

# GTFS2EMIS an R package to estimate public transport emissions based on GTFS data

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**Abstract.** The abstract goes here. It can also be on *multiple lines*.

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## 1 Introduction

Transport emissions have been widely recognized among the leading and growing contributors to global emissions (Caiazzo et al., 2013; Nocera et al., 2018, ). There is also scant evidence of how transportation activities impact air quality in cities (Landrigan et al., 2018), aggravating the negative short- and long-term effects pollution has on children premature deaths (Currie and Walker, 2009), cardiovascular diseases (Brook et al., 2010; Turner et al., 2016), ischemic stroke (Wellenius et al., 2012) and cognitive development (Chen et al., 2017; Fu et al., 2019; Shehab and Pope, 2019; Zhang et al., 2018). This has a higher impact in low and middle-income countries (Combes and Franchineau, 2019), especially in more vulnerable groups, such as elderly people (Yap et al., 2019) and children (Braga et al., 2001; Gauderman et al., 2015). Understanding the spatial and temporal patterns of emissions is a key factor to adopt more precise public policies to reduce air pollution exposure (Clark et al., 2014; Targino et al., 2018), improve the housing and land use planning, and subsidize public investments. Particularly with public transport policies, extensive efforts have been made to quantify air pollution patterns and to understand the impact of fleet technology, fuel, topography, and route choices on overall levels of air pollution (refs).

Most of the studies on public transportation emissions focus on emissions monitoring with remote sensing devices (refs), onboard diagnosis using PEMS (refs), vehicle counts data (refs), radar equipments (refs), public transport GPS data (refs), and fuel based estimates (top down approaches). However, due to a restriction of spatial application, or costly local data collection, some of these approaches might not be easy to scale for other cities. Other approaches, such as air quality analysis (refs), satellite data observations (refs) would represent the final state of air quality but ultimately do not look only at bus emissions. Studies that identify and map pollution in low and middle-income countries are still needed, particularly when easily reproduced.

Our analysis contributes to the public transport emission literature by developing a novel methodology that leverages a widespread open data format for public transport networks known as General Transit Feed Specification (GTFS) to estimate vehicle emissions in a high spatial and temporal resolution. The method is presented in a R package “gtfs2emis” to allow friendly and reproducible use for different applications. In this paper, we present estimates on CO<sub>2</sub>, NO<sub>x</sub>, PM<sub>10</sub>, CO, CH<sub>4</sub> hot exhaust emissions for 24 cities in the world, considering a typical business day on October 2019 — as a baseline date. A comparison of the vehicle emissions rates of those transport networks is also presented, along with a discussion on the versatility and limitations of the method.

The remainder of this paper is organized as follows. Section two presents a brief literature review on public transportation emissions. Section three describes the data and methods for the public transport data, emission factors databases and vehicle emissions estimates.. Section four presents the results, looking at the overall levels of pollutant emissions and its spatial and temporal resolution behavior. Finally, section five presents the final remarks and discusses some environmental insights that can be drawn from the package.

## 2 Methods

### 2.1 Transport model

#### 2.1.1 GTFS data

The method used in the paper leverages a global standard format for public transport data known as General Transit Feed Specification (GTFS). The GTFS data of a given public transport system is collected in a ZIP file, that brings detailed geolocated information on scheduled services including its stops, routes, trips, stop times and calendar organized in a structured text file.

This format was originally created in the mid-2000s by Google and Portland transport authority and it has since then become adopted worldwide by more than 600 cities (noa, b). The simplicity of this data format and its wide adoption creates a common ground for researchers and practitioners across the globe to develop and share computational methods that can be seamlessly deployed across multiple cities to manage fleet allocation, plan transport services, etc. Detailed aspects of the GTFS contents are found in (noa, c).

We expand the sample of cities with GTFS data collected directly from local transport authorities and from Transit Feed archives - the largest GTFS open data repository website. The GTFS data were pre-processed to filter by bus routes and to check consistencies on the required files (e.g. agency, stops, routes, trips, stop times). The months of October and November 2019 are used as the baseline date for the emissions estimates, in order to avoid possible differences in public transportation schedules due to the COVID-19 pandemic. A summary of the main GTFS information is described in Table 1, together with the fleet data.

## 2.2 GTFS2gps

The process to convert GTFS files to GPS-like spatial data points is done for every trip of the schedule. It interpolates the space-time position of each vehicle in each trip considering the network distance and average speed between stops. It samples the timestamp of each vehicle every 50m.

55 Once a GPS data format is generated from GTFS, a few adjustments on speed is made. Since the mean speed is estimated in a street link between two bus stops (e.g. stop “i” and “i+1”), the data on departure time of “i” and arrival time of “i+1” is necessary. If “i+1” arrival time is very close or the same as the departure time of “i”, the speed will be very high (>100 kph) or infinite. In such cases, we consider the speed to be the mean speed of all the trips in this specific bus route. Therefore, the departure times of the GPS are recalculated based on the new travelled speeds. This adjustment is also necessary in street links  
60 without valid arrival or departure times: before the first bus stop of the route (where only arrival time is available); after the last bus stop (only departure time is available); and trips with invalid stop times.

## 2.3 Emission model

### 2.3.1 Emission factors

Emission factors (EFs) are empirical functional relations between pollutant emissions and the activity that causes them (Franco  
65 et al., 2013). This study uses EF based on Environmental Sanitation Technology Company (CETESB) — for Brazil; California Air Resources Board (CARB) — for the California U.S; Motor Vehicle Emission Model (MOVES) for regions in U.S. outside California; European Environment Agency (EEA) — for European countries. Among these sources, EMFAC, MOVES and EMEP/EEA have speed-dependent emission factors. For the Brazilian cities’ estimates, the local EF is scaled to the EMEP/EEA function considering the average speed of the vehicle driving cycle. The brazilian emission factor is related to speed by the  
70 expression

$$EF_{i,j,k,l}^{scaled} = EF_{i,j,k,l}^{local} \frac{EF(V_i)_{j,k,l}}{EF(V_{dc})_{j,k,l}}. \quad (1)$$

where  $EF_{i,j,k,l}^{scaled}$  is the scaled emission factors for each street link  $i$ , bus type  $j$ , fuel  $k$ , age  $l$ ;  $EF_{i,j,k,l}^{local}$  is the local emission factor;  $EF(V_i)_{j,k,m}$  and  $EF(V_{dc})_{j,k,l}$  is the EEA emission factor at the speed of  $V_i$ ; and the driving cycle  $V_{dc}$  of FTP-25 (33 kph).

75 The CARB’s (California Air Resources Board) EMFAC (EMission FACtor) model estimates statewide and regional emissions inventory by multiplying emissions rates with vehicle activity data. The running exhaust emission factors are distributed according to speed bins from 5 to 90, with 5 mph incremental. It allows modeling one season (summer, winter or annual average) due to temporal variations of EF due to meteorological conditions (temperature and relative humidity); and geographic area (Statewide, Air Basin, Air District, Metropolitan Planning Organization, Country and Sub-Area). Detailed data  
80 on emission factors are found in noa (a).

**Table 1.** Emission factor sources, related bus categories and variables associated.

Source	Buses categories	Variables
CETESB	Micro, Standard, Articulated	Age, Fuel, EURO stage
EMFAC model	Urban Buses	Age, Fuel
EMEP/EEA	Micro, Standard, Articulated	Fuel, EURO stage, technology, load, slope
MOVES U.S EPA	Urban Buses	Age, Fuel

Table footnotes

**Table 2.** Association between model year, PROCONVE Norm and EURO stage for the brazilian fleet (adapted from ICCT).

PROCONVE Norm	EURO equivalent	Year range
P4	II	1998 - 2003
P5	III	2004 - 2011
P8	V	2012 - 2019

Table footnotes

European exhaust emission factors are presented in the EMEP/EEA air pollutant inventory guidebook, considering the COPERT 5.4 Software version. This study considered average load on all trips and zero slope rate for all studied cities. Urban Buses are presented in three main categories, which are Urban Buses Midi ( $\leq 15$  t), Standard (15 - 18 t), Articulated ( $>18$  t), Urban Diesel Buses Hybrid, CNG (Compressed Natural Gas) Buses. The speed dependent emissions factors for diesel urban buses have been taken from HBEFA (Handbook Emission Factors for Road Transport), for Euro I to Euro VI emissions standards. Distinct parameters of EF were considered for Euro V standard, according to the control technology, that can be Exhaust Gas Recirculation — EGR or Selective Catalytic Reduction — SCR. According to EMEP/EEA, it is estimated that 75% of Euro V heavy-duty vehicles are equipped with SCR. For the category of CNG buses, it has an additional emission standard known as Enhanced Environmental Vehicles (EEV), since it may have different combustion, after-treatment technology, and are associated with lower PM and NOx emission rates compared with diesel buses (add source). Only older CNG buses are classified in EURO I, II, or III. Detailed aspects of hot exhaust emissions rates of Europe are found in the EMEP/EEA guidebook.

**2.3.2 Emission estimates**

The estimates of hot exhaust emissions for each trip is given by

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$$EH_{i,j,k,l} = L_i \times EF_{i,j,k,l}$$

(2)

**Table 3.** Summary of all vehicle classes covered by the Tier 2 methodology

Urban bus category	Euro Stage
Urban CNG buses	Euro I, Euro II, Euro III, EEV
Urban buses	Conventional, Euro I - Euro VI
Urban Diesel Hybrid	Euro VI
Urban biodiesel buses	Conventional, Euro I - Euro VI

Table footnotes

where  $EH_{i,j,k,l}$  is the emission for the street link  $i$ , vehicle category  $j$ , fuel  $k$  and age  $l$ ;  $L_i$  is the length of the street link  $i$ (km);  $EF_{i,j,k,l}$  is the emission factor (g/km). In order to evaluate emissions spatially, the overall emissions are allocated into a 350m resolution grid (H3 resolution from Uber).

**2.3.3 Emission post-processing**

100 Subsubsection text here.

**3 Estimate Curitiba’s emissions using GTFS2emis model**

**3.1 Traffic data for Curitiba**

**3.2 Emission factors**

**3.3 Emission estimates**

105 **4 Discussions and Conclusions**

*Code and data availability.* use this to add a statement when having data sets and software code available

*Sample availability.* use this section when having geoscientific samples available

*Video supplement.* use this section when having video supplements available

## Appendix A: Figures and tables in appendices

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120 *Author contributions.* Daniel wrote the package. Josiah thought about pottery. Markus filled in for a second author.

*Competing interests.* The authors declare no competing interests.

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*Acknowledgements.* Thanks to the rticles contributors!

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