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Additional Information

From traffic data to GHG emissions: a novel bottom-up methodology and its application to Valencia city

Abstract

Sustainable cities will only be possible with effective local measures tackling Greenhouse Gas (GHG) emissions. Transport and mobility represent the main sources of these emissions, particularly in urban settings. National and local public administrations need accurate and more responsive tools to quantify GHG emissions. Digitisation and ICTs are key elements in the development of such tools, which, additionally, have to be based on robust methodologies validated by the scientific community. This research presents a bottom-up methodology for the quantification of road traffic's GHG emissions with higher levels of immediacy and spatial resolution when compared to other already existing methods. The methodology uses data from the urban traffic control and monitoring systems as a baseline to calculate emissions. A pilot test has been conducted in Valencia city (Spain). Its results show a highly detailed picture of GHG emission in the city with high temporal (hour) and space (street) resolutions. The emission patterns reflect the dynamics of the city and its citizenship mobility. Since the tools developed for the pilot test can be adapted to other cities, public decision-makers could benefit from a precise diagnosis system based on traffic data to offer and evaluate solutions to reduce road transport GHG emissions.

Keywords: GHG; Urban Road Transport; Real time emission monitoring; Climate Change; Decision Making Tool.

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[1]These authors contributed equally to this work.

1. Introduction

Climate change is one of the most pressing global challenges the international community is facing today. This challenge leads decision-makers to adopt actions and policies to reduce climate change causes and mitigate its effects. In this context, greenhouse gases (GHG) emissions reduction policies are key in any long-term plan tackling climate change. For example, the European Union (EU) has recently set out a clear vision in the European Green Deal on how to achieve climate neutrality by 2050. The EU aims to increase its reduction targets of GHG emissions in 2030 by at least 50% (around 55% as compared to 1990 levels) (European Commission, 2020).

In order to meet these EU and national policy framework goals, mitigation actions must be efficiently converted into the immediate local level (Wilson, 2006). Consequently, more than 300 cities inside and outside of the EU, signed the Covenant of Mayors for Climate and Energy (European Commission, 2019), signalling their engagement to reduce GHG emissions by at least 40% by 2030 (European Commission, 2018).

Decision-makers need to ensure that local government plans can be fully understood, supported and monitored by the general public as well as other administrations. However, often, public decision-makers at the local level lack the necessary tools to support their strategic planning in a quantitative, objective, and transparent manner. Climate change mitigation measures must be based on a rigorous, accurate and up-to-date quantification of GHG sources. This is a basic requirement from the European Commission to support local government administrations (European Commission, 2014). Despite this requirement (Intergovernmental Panel on Climate Change (IPCC), 2006), the current GHG calculation methods are best-suited to the national than to the local level (Engo, 2019).

Current action plans and measures are based on Base Emissions Inventories (BEI) and Monitor Emissions Inventories (MEI) (European Commission, 2019)

most commonly developed with top-down methodologies (Dai et al., 2016). Whilst top-down inventories are rigorous and complete on a year-average and country-wide basis, statistically, its extrapolation to a local scale is often not tenable. Local action also calls for a higher temporal resolution to allow policy measures to be followed and supported by citizens. Spatially and temporally disaggregated emission inventories are specially required for reliable and accurate air quality predictions (Leonidas & Zissis, 2019) and GHG monitoring. For example, the emissions' air concentration in an urban hotspot[2] cannot be calculated using year-long average data, since concentrations depend on both to the emission rate profile as well as the weather conditions.

Road transport emissions have important impacts on urban air quality and global warming (Colvile et al., 2001), accounting for about 20% of total fossil fuel consumption (International Energy Agency, 2014). In the European Union (EU), road transport contributes one-fifth to total GHG emissions, with passenger cars being the main contributor to CO_2 emissions with 75% of the total (European Commission, 2015; European Environment Agency, 2012, 2015). The transport and mobility sector is furthermore the only major sector in EU that continues increasing its GHG emissions (European Commission, 2016b) despite strong political and social mitigation efforts. This highlights the potential of this sector to reducing EU's emissions and deliver to the EU's commitment under the Paris Climate Change Agreement (see (European Commission, 2016a)).

To estimate GHG emissions from road transport and mobility, the Intergovernmental Panel on Climate Change (IPCC) puts forward two alternative approaches based on independent data sets: 1) Fuel sold in the field study area and 2) Vehicle Kilometres Travelled (VKT) (Intergovernmental Panel on Climate Change (IPCC), 2006). The first method is a good approach to quantify emissions at wider regional or national levels, whereas the consumed and sold fuel in a specific geographical area may be considered to be approximately equal.

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[2] A hotspot is a place characterised by substantially above-average levels of emissions.

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The second method, VKT, needs more variable and data sets to estimate GHG. Typical data needed by these method includes the number and characteristics of vehicles, the kilometres travelled by each vehicle and how those kilometres were made (velocity, acceleration, etc.). The estimation of GHG can be done both nationally and locally if sufficiently disaggregated data are available. When some of the VKT method inputs are obtained from a statistical sample of observations, the extrapolation of the result to a whole area has been traditionally regarded as a serious limitation to apply the VKT methodology.

In addition to the above mentioned limitations of the two IPCC approaches, traffic variability represents another challenge when using GHG calculation methodologies. Firstly, traffic conditions vary depending on city areas as well as the day times when emissions are measured. In order to meet existing mobility needs, spatial and temporal resolutions of road transport emissions are key not only to assess air pollution (Leonidas & Zissis, 2019) and monitor GHG emissions, but also to offer evidence to local policy-makers when preparing proposals for GHG reduction plans or evaluating the already ongoing ones.

IPCC estimations based on the fuel sold in a specific study area lack enough spatial resolution to be effective in city-level GHG calculation. Furthermore, IPCC estimations do not differentiate emissions originated between different type of vehicles. This differentiated information is crucial in regards to urban sustainability policies. Thus, these important limitations call into question the usefulness of this type of estimations at the urban level.

This paper proposes a bottom-up methodology to quantify urban traffic emissions with high spatial and temporal resolution. In addition to this, the proposed methodology addresses the GHG measurement problem at the city level. The recommended method is based on IPCC VKT datasets and the automated information gathering from traffic management systems. The methodology has been applied to Valencia city (Spain) as a proof of concept, which have implied the developing of new tools to acquire and filter the data and to estimate the GHG from the resulting information. The results obtained from the pilot imple-

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mentation portrays a detailed picture on the spatial and temporal distribution of actual emissions in the city.

The paper is structured in six sections. Following the introduction, a selection of related works are explained and discussed (Section 2). The developed methodology is described in Section 3, including its implementation in the pilot city. Section 4 includes some representative results obtained from the analysis of a four-year dataset (2016-2019) and discusses briefly some of the conclusions that can be outlined. These elements and their representativity are discussed in Section 5. Finally, main conclusions and future work are presented in Section 6.

2. Related works

Road traffic emission inventories can follow either "top-down" or "bottom-up" approaches. These approaches will be used depending on geographical scope, level of data's detail as well as its availability (Colvile et al., 2001). On one hand, top-down approaches are aimed to high geographic level, e.g. nationwide, using aggregated statistical data. A spatial disaggregation process is necessary to determine local emissions from original spatial level, usually nationwide. Local level data has lower accuracy than nationwide because the approximations used in the disaggregation process. On the other hand, bottom-up approaches require large data sets (total kilometres travelled, number of vehicles, vehicle characterisation, GHG measurements, etc.) and advanced computing processes that summarise the data sets. When data sets are not accessible, several assumptions to get data approximations need to be undertaken affecting whole process accuracy.

In regards to the top-down approach, inventories are the commonly used tools in Europe. These are made mainly using software systems such as various COPERT versions (Computer Program to Calculate Emissions from Road Traffic) (Leonidas & Zissis, 2019) and MOBILE (Environmental Protection Agency, 2002). COPERT based methodologies have been used to estimate and compare air pollutant emissions in Spain (Burón et al., 2004; Burón et al., 2005), Sardinia

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(Italy) (Bellasio et al., 2007), Ireland (Ryan et al., 2009) and two different areas in China (Song & Xie, 2006). MOBILE has been used to assess the vehicular emissions in Shanghai city (China)(Li et al., 2003).

A hybrid methodology resulting from the two approaches is used in other works to develop air pollutant emission inventories, namely the travelled vehicle kilometres (VKT) from a bottom-up approach and variables from wide areas (e.g, population or road lengths) typical from top-down approaches. Examples of such works are (Ramachandra & Shwetmala, 2009) and (Saija & Romano, 2002). In any case, results obtained following this methodology show low spatial resolution.

Several studies using tools for urban simulation of traffic behaviour (to calculate road traffic emissions), adopt a bottom-up approach. For example, (Beelen et al., 2009) obtained a mapping of background air pollution across the EU on a 1×1 km spatial resolution. (Daniel de la Hoz & Shepherd, 2010) carried out a study on the evolution of CO_2 emissions in Madrid (Spain) defining traffic behaviour based on data from 1990s to plan different strategies at the local level to achieve proposed GHG emission reduction targets aiming to predict several 2030 scenarios. In (P. Iodice & Migliaccio, 2010), an emissions inventory of the main environmental pollutants in Napoli (Italy) using mobile fleet distribution was obtained using COPERT. Elena and Christidis propose a unified scheme to assess the GHG emissions impact of road transport infrastructure plans to estimate transport demand with associated energy consumption (Elena López & Christidis, 2010). This scheme aimed to help decision-makers. The authors used a system based on a Geographical Information System (GIS), origin-destination matrices, length and journey time, and other variables. In (Perez-Lopez et al., 2013) the EMEP/EEA Tier 3 methodology is used to determine the evolution of GHG emissions from the road transport sector. Specifically, the study is performed in Spain for the 2005-2010 period quantifying emission of 12 polluting gases according to IPCC standards. This quantification is based on measurements of traffic intensity in stretches, vehicle characteristics of the circulating

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fleet, driving modes, and VKT.

However, the previous works discussed show different limitations regardless of the approach used such as: (a) the use a fuel balance from national extrapolations to calculate the energy consumption of road transport in a city; (b) the maximum accuracy achieved for observed spatial resolution is square kilometres; (c) emission inventories are made using standardised software for specific periods, not continuously over time; and (d) use of simulations to estimate hard-to-measure variables.

To overcome these limitations, an innovative bottom-up methodology has been developed. The main improvements of the methodology can be summarised as follows:

    a. **not based on simulations**.

    b. mainly **based on actual data**, minimising the use of disagregation processes.

    c. quantify emissions by **using a novel calculation model**.

    d. quantify emissions by taking into account the **local mobile fleet** characteristics.

    e. the process has to be done **in real time**, so the model can act on alarm situations in sectors or neighbourhoods of the city.

    f. the spatial resolution has to reach a level of **accuracy at street level**, even distinguishing different sections in the same street.

    g. the emissions can be **categorised by type of vehicle and type of fuel**.

3. Material and methods

This section explains the proposed methodology and the pilot test implementation process. As in any other bottom-up methodology, the results of our methodology will be based in fine grain measurements, in our case data from

the pilot city traffic control system. This raw data will be filtered to increase its quality and then transformed into equivalent CO_2 kilograms. These data transformations are based on several formulas in which data from other sources will be needed (like vehicle fleet information).

3.1. Pilot test city

Valencia city has almost $800\,000$ inhabitants and is the centre of an extensive metropolitan area with more than one and a half million inhabitants. It is located on the East coast of Spain. 83% of employees in Valencia work in service sectors. However, the city has an important industrial base with 14% of employment.

The pilot city has declared a special interest in the mitigation and adaptation to Climate Change. On February 10, 2009, the municipality of Valencia joined the Covenant of Mayors with a commitment to reduce 40% of GHG emissions by 2030 with respect to the GHG emissions in 2007. Within this policy framework, it must be pointed out that the road transport and mobility sector represents about 60% of the total BEI quantified GHG emissions. However, BEI quantification is based on a top-down approach and aggregated data with low temporal and spatial resolution. This poses a huge limitation to a swift and efficient decision–making. Moreover, the monitoring and control of the implemented measures are highly limited due to the low temporal resolution.

3.2. Methods

The process of transforming the traffic data into GHG emissions depends on the circulating vehicles and how they convert fuel into emission. On the other hand, the vehicles circulate on the streets of the city, which will be modelled as a network. The methodology we followed for the data treatment and network definition is detailed in the following subsections.

3.2.1. Analysis and categorisation of the vehicle fleet

The requested data for categorising and characterising the units that make up the vehicle fleet are: number of vehicles with their main distinctive features

(type of vehicle, engine technology, and fuel category used).

As sources of emissions, only those vehicles that consume one of the various types of fuel (petrol, diesel) and their liquid or gaseous derivatives (biofuels, gas and biogas) are considered.

In the IPCC report (Intergovernmental Panel on Climate Change (IPCC), 2006) the section that covers polluting emissions from transport corresponding to road traffic of vehicles is coded as "NFR1.A.3.b.i-iv Road transport". NFR stands for "Nomenclature for Reporting", which refers to the format for reporting national data in accordance with the Convention on Long-Distance Transboundary Air Pollution (CLRTAP). In relation with this code there are four different categories of vehicles (see Table 1).

Table 1: Categorization of vehicle types according to NFR code. Source: EMEP/EEA air pollutant emission inventory guidebook 2016, updated July 2018.

NFR Category	Title
1.A.3.b.i	Passenger cars
1.A.3.b.ii	Light commercial trucks
1.A.3.b.iii	Heavy-duty vehicles including buses
1.A.3.b.iv	Mopeds and motorcycles

As stated, according to IPCC guidelines we classify the main features of the mobile fleet with three variables for each vehicle: the vehicle type, the fuel used by it and the technological regulations used when manufacturing the vehicle. The available values of these variables are shown in Table 2.

Table 2: The three variables defining the mobile fleet and their values

Vehicle type	Technological regulations	Fuel type
Passenger cars	Conventional	Biomethane
Light commercial vehicles	ECE-15.14 and previous	Butane
	EURO 1,2,3,4,5	Diesel
Light trucks	6-2016, 6-2017 and later	Ethanol
Heavy trucks	EURO I, II, III, IV, V	LPG, CNG, LNG
Buses	VI-2016, VI-2017 and later	Petrol
Motorcycles		Others
Mopeds		
Others		

The database of the Directorate-General for Transport (DGT) statistical portal (Dirección General de Tráfico, 2020) was used to obtain the evolution and particularities of the available attributes of the mobile fleet and its distribution in the timeline of the studied years.

Then, to analyse the temporal variability, an analysis of these data was carried out with monthly granularity and annual aggregations. The available attributes were filtered to obtain an average value of 626 different vehicle categorisations, out of an average fleet of approximately 460 000 vehicles.

The age of the different categories was correlated with the technological regulations that correspond to the specific time range. Following this approach, we managed to reduce the different categorisations to an average value of 136.

Finally, to assign the influence of each vehicle categorisation obtained to the emissions of the pollutants studied, we calculated the relative weights (RW) of each one based on their percentage with respect to the total number of vehicles, affected by the average distance travelled by category vehicle on urban

roads (%UD).

As a result, we were able to set up a database consisting of vehicle types, fuel, technological regulations, relative weight (RW), and percentage of urban mileage (%UD) for each of the vehicle categories included in our categorisation. Figure 1 depicts the methodological process followed.
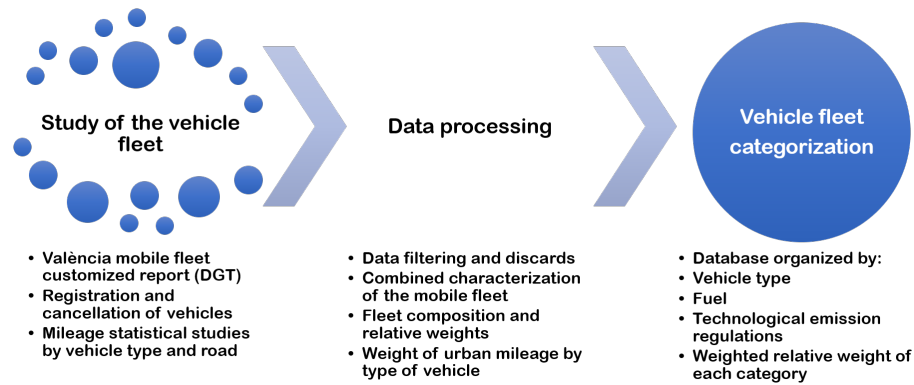

Study of the vehicle fleet

- València mobile fleet customized report (DGT)
- Registration and cancellation of vehicles
- Mileage statistical studies by vehicle type and road

Data processing

- Data filtering and discards
- Combined characterization of the mobile fleet
- Fleet composition and relative weights
- Weight of urban mileage by type of vehicle

Vehicle fleet categorization

- Database organized by:
- Vehicle type
- Fuel
- Technological emission regulations
- Weighted relative weight of each category

Figure 1: Sequential methodology

3.2.2. Determination of emission factors for pollutants

The Core Inventory of Air Emissions working group (CORINAIR) is considered as a pioneer initiative in analysing emissions at the European level, which consists of developing emission inventory methods. It began in 1987 with the aim of developing a system to determine the appropriate factors to measure vehicle emissions. A computer program, COPERT , was subsequently developed to assist its implementation (Burón et al., 2004)(Wang et al., 2018).

A common use of the COPERT methodology is to produce emission inventories generated by road transport based on fuel sales. From a geographical perspective, this criterion is valid for countries or regions (top-down approach) but not for urban settings. In urban settings, an energy balance (bottom-up approach) is more appropriate than a fuel balance to determine the emission factors needed to calculate the CO_2 emissions. These emission factors are derived from dif-

ferent consumption and efficiency factors as follows from the following generic expression (Mahesh et al., 2018):

$$EF = \frac{EC}{CV} \cdot RATIO = FC \cdot RATIO \tag{1}$$

where the EF is the Emission Factor, EC is the Energy Consumption (MJ/km), CV is the Caloric Value of fuel (MJ/kg$_{fuel}$), $RATIO$ is the proportion of contaminant in fuel (g$_{CO_2}$/kg$_{fuel}$) and FC is the Fuel Consumption (kg$_{fuel}$/km).

This expression is individualised for each polluting gas corresponding to each type of vehicle and fuel, e.g. CO_2 emission factor of the passenger car EURO 6 using diesel, and then applied to each monitored stretch.

To obtain an aggregate, the emission factors obtained must be multiplied with their relative weights (RW) against the total number of vehicles, and by the percentage of urban mileage (%UD) in comparison with the total mileage, of each vehicle category (defined by type of vehicle, used fuel, and technological regulations). Furthermore, to obtain the emissions in equivalent CO_2 the global warming potential (GWP) of each pollutant has to be considered: 1 for CO_2, 28 for CH_4 and 265 for N_2O (these values are extracted from Myhre et al. (2014)).

The above described COPERT–based scheme was used only for the estimation of the emission factors (Figure 2 outlines the flow diagram), but not for the quantification of GHG emissions. To allow quantifying GHG and pollutant emissions, we have developed a new aggregation scheme relying on metrics and data more suited to the urban environment (bottom-up approach) as it will be described in the next subsection.
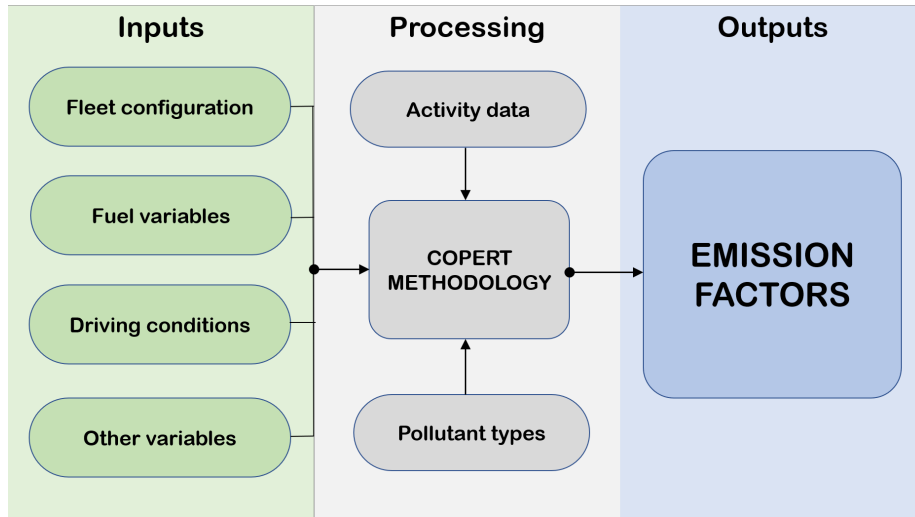
Figure 2: COPERT usage flow chart

The extensive reviews and cross-checks of the transport data along with the re-
liability of the data sources, ensure the high quality of the data set obtained for
the different emission factors. The emission factors are extracted using a model
based on local scope specification, in accordance with the IPCC recommen-
dations for emission inventories (Intergovernmental Panel on Climate Change
(IPCC), 2020).

3.2.3. Network model description

We have defined the concept of road segment as a road stretch with a given
distance between intersections in which the number of input vehicles is equal
to the number of output vehicles. The starting point to develop the network
of road segment is the traffic control system characteristics. In the pilot city,
the traffic control system is made up of 3500 sensors (mainly induction loops)
producing data every 10 minutes (see Figure 3). From the location of those
sensors, a total of 1326 measured road segments distributed have been defined
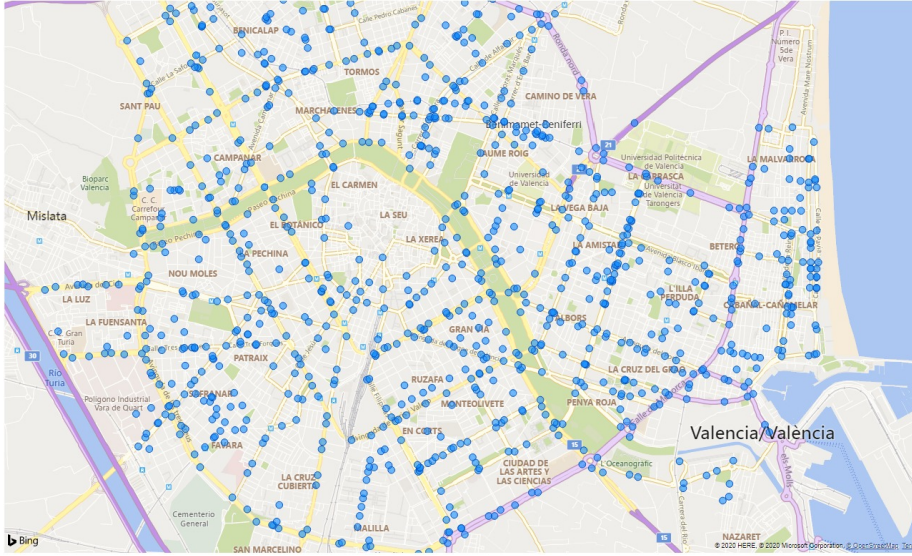across the pilot city.

Figure 3: Location of induction loops of traffic control system

In each monitored road segment s, the ITA_s value represents the number of vehicles that crossed the given segment within a prescribed time window. Each sensor signals contributes to traffic intensity values (ITA) of one or more monitored road segments. This magnitude is described in the following equation:

$$\text{ITA}_s = \sum_{i=1}^{n_s} \text{C}_{i,s} \cdot \text{P}_{E,i} \tag{2}$$

where each measured road segment is affected by a varying number of sensors (n_s), $P_{E,i}$ is the electric output that characterises the response of the i-th sensor, and $C_{i,s}$ is the coefficient that quantifies the effect of the i-th sensor on the road segment s. Despite the fact that original data have a ten-minute period, we have increased the period to one hour in order to allow a reasonable balance between data manageability and time resolution.

If, as in this case, no specific information is available on the actual vehicle distribution that circulates in a certain road segment s, we can mistakenly assume that the distribution is statistically homogeneous and represented by the vehicle

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category distributions obtained for the whole city. This underestimation would be wrong since the amount of a given type of vehicles within the distribution of categories does not depend on the road segment index s. So, the conversion between intensity data and CO_2 emissions during the prescribed time window results from expression 3:

$$E = \left(\sum_{s=1}^{N} \mathrm{ITA_s} \cdot \mathrm{l_s} \right) \cdot \left(\sum_{v} \rho_v \sum_{g} \mathrm{EF_{v,g}} \cdot \mathrm{GWP_g} \right), \qquad (3)$$

where the three indices are referred to the target road segment s, the vehicle typology v and the type of greenhouse gas g. N is the total number of monitored road segments included in the system.

The different elements of the equation are:

- $\mathrm{ITA_s}$: Vehicle intensity of the road segment t in the one-hour time interval (#vehicles/hour).

- l_s: Length of the road segment s (km).

- ρ_v: Number of vehicles with the typology v (#vehicles).

- $\mathrm{EF_{v,g}}$: Emission factor (see Equation 1) of the vehicle typology and fuel used v for the polluting gas g (g_{CO_2}/km).

- $\mathrm{GWP_g}$: Global warming potential of the gas g: 1 for CO_2, 28 for CH_4 and 265 for N_2O (from Myhre et al. (2014)).

3.3. Data description

The Smart City Office of Valencia city has provided its dataset for the current study. It compiles four years of measurements of traffic intensity across the city, from January 2016 to December 2019. Originally, the dataset was provided as independent files (one per year), but currently a server system has been prepared to allow a real-time transfer of data.

The dataset is composed by $\mathrm{ITA_s}$ (see Section 3.2.3) from a total of 1326 monitored road segments, 10 of which correspond to bus lane–type road segments,

115 to bicycle lanes and the rest to the remaining road traffic. The information from the bicycle lanes was disregarded for this study. Table 3 shows the summary statistics for this dataset.

Table 3: Description statistics of the series in datasets. ITA in vehicles per hour (v/h) and Segments Lengths in meters (m).

Data series	Min.	Max.	Mean	Median	Std. Dev.	Variance
ITA 2016 (v/h)	0	7636	456	233	551	303
ITA 2017 (v/h)	0	47 091	458	231	577	332
ITA 2018 (v/h)	0	5543	449	228	543	294
ITA 2019 (v/h)	0	6153	439	222	531	282
Seg. Lengths (m)	17	1343	216	200	134	18

3.4. Data processing

The retrieved information had a format that made it difficult to locate each monitored road segment. A first step in the data analysis was to get a precise location of each sensor, with its corresponding latitude and longitude.

In addition to this, raw signals from induction loops can be affected by different errors. The errors must be detected and corrected to eliminate abnormal data with a potentially high impact on the statistical quality of the outcome. The errors may result from sensor failures of any of the loops that contribute to a given road segment, but also to different events such as stretch, physical interventions on the road, closed street, parades, etc. In Figure 4, three typical examples of raw data with errors are shown.
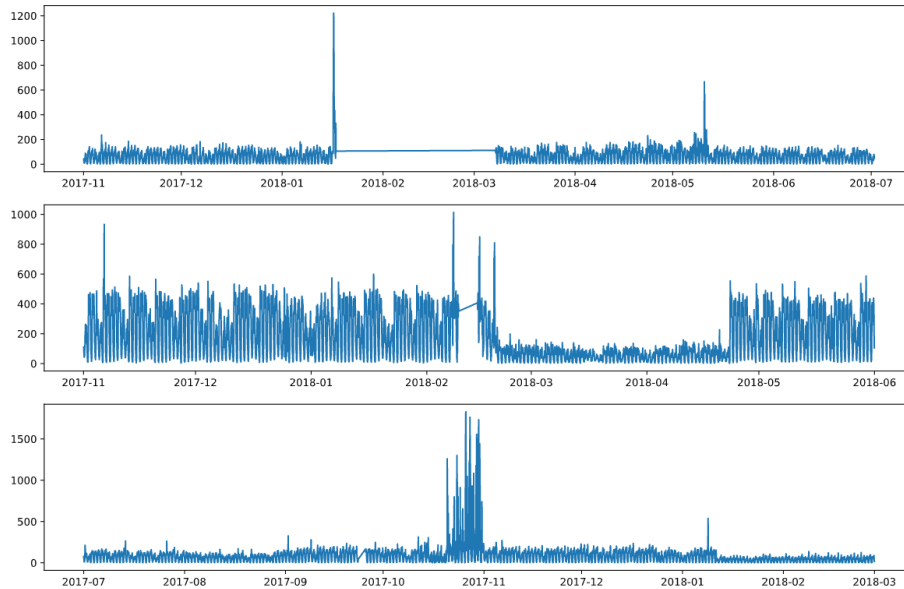
Figure 4: Vehicle intensity of several measurement points showing typical anomalies: missing data (upper and middle graphs) and outliers (in all the graphs).

To discard signals with errors, filtering was performed in those road segments where a high percentage of data is missing over study length. A threshold has been established that allowed us to discard those detectors whose corresponding data set what not complete during the four year survey. Specifically, we used the 95% percentile criterion and, as a result, 468 detectors were found to be non-compliant and subsequently discarded.

Finally, an account assignment was made for the outliers (generated from the average data) and no outliers (obtained for the same stretch at the same month, weekday and hour). The daily seasonality is also taken into account. So, are not included in the calculation of this average. This assumption will be justified in the following section.

4. Results

In this section, we will present the main results of the application of our methodology to the complete four–year (2016 – 2019) dataset of the traffic in the pilot city. The first step is the application of the COPERT–based methodology to collect the emission factors. Emissions have been identified as a result of the filtering procedures described in Section 3.2.2. Our analysis allows deriving a timeline and a spatially disaggregated view of the emissions in the city. This view allows drawing an initial preliminary analysis of the observed trends, which can be extremely useful for future decision-making.

A detailed analysis of the resulting information is beyond the scope of this paper, which pays more attention to the methodological aspects of the survey.

4.1. Emission factor for pilot city

The value of the average emission factor of the mobile fleet used in this work is 205.47 g CO_2-eq/km. This value has been obtained from the database of the city's mobile park in 2017, the latest update of the vehicle fleet published by DGT (Dirección General de Tráfico, 2020). Unfortunately, there is currently no accessible information that allows to link a given road segment traffic intensity with the types of vehicles passing that road segment. Hence we used the average distribution of vehicle type categories for the whole city.

Regarding the change in the fleet distribution with time, although there is accessible information on an annual basis about registration and removal of vehicles, it was neither possible to determine the type of these vehicles, nor their emission technology, nor the fuel used. Thus, this source of information did not contribute to an improved accuracy of estimations. A basic sensitivity analysis was carried out to see how the EF would have been affected if all the updates had been in the highest and lowest emitting vehicle classes. The results showed no significant differences in average EF value, the one used in the pilot. For this reason, and given that the 2017 data are the most current, it was decided to use that year's fleet composition data for the four years studied (2016 to 2020).

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4.2. CO$_2$ emission results

The model based on the methodology object of this research allows us to obtain GHG emissions from urban road traffic on the measured sections in the pilot city of Valencia. We can disaggregate these values by type of vehicle (see Figure 5) or by fuel used (see Figure 6) for each of the measurement points in the city (see Figure 3). The figures show how emissions from passenger cars and diesel fuel stand out over the rest of the types of vehicles and fuels, with percentages of 62% and 81% respectively.
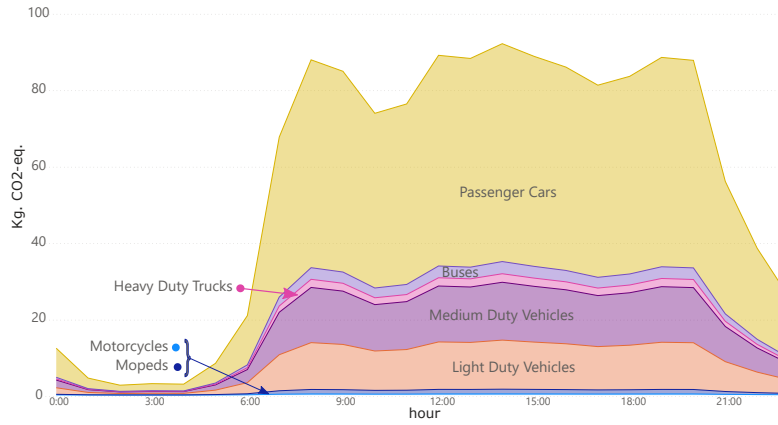
Figure 5: GHG emissions by type of vehicle in one measurement location.
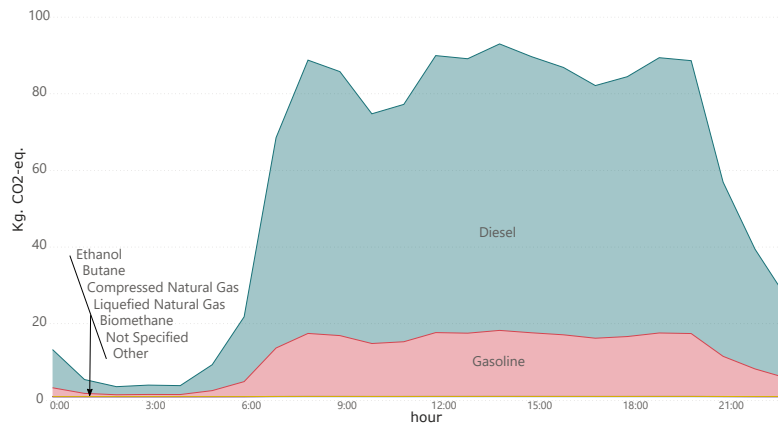
Figure 6: GHG emissions by type of fuel in one measurement location.

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After showing the resolution of the graphical representation of results, this section provides an analysis of the CO_2 emissions data that comes from the vehicle detectors available from 2016 to 2019. Bellow, the analysis is organised to observe the annual data following different criteria.

Firstly, Figure 7 shows how CO_2 emissions are influenced by year seasonality. So, they vary significantly throughout the months of the year (each curve represents one specific year). To facilitate the comparison, the time series on the horizontal axis is set from January to December uniformly, while in the vertical axis the daily average of tons of CO_2 equivalent is placed. As can be seen, the monthly changes in CO_2 emissions stay relatively constant throughout the years showing a common pattern.
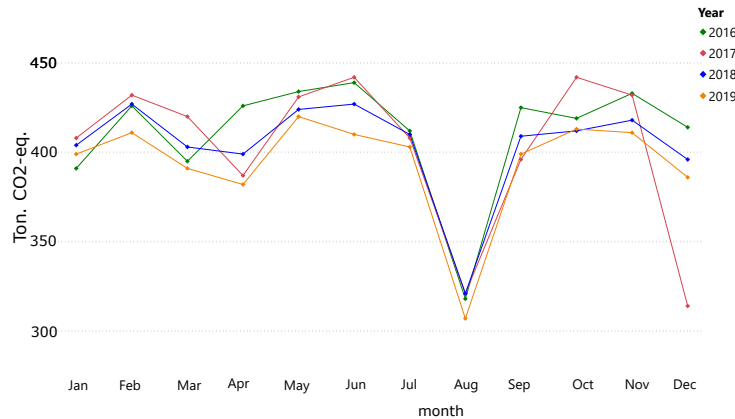
Figure 7: Average daily equivalent CO_2 emission per month for years 2016 to 2019

Figure 8 shows a comparison of average daily emissions during a week for each year. In order to have a better comparison, the time series on the horizontal axis is set from Monday to Sunday uniformly. In contrast, in the vertical axis, the average of tons of CO_2 equivalent is placed. To compare the difference between average emission on working days, weekends and holidays is essential to consider the working days from Monday to Friday; Saturday and Sunday are deemed weekends, and holidays are days off that fall on weekdays.
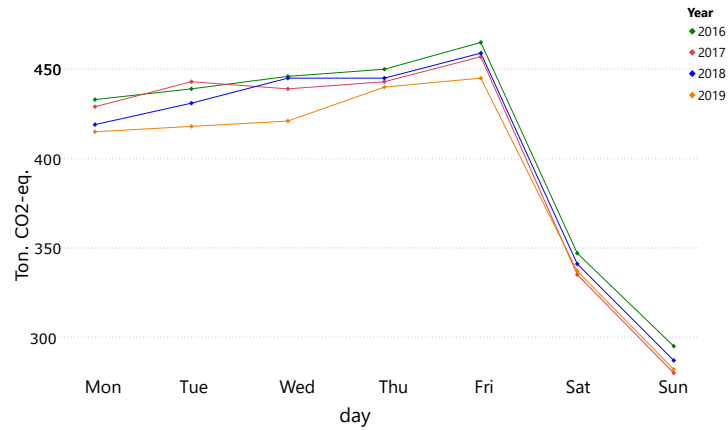
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Figure 8: Average daily equivalent CO_2 emission according to the weekday for years 2016 to 2019

As a general weekly trend, CO_2 emissions show a stable and regular increase throughout the workdays. The increased mobility towards the weekend houses may explain this increase in traffic towards Friday. Weekends, predictably, result in a substantial drop of CO_2 emissions, about 16% and 30% compared to the average of the workdays respectively. Trends and emission values are quite similar along the years allowing to establish patterns and draw conclusions that may be valuable for planning purposes.

A similar comparative can be done taking into account the labour characteristic of days. In Figure 9, the boxes represent the graphical representation of CO_2 emissions by different day types: workdays, weekends and holidays. Grey box plots indicate the range of values according to the percentiles and median for each type of day being very similar.
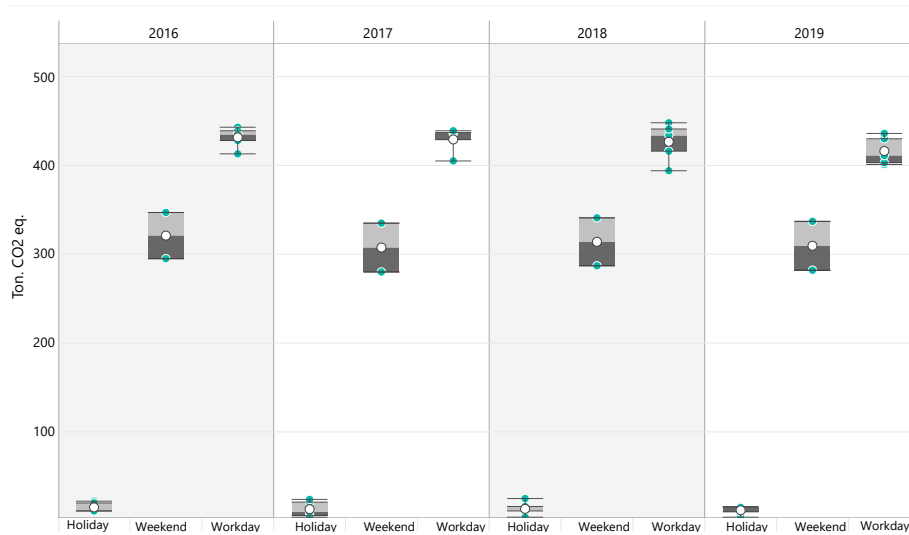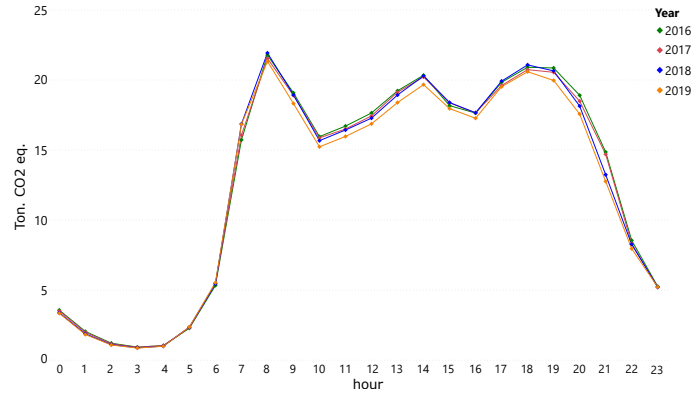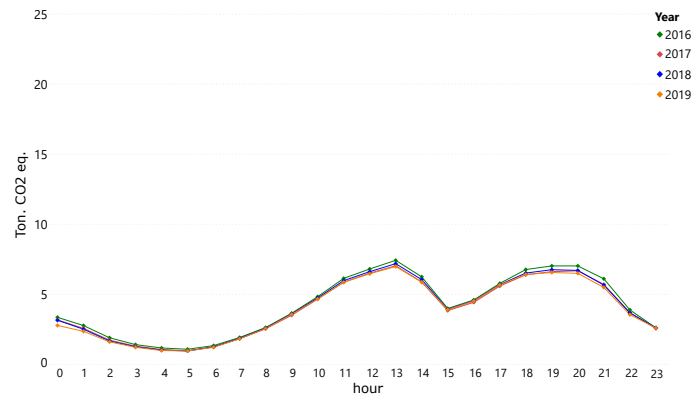
Figure 9: Average daily equivalent CO_2 emission comparison among workday, weekends and holidays

To compare average hourly emission in a day, Figure 10 shows 24 hours of an average day for each workday and non-workday in the horizontal axis. Each curve represents a year. The vertical axis presents the average of tons of CO_2 equivalent. Visual comparison of both plots in Figure 10 indicates that from 00:00 up to 4:59, CO_2 emissions are slighter higher on non-workdays than a working day, but from that moment the emissions are lower on non-workdays.

Figure 10: Average hourly equivalent CO_2 emission during (a) workdays and (b) non-workdays (weekends and holidays) for years 2016 to 2019

The previous results show timeline plots in different scales (monthly, weekly and hourly), but the described methodology also allows associating emission to more specific locations within the urban settings, i.e. to study emissions from a spatial perspective.

For a qualitative comparison between the different city areas, we provide a geographic map (see Figure 11 with the total amount of CO_2 emitted in 2016). In order to prevent all areas being associated with the same number of monitored road segments, the total CO_2 emissions were normalised with the total number

of kilometres sensorised within each of the areas $A_k, k = 1 \ldots 68$ in which the city was divided. This length is given by $L_{A_k} = \sum_{t;t \in A_k} l_t$.
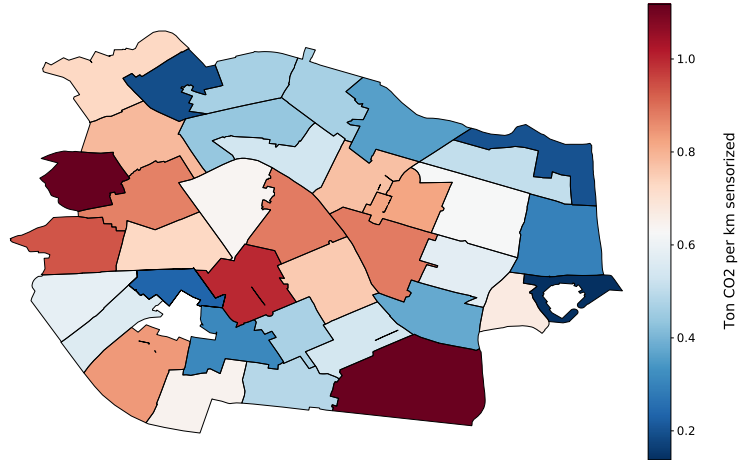

Figure 11: Total equivalent CO_2 per kilometre sensorised for the different zones of Valencia in 2016.

4.3. CO_2 emissions trend in Valencia

One of the difficulties to characterise the historical trend of CO_2 emissions in the studied period is the need to define stable criteria or references for enabling an accurate comparison. One possible perspective is shown in Figure 12, where the Cumulative Distribution Function (CDF) of daily emissions is compared on a year by year basis. This allows not only seeing quantitative trends in absolute emissions, but also if the distribution itself is changing. The CDF related to year 2019 is most of the times at left with respect to the rest being 2016 at the utmost right. This clearly outlines that 2019 emissions were lower specially in the range of days in which emissions are statistically higher.
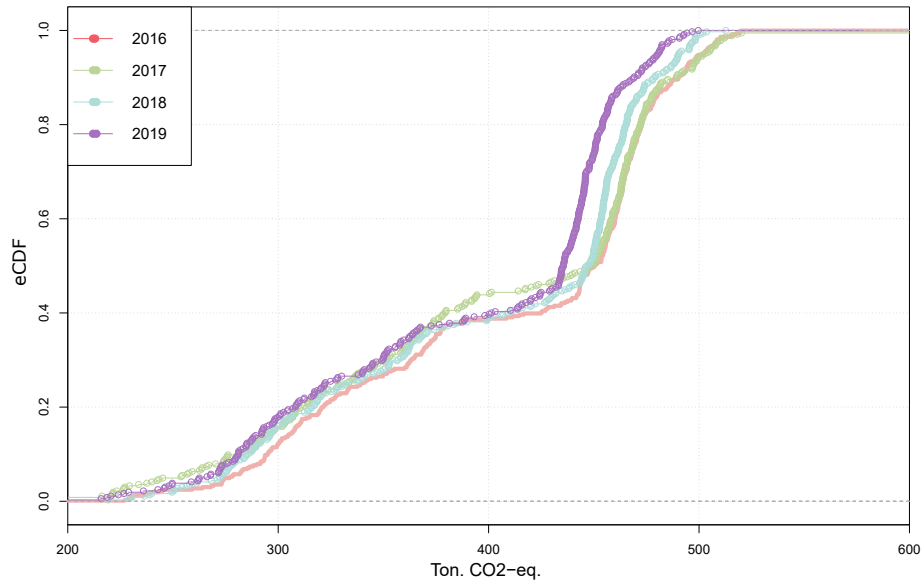
Figure 12: CDF plot for daily equivalent CO_2 emission for years 2016 to 2019.

In order to check the statistical significance of the outlined trends, a p-value table obtained by means of a Kolgomorov-Smirnov test (Marsaglia et al., 2003) applied to pairs of year checking for equality and order is shown in Table 4. The analysis points out that only in the case of pair 2016–2017, none of the ordering or equality hypotheses can be rejected. In any case, the hypothesis that emissions show a diminishing trend throughout the years is always associated with the highest p–value. For the rest of the year pairs, there is a pattern in the test: the years are not coming for same distribution (reject equal null-hypothesis with a p-value under 0.05), neither can be the more recent year considered to have a lower distribution than the less recent (reject less null-hypothesis with a p-value under 0.05). The conclusion is that there is evidence to suggest, from a statistic viewpoint, that emissions were at steep decline of 95%, as it has been previously argued.

Table 4: Results of Kolgomorov-Smirnov comparison tests for whole year emission

Compared pairs	Greather	Equal	Lower
a vs. b	$a > b$	$a = b$	$a < b$
2016 vs. 2017	0.872	0.497	0.253
2016 vs. 2018	0.976	0.001	0.001
2016 vs. 2019	0.993	3×10^{-13}	1×10^{-13}
2017 vs. 2018	0.299	0.013	0.006
2017 vs. 2019	0.453	2×10^{-11}	1×10^{-11}
2018 vs. 2019	1	7×10^{-8}	3×10^{-8}

This evolution, from a geographical perspective, is shown in Figure 13. The maps in the figure show the cumulative difference from base year 2016 (Figure 11 shows base year total emissions). The maps show small variation in most of the districts, on the scale red zone if it increases and on the blue if it decreases.
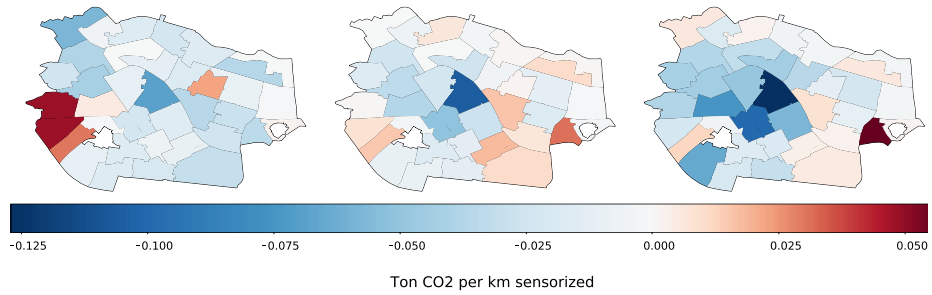

Figure 13: Progression of the total CO_2 per kilometre sensorised for the different zones of Valencia in 2017 (left), 2018 (centre) and 2019 (right), in comparison with the emissions in 2016.

5. Discussion

The developed methodology allows real–time monitoring of GHG emissions generated by road traffic in a city with traffic monitoring system, as is the case in the

pilot city. Therefore, it is possible to carry out continuous air pollution/quality assessments by city sectors due to the high spatial and temporal resolution of the developed model.

Focusing on CO_2 emissions, we are able to acquire an intensive knowledge on daily emissions with a high degree of hourly granularity, also with high accuracy as in our case, comparative studies can be carried out to determine the most influential factors in the amount of emissions (day of the week, time, etc.) and if these factors are maintained throughout years.

One of the most significant aspects to analyse is the daily emissions profile for each month of the year. The developed methodology and the obtained results shown in Figure 7 demonstrated how these annual profiles are qualitatively similar throughout the series studied between 2016 and 2019. Every year they show the same seasonality pattern as it is expected for the real traffic-related emissions. The most outstanding differences are found in those months in which a larger number of citizens enjoy their work holidays along with their children while they are having their school holidays:

- March: the local festivity in the pilot city of Valencia *Fallas* has a strong impact on the normal functioning of the city between 1st and 19th, and this is more intense from 14th to 19th.

- Eastern Holidays (March-April). Specific dates vary depending on each year's calendar.

- August: usual summer-holiday-month in the pilot city, which usually lasts from two to four weeks

- December: days 6th and 8th are national holidays. Christmas holidays, at schools from the 22nd until the 7th of January, are 24th, 25th and 31th the most crucial days

Similarly, the developed methodology and the obtained results allow also demonstrating a clear similarity of the weekly pattern between the different years, with

a significantly lower emission values on weekends (Figure 8).

By analysing the results, it becomes clear the difference between work and vacation patterns. This leads us to assume that there might be three categories: working days, weekends, and holidays. As a first step of a more exhaustive analysis, a graphic representation of the data has been carried out in Figure 9. The differences observed between these three types of days are stable throughout the years and are clearly identifiable in the graphs in Figure 10, where the trends between working days and non-working days can be demonstrated on a single scale.

After the descriptive analysis, the interpretation of Figure 10 (a) is in accordance with the school and work activity in the pilot city. The start time of these activities is between 7:00 A.M. and 9:00 A.M. , a period with increased emissions. The second peak that appears coincides with the end times of the working days and with lunchtime between 1:00 P.M. and 3:00 P.M. Finally, a third less pronounced peak corresponding to the departure from work and/or extracurricular activities between 6:00 P.M. and 8:00 P.M. is again observed, followed by a drop with the shops closing and the end of the working activities.

The pattern shown for non-working days in Figure 10 (b) differs significantly from Figure 10 (a): it is quantitatively smaller and has a less pronounced profile, showing only two increments and with smoother variations. A delay in the start of activity in the city as well as the influence of a possible leisure factor in the late afternoon can be also observed.

The spatial precision of the model allows to assign and represent qualitatively and quantitatively the emissions of the different areas segmented in the city. These results are shown in Figure 11 with data from 2016. There is a clear correlation between the areas that reach higher levels of contamination with city's main entry and exit routes.

Based on the year 2016, Figure 12 and Table 4 shows the comparison of CO_2 levels with the rest of the years in the time series studied, confirming a steady de-

cline in emissions starting from 2017 until the last analysed year (2019). Finally, the results shown in Figure 13 demonstrated the evolution of emissions spatially, showing the values for the different sectors of the city through the years. Specifically, a clear decrease can be observed in the city centre. One possible cause may be the actions on urban mobility launched by the local administration, such as the creation of new sections of bike lanes and the pedestrianisation of some streets. In the opposite direction, one of the main accesses to the city and the port activity area have increased their emission levels. It should be taken into account that all these observations must be viewed in the broader context of general economic activity indicators that, altogether, will offer a clearer picture about the influences and causes that are on the basis of the observed trends.

Our results are obtained from a hypothesis based on certain initial assumptions. Far from the necessary extrapolations carried out in top-down methodologies, our bottom-up methodology is based on actual traffic measurements within the pilot city and from a specific mobile fleet. In its present form, the developed network model uses the same formulation for all the monitored segments which results in a single average value of the emission factor of 205.47 $g\,CO_2$-eq./km. The application of the developed model allows to classifying hours, days and months based on their emissions' patterns, showing that the resulting picture is coherent with the real activity of the pilot city. However, for an absolute quantification of GHG emissions we assume that our procedure involves some uncertainty.

This methodology also intends to show polluted areas of the city on a timeline, showing how pollutant and GHG concentrations vary among neighbourhoods or districts.

In summary, applying the methodology developed to the data collected by the traffic management system of the pilot city, we have obtained a series of descriptive methods of analysis of this data, which should support to acquire advanced knowledge and comprehension what agents/variables (instants of time, places in the city, employment patterns, meteorology...) are significant in the traffic

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behavior and, therefore, in GHG emissions and other pollutants.

6. Conclusions and Future Work

Tackling climate change is a challenge for society and, therefore, for our cities. Road transport and mobility is a key element to mitigate climate change because it is responsible of more than 20% of total greenhouse gases (GHG) emissions in the EU. This value has been obtained from known and proven measuring processes based on top-down methodologies. Yet, top-down methodologies are not appropriate for local policy-makers due to their very low degree of spatial and temporal resolution.

We have designed, developed and applied a new bottom-up methodology that uses the data from traffic monitoring systems combined with the Vehicle Kilometres Travelled (VKT) methods recognised by the Intergovernmental Panel on Climate Change (IPCC), in order to improve the state-of-the art. IPCC VKT allows getting the factors relating emissions and the specific city mobile fleet. The developed and tested methodology defines how to combine those factors with the data from traffic monitoring systems in order to get GHG emission estimations with high spatial and temporal resolution.

In this research, we have applied the methodology to data from the pilot city. IPCC VKT data gives an average value of $205.47\,\mathrm{g}\,CO_2$-eq./km for the emission factor. This value has been applied to the data obtained throughout a period of four years from the control traffic system of Valencia.

The results obtained can be used in different scenarios. On one hand, as the spatial distribution of GHG emissions has a good resolution, it allows detecting emission hot-spots in the city or comparing the measures with citizenship perception for social evaluation. On the other hand, the temporal resolution allows detecting emission patterns that can be used to develop or modify the city policies and regulations.

The developed methodology and tools can be used by policy-makers to improve

planning and monitoring of climate and mobility policies in a quantitative, objective, and transparent manner. The possibilities of a close-in-time follow up of the effect of traffic related mitigation measures will in particular enable public stakeholders to detect the effects of their city policies in a virtually instant way. Policies enabling a bidirectional feedback between end-users and system managers will be subsequently possible in ways that could not be possible before.

There are still open issues for future research and technological developments. The first challenges we are currently addressing are how to enable a real–time connection between our algorithms and traffic control system. Furthermore, the analysis of data itself is still a pending issue. Third, as discussed in the above paragraphs, the methodology itself has room for improvement and validation in cities with lower degree of traffic sensor systems.

With the development and deployment of new technologies in traffic management (advanced induction-loop sensors, vehicle recognition cameras, etc.), it will be possible to track emissions even more accurately, individualising the category of vehicles circulating in each segment or even their kinematic parameters (velocity, acceleration and stops). Together with the large number of detection loops available, this will allow an accuracy not achieved so far in this type of studies and also to characterise uncertainties associated with the simplifying hypothesis made in our study about the absolute quantities of GHG gases released to the atmosphere.

The real time connection to traffic control system will reduce the time need for evaluating the impact of new regulations, improving the decision making process. Additionally, anomaly GHG emissions levels could be detected making easier their diagnosis.

The results obtained in the pilot city seem to show reductions of the GHG emission year after year from 2016 to 2019, but a deeper analysis of the data is needed to detect what have been the main drivers of these changes and their relative significance.

The application of the developed methodology to other cities and the analysis of the results would enlarge the base of experience in using our method and pave the way to a wider application to mitigate Climate Change.

Finally, our research group is integrating all the tools needed for the methodology with other tools developed to study the GHG emission at local level (building efficiency, renewable energy use and production, etc.) This integration will largely standardise, enable automatism and simplify the process of constructing the emissions inventories at city scale, which is a necessary step forward to mitigate GHG emissions based on solid and quantifiable policies.

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