial resolution	Time resolution
	Kato and Akimoto (1992)	SO2 and NOx	1975, 1980, 1985, 1986 and 1987	East Asian, Southeast Asian and South Asian countries	1◦×1◦	Annual
TRACE-P	Jacob et al., 2003	CO2, CH4, N2O, O3, CFC, CO, SO2	2000	Over western Pacific		
INTEX-B	Zhang et al., 2009	CO2, CH4, N2O, O3, CFC, CO, SO2	2006	Over western Pacific		
REASv1.1	T. Ohara et al, 2007	SO2, NOx, CO, NMVOC, BC, OC, CO2, NH3, CH4 and N2O	From 1980 to 2020	East, Southeast and South Asia	0.5◦×0.5◦	Monthly
REASv2.1	J. Kurokawa et al, 2013	SO2, NOx, CO, NMVOC, PM2.5, PM10, BC, OC, CO2, NH3, CH4 and N2O	From 2000 to 2008	East, Southeast, South Asia, Central Asia and Russia Asia	0.25◦×0.25◦	Monthly
REASv3.1	J. Kurokawa et al, 2019	SO2, NOx, CO, NMVOC, PM2.5, PM10, BC, OC, CO2, NH3, CH4 and N2O	During 1950-1955 and from 2010-2015	East, Southeast, South Asia, Central Asia and Russia Asia	0.25◦×0.25◦	Monthly
MIX	Tsinghua University (Zhang et al., 2009; Li et al., 2014; Zheng et al., 2014)	SO2, NOx, CO, NMVOC, NH3, PM10, PM2.5, BC, OC and CO2	2008 and 2010	East, Southeast, South Asia, Central Asia and Russia Asia	0.25◦×0.25◦	Monthly

Table 2. General information on HCMC emission inventory

Item	Description for targets
Species	SO2, NOx, CO, NMVOC, BC, OC, CO2, NH3, CH4, N2O, PM10 and PM2.5
Years	2009 - 2016
Area	Ho Chi Minh city, Vietnam
Emission sectors	(1) transportation, (2) manufacturing industries and (3) residential building
Spatial resolution	1 km
Temporal resolution	Annually

Table 3. Average daily vehicle kilometre travelled of vehicle types in HCMC (N.K. Oanh et al, 2015)

Vehicle types	Average daily vehicle mileage traveled (km/day)
Motorcycle	19
Bus	195.6
Taxi	124
Personal car	33.4
Truck	31.4

Table 4. Number of registered vehicles by type in HCMC over years

	MC	Car	Taxi	Bus	Truck
2009	4013208 [b]	257132 [b]	10300 [c]	2814 [d]	85623 [e]
2010	4340530 [b]	283810 [b]	12600 [c]	3016 [d]	101961 [e]
2011	4721123 [b]	317816 [b]	13900 [c]	3370 [d]	114052 [e]
2012	5171000 [b]	337743 [b]	15000 [c]	3587 [d]	162676 [e]
2013	5558000 [a]	315943 [a]	15500 [a]	3358 [a]	185501 [a]
2014	6318000 [b]	379763 [b]	17000 [c]	3596 [d]	197057 [e]
2015	6863707 [b]	532835 [f]	23853 [d]	3833 [d]	226677 [e]
2016	7266000 [b]	595349 [f]	26651 [d]	4283 [d]	269294 [e]

(a) N.T.K.Oanh et al, 2015
(b) Statistical data provided by The Transport Department of HCMC.
(c) JICA, 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

Table 5 The emission factors (g.km-1.vehicle-1) from literature review

Pollutant	MC	Car and Taxi	Bus	Truck
CO	12.59 [b]	2.21 [b]	6.91 [a]	3.10 [b]
NOx	0.19 [b]	1.05 [b]	16.95 [a]	17.00 [b]
SO2	0.01 [c]	0.17 [b]	0.64 [b]	1.06 [b]
CH4	0.12 [d]	0.00 [d]	0.08 [d]	0.06 [d]
PM2.5	0.02 [f]	0.03 [f]	0.90 [f]	1.10 [f]
PM10	0.09 [c]	0.30 [b]	2.08 [a]	3.28 [b]
NMVOC	2.34 [e]	15.02 [e]	89.92 [e]	89.92 [e]
BC	0.01 [f]	0.00 [f]	0.00 [f]	0.00 [f]
OC	0.02 [f]	0.00 [f]	0.01 [f]	0.01 [f]
NH3	0.00 [g]	0.10 [g]	0.00 [g]	0.00 [g]
N2O	0.00 [f]	0.00 [f]	0.00 [f]	0.00 [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) Rui-Qiang Yuan 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.

Table 6 Annual fuel consumption in HCMC in 2013, 2014, 2015 and 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 consumption (TJ/ year)			Ratio of Final Fuel Consumption by Sub-Sector in Vietnam in 2014 (%)	
	Fuel type	2013	2014	2015	Manufacturing industrial sector	Residential sector
1	Gasoline	115855	119247	134544	0	0
2	Diesel	120218	141229	180686	16%	1%
3	Heavy oil	15976	16540	19334	86%	1%
4	Kerosene	1664	1607	1901	12%	74%
5	LPG	2268	2246	2541	15%	55%
6	Natural gas	1463	1441	1567	100%	0%

Table 7 Emission factors for Manufacturing industrial and construction (a) and Residential (b) sectors from the compiled database provided by the Atmospheric Brown Cloud - Emission Inventory Manual (ABCEIM) by Shrestha et al. (2013) PM2.5 and PM10 was merged into PM for Residential sector in this database (except SO2) (unit: kg/ TJ)

unit: kg/ TJ	Diesel		Heavy oil		Kerosene		LPG		Natural gas	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
CO	15.00	-	15.00	-	15.00	167.57	10.00	78.65	2000.00	-
NOx	222.00	-	145.00	-	167.00	24.94	56.00	37.21	53.00	-
CH4	3.00	-	3.00	-	3.00	2.04	1.00	2.96	1.00	-
PM2.5	0.83	-	17.00	-	10.00	-	-	-	0.04	-
PM10	3.30	-	27.40	-	10.80	43.08	-	5.50	0.04	-
NMVOC	5.00	-	5.00	-	5.00	8.84	5.00	33.83	5.00	-
BC	3.90	-	0.90	-	5.50	20.41	-	4.23	0.00	-
OC	0.00	-	0.37	-	1.70	2.04	-	1.06	0.02	-
NH3	0.01	-	0.10	-	-	-	-	-	1.31	-
N2O	0.60	-	0.60	-	0.60	1.59	0.10	1.90	0.10	-
CO2	74100.00	-	77400.00	-	71900.00	70975.06	63100.00	63002.11	56100.00	-

- Not available.

Table 8. 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. USD)	22.43	25.74	27.61	29.48	32.51	35.5	38.1	41.36
Population (1000 people)	5981	6189	6406	6629	6861	7100	7348	7605

Table 9. Electricity consumption of Manufacturing Industries and Construction and Residential sectors and grid emission factors in HCMC in 2013, 2014 and 2015, provided by Electricity of Vietnam (EVN)

Item	2013	2014	2015
Electricity consumption from Manufacturing Industries and Construction sector (kWh/year)	7186161.42	7557369.66	8094021.38
Electricity consumption from Residential sector (kWh/year)	7073622.59	7452131.41	8132452.78
Grid emission factors (ton of CO2/MWh)	0.75	0.78	0.79

Table 10. Annual emissions for each species from Transportation sector in HCMC from 2009 to 2016 (Gg.yr-1)

Unit (Gg)	2009	2010	2011	2012	2013	2014	2015	2016
CO	370.50	401.50	437.40	479.76	513.07	583.73	641.92	682.61
NOx	32.93	37.63	41.91	52.84	56.97	62.33	73.58	84.79
SO2	2.65	3.01	3.36	4.09	4.29	4.78	5.91	6.77
CH4	3.30	3.58	3.89	4.29	4.61	5.23	5.70	6.06
PM2.5	1.97	2.26	2.51	3.21	3.51	3.82	4.40	5.07
PM10	8.37	9.47	10.50	12.82	13.74	15.22	17.99	20.44
NMVOC	277.53	312.83	347.73	414.96	435.23	486.61	591.17	670.50
BC	0.12	0.13	0.14	0.16	0.17	0.19	0.21	0.22
OC	0.53	0.58	0.63	0.69	0.74	0.84	0.92	0.98
NH3	0.79	0.88	0.98	1.05	1.00	1.19	1.64	1.83
N2O	0.15	0.17	0.18	0.20	0.21	0.24	0.27	0.29
CO2	10784.00	11824.00	13020.00	14309.00	14712.00	16879.00	20162.00	21999.00

Table 11. Annual emissions from fuel consumptions in Manufacturing industrial and construction (a) and Residential building (b) sector (PM2.5 and PM10 are merged into PM in Residential sector according to ABCEIM by Shrestha et al, 2013)

Unit (Gg)		CO	NOx	SO2	CH4	PM2.5	PM10	NMVOC	BC	OC	NH3	N2O	CO2
2009	(a)	2.37	4.41	1.09	0.07	0.17	0.31	0.12	0.06	0.00	0.00	0.01	1798.59
	(b)	0.31	0.07	0.01	0.00		0.01	0.05	0.03	0.00	0.00	0.00	163.83
2010	(a)	2.71	5.06	1.25	0.08	0.20	0.35	0.14	0.07	0.00	0.00	0.02	2063.56
	(b)	0.32	0.08	0.01	0.00		0.01	0.05	0.03	0.00	0.00	0.00	169.53
2011	(a)	2.91	5.43	1.34	0.09	0.21	0.38	0.15	0.08	0.01	0.00	0.02	2213.53
	(b)	0.33	0.08	0.01	0.00		0.01	0.05	0.03	0.00	0.00	0.01	175.47
2012	(a)	3.11	5.80	1.44	0.09	0.23	0.40	0.16	0.08	0.01	0.00	0.02	2363.50

	(b)	0.34	0.08	0.01	0.00		0.01	0.05	0.04	0.00	0.00	0.01	181.58
2013	(a)	3.43	6.39	1.58	0.10	0.25	0.44	0.18	0.09	0.01	0.00	0.02	2606.63
	(b)	0.36	0.09	0.01	0.01		0.01	0.06	0.04	0.01	0.00	0.01	187.93
2014	(a)	3.44	7.21	1.76	0.11	0.26	0.47	0.19	0.10	0.01	0.00	0.02	2891.34
	(b)	0.35	0.08	0.01	0.01		0.01	0.06	0.04	0.00	0.00	0.01	183.39
2015	(a)	3.82	8.97	2.17	0.14	0.31	0.55	0.24	0.13	0.01	0.00	0.03	3557.52
	(b)	0.41	0.10	0.01	0.01		0.01	0.06	0.04	0.01	0.00	0.01	212.92
2016	(a)	4.15	9.74	2.36	0.15	0.34	0.60	0.26	0.14	0.01	0.00	0.03	3861.90
	(b)	0.42	0.10	0.01	0.01		0.01	0.07	0.04	0.01	0.00	0.01	220.36

Table 12. Annual CO2 emissions from electricity consumptions in Manufacturing industrial and construction sector and Residential sector (emission for years marked with * were calculated from electricity consumptions provided by JICA, 2017, while other emissions for other years 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

Table 13. Comparison of transportation emission estimated in this study with emission calculated in previous studies for 2013 and 2016.

Unit	**N.T.K.Oanh et al, 2015**	**JICA, 2017**	**L.T.P.Linh, 2018**	**This study**	
(Gg)	**2013**	**2013**	**2016**	**2013**	**2016**
CO	*1252*			*513.07*	
NOx	*61*			*56.97*	
CH4	*33*			*4.61*	
BC	*1.77*			*0.17*	
OC	*6.65*			*0.74*	
N2O	*0.50*			*0.21*	
CO2	*10722*	14693	10890	*14711.59*	21998.72

Table 14. Comparison of sharing ratios of emission from MC and personal car (PC) in this study and previous studies for 2010 and 2013 (Unit: %)

Unit (%)	**H.Q.Bang, 2010**	**N.T.K.Oanh et al, 2015**		***This study***		
	2010	**2013**		***2010***	***2013***	
	MC	**MC**	**PC**	***MC***	***MC***	***PC***

CO	94	85	12	*94.40*	*94.60*	*3.50*
NOx	29	80	14	*15.60*	*13.20*	*14.90*

Table 15 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 16 Comparison of emission factors used for Industry sector in this study and in REAS v2.1.

(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 17 Comparison of emission factors used for Domestic sector in this study and in REAS v2.1

(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	-	-

Table 18. Uncertainties (%) of emissions of three key sectors in HCMC

	CO	**NOx**	**SO2**	**CH4**	**PM2.5**	**PM10**	**NMVOC**	**BC**	**OC**	**NH3**	**N2O**	**CO2**
Transportation	±23	±24	±26	±23	±23	±18	±24	±34	±34	±27	±31	±22
Industry	±25	±13	±12	±42	±70	±71	±15	±10	±13	±11	±40	±4
Residential	±19	±15	±15	±82	±53		±20	±63	±56	±53	±71	±5
Total	**±19**	**±24**	**±22**	**±23**	**±31**		**±25**	**±31**	**±34**	**±27**	**±31**	**±20**